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Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting

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ABSTRACT

The electric grid is changing. With the smart grid the demand response (DR) programs will hopefully make the grid more resilient and cost efficient. However, a scheme where consumers can directly participate in demand management requires new efforts for forecasting the electric loads of individual consumers. In this paper we try to find answers to two main questions for forecasting loads for individual consumers: First, can current short term load forecasting (STLF) models work efficiently for forecasting individual households? Second, do the anthropologic and structural variables enhance the forecasting accuracy of individual consumer loads? Our analysis show that a single multi-dimensional model forecasting for all houses using anthropologic and structural data variables is more efficient than a forecast based on traditional global measures. We have provided an extensive empirical evidence to support our claims.

1. Introduction

The electric grid is going through a major change. Smart grid initiatives around the world are pushing the grid into a more robust, dynamic and open system which will bring consumers and their devices directly into the management realm of the grid. This integration of IT provides a great opportunity for improving and enhancing DSM and DR programs. Such programs can be improved with intelligence, pervasive device management or renewable integration for increased throughput. Various DSM planning strategies have been proposed for smart grids but to implement such planning methods the knowledge of the amount of energy demand at house level is a must. This requires a short term load forecast for houses, and in some cases even devices. To this end in this paper we propose two unique concepts for short term load forecasting of houses through which accuracy for forecasting loads of houses can increase by as much as 50%. This provides an important cog in our proposed smart grid architecture for demand side management discussed in Appendix A.

Forecasting for larger loads such as city or the entire grid has been achieved with relatively high accuracy [1]. But for smaller populations such as a building, or a micro-grid the dynamics change so drastically that standard STLF tools require certain re-adjustments [4]. For even smaller consumer group, such as individual houses, the volatility in dynamics is even more pronounced as can be seen from discussion in Section 2. To forecast for such system we need to look at the STLF modeling, tools, and data. There are two pertinent questions to engineer these re-adjustments for STLF for individual houses in a system that we answer in this paper. First is that can we forecast energy load using the existing short term load forecasting model? Second question is that is the knowledge used for existing forecasting models sufficient?

Kim and Shcherbakova point out at the lack of data about user as one of the major reason failure for DSM and DR programs [20]. But our initial results showed that simple correlation between house load and house characteristics is weak as shown in Fig. 1. The strongest influence on demand is weather. This was observed on anthropologic and structural data collected from 205 houses in Eskistuna, Sweden. However, we observed a subtle relationship between user characteristics and consumption.

Our contributions use this subtle relationship between house statistics and consumption. The relationship between energy use and occupant and building characteristic is such that on a single house level it is insignificant. This can be observed from results

Abbreviations: STLF, short term load forecasting; STMLF, short term multiple loads forecasting; ANNs, artificial neural networks; DR, demand response; MSE, mean squared error; MLR, multiple linear regression; SVM, support vector machines; AMR, automatic meter reading; Cid, consumer id; AI, artificial intelligence; ARIMA, autoregressive integrated moving average; GARCH, generalized autoregressive conditional heteroske dasticity; Var, variance; Acc, accuracy.

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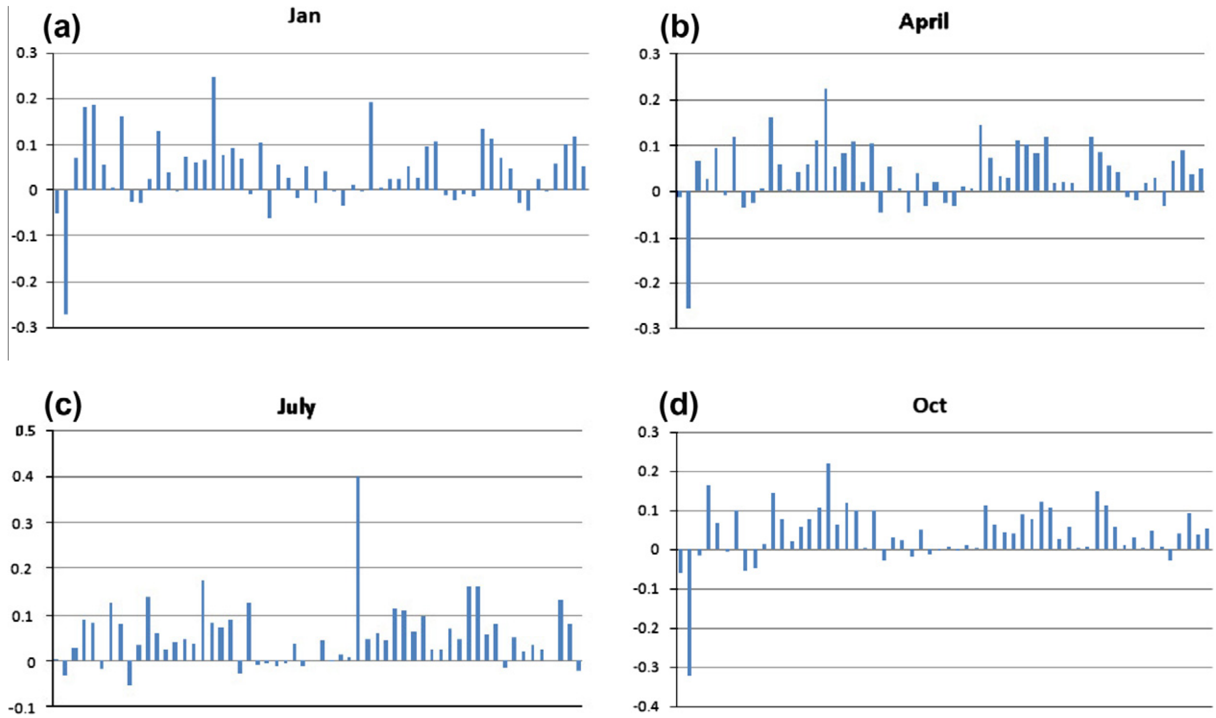

Fig. 1. Correlation of anthropologic and structural variables with house loads for the four test months ((a) January, (b) April, (c) July and (d) October). The most consistent correlation is with attribute 2 (temperature). The highest correlation of 0.39 is with attribute for the month of July. This attribute represents answer to the question translated to "Do you heat your pool?".

Table 1
Forecast accuracy for six commonly used forecasting methods and our proposed method for a week in month of January. Columns 1–4 represent results using only time series and global parameters. Columns 5 and 6 are forecast accuracy using richer data set. Column 7 shows accuracy of our proposed system.

GARCH (%)	Exponential smoothing (%)	MLR (%)	ANN (%)	MLR (with rich data) (%)	ANN (%)	Proposed STMLF method (%)
47	31	49.1	38	49.2	36	60

of MLR and ANN forecast using richer data as shown in Table 1. The increase in accuracy is marginal. But across the population the impact can be identified and quantified for forecasting. To effectively use this impact we build a single succinct model for all the houses. That is we provide to a single ANN trainer time series data for all the houses. Each training example contains the date, time, consumption load and the anthropologic and structural data of that load. Since we provide data for all the houses, data points with similar characteristics re-enforce trends for a more crisp model resulting in a more stable and accurate forecast.

To illustrate how this work let us take example of two houses, one with school going occupants and the other without such occupants. The bulk of energy consumption in both cases will be driven by weather pattern. The colder it is the more energy will be used. But for houses with school going occupants, the energy usage in the early hours of weekdays will be different than the others. Furthermore, This will be common in all the houses with school going children.

The idea is that we train a single multi-dimensional model using the data from all the houses. This on its own will mean that the forecast will be average load for each hour for all the houses. This is where our second contribution comes in. We augment this single model by adding the anthropologic and structural data to the model. This additional information allows certain modelers to make sub-groups within the model for particular anthropologic and structural population groups. In our example if the modeler is able to identify the relationship of a house having school going occupants with extra energy consumption in earlier hours on weekdays then this will allow the model to add a premium to consumption over what the weather pattern will forecast. Since all houses with school going children will have similar trends, if a single house has a different trend for a short period of time, for instance because child being sick and missing school, then a global modeler will not over-fit the model and still forecast accurately when the local temporal phenomenon expires. Note that an exponentially high number of sub-classes exist for the population but a combined model adds and subtracts premiums over the base forecast to derive a more crisp load for each house.

This modeling method is inherently different from modeling for each house independently (STLF). It is also different from modeling for all the houses without the anthropologic and structural data. We would like to stress here that the forecasting engine (ANN) is not part of the contribution. The contribution is the new modeling paradigm – short term MULTIPLE load forecasting (STMLF) and the use of anthropologic and structural data within STMLF. As we will show this combination increases forecast efficiency for both AI based and statistical forecasters. To stress on the improvement of forecast based on our contribution and avoid engine specific enhancements we use the simplest of statistical and AI forecasters.

2. Problem description: issues in house level forecasting

The future DSM and DR techniques of smart grids will have a fine grained control of the end-user loads. This control will requires a reliable forecast for house loads. There are two options for

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Table 2
Comparison of volatility measure of individual loads, microgrid loads and standard grid loads.

System	Individual loads (University of Calgary)	Micro-grid power system	Alberta's	Ontario's power system
Standard deviation of rate of change	0.82	3.83×10^{-2}	1.84×10^{-2}	2.69×10^{-2}

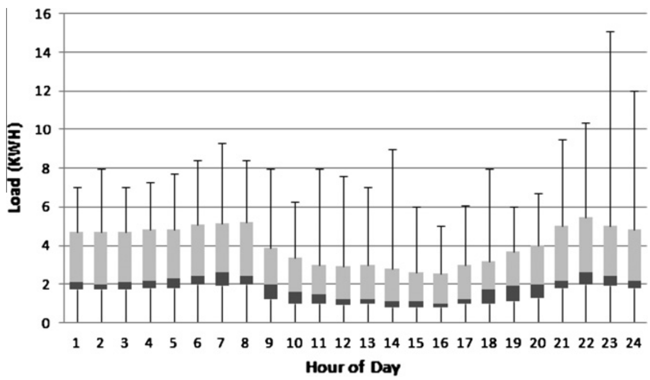

Fig. 2. Box and whisker plot for consumers load over a 24 h period of 204 houses from Eskistuna, Sweden. Whiskers point the maximum load for the hour upper and lower box edges are 25th and 75th quartiles respectively and the line in box is the median. On *X* axis is time at intervals of 1 h and *Y* axis is load in kW h.

forecasting. One is to forecast individual house loads independently and second is to aggregate the loads and construct a single forecasting model.

But forecasting for smaller populations is a much difficult task since in larger populations, smaller loads tend to attenuate or neutralize to produce a stable time-series. But for a single house load, the system volatility is so extreme that forecasting becomes difficult. As shown in Table 2 volatility is two orders of magnitude larger than the volatility of a region and micro-grids. This high volatility resulted in less than ordinary forecasting for standard tools used for large scale forecasting as well as for those used for micro-grid load forecasting as shown in Table 1. Here we forecasted energy load for each house using four commonly used forecasting techniques. GARCH [5] is a commonly used time series analysis technique, exponential smoothing and multiple linear regression (MLR) [7] are statistical methods. Whereas GARCH and exponential smoothing forecast based on time-series alone, MLR attempts to model the relationship between multiple explanatory variables and a response variable. This makes MLR and artificial neural network, an artificial intelligence based technique, candidates for forecasting with richer data. As can be seen, none of the forecasters could attain accuracy of more than 50%.

Irrespective of accuracy results an important consideration for modeling this system is the scalability of the proposed technique. Since a forecast is needed for each house, this means that for each house we will need to invest processing power. As we will shown in Section 3 this makes the system unscalable for large populations. To make this system applicable for smart grids, a more succinct and robust model is required which $STMLF_2$ is able to provide.

On the other hand, using the existing methods and data, Forecasting for aggregated load is not feasible since within a population, different houses have different loads. This is evident from the box and whisker plot in Fig. 2 for a 24 h period for load data of a single day of 204 houses from Eskistuna, Sweden. The whiskers show the maximal 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 middle the median). If we construct a model using only global phenomenons then irrespective of forecasting engine, there is no way to differentiate between loads which are close to mean and which are not. This causes an accuracy drop and increase in mean square error (MSE).

However, it is argued that since the load forecasting tools so far needed forecast for entire population, data which effected the entire population equally was sufficient to model the total load. But since each house has its own characteristics, it is worthwhile to consider characteristics of a house for forecasting energy load.

There are two types of data variables which affects the load consumption: anthropologic aspects and structural variants.

Anthropologic	Structural	Pseudo-anthropologic
How many people live on property for most of the year? How many children on property a. aged 0 - 12 years b. aged 13-19 years	What type of property is the house? (flat, exposed house) How many floors of property?	What is the average indoor temperature in the building during the winter? List of household appliances used on the property
Did number of children change a. aged 0 - 12 years b. aged 13-19 years	What type of walls has the property?	Is any form of energy-consuming hobby or business in the property?
To what extent the household members usually reside in the home during the weekdays? Number of adults who usually reside in the property at different times of day? (morning, evening, night) Number of children who usually reside in the property at different times of day? (morning, evening, night)	Which of the energy-saving installations exist in the property? (Insulations etc.) Which of the following ventilation systems has the property? How much living space has the property? How many ancillary rooms has the property?	Has the property been uninhabited for a long period since January 1, 2002? What year was the property built? Total annual consumption: number and unit (e.g. kWh, m3 oil, m3 firewood, etc.)
	Are there ancillary rooms with heated spaces (minimum 10 ° C) in connection with the dwelling?	energy for heating and hot water: number and unit
	What is the building's wall thickness?	
	What kind of basement has the property?	
	Does the building has electric water heaters?	

Fig. 3. Classification of survey questions. We classified questions as anthropologic (human centric), or structural (building specific) and pseudo-anthropologic which are occupants impact or usage of structural facilities.

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Anthropologic aspects are occupant characteristics such as number of occupants and age while structural variants capture the physical characteristics of the house. To construct a forecasting model which can differentiate between consumers we conducted a survey consisting of both anthropologic and structural questions. The details of the survey are provided in Fig. 3.

This questionnaire combines a mixture of anthropologic (Column 1) and structural (Column 2) questions and pseudo-anthropologic (Column 3) questions. These questions are aimed at capturing a variety of information that ranges from the ages of occupants and their general behavior of occupation to the type of walls, heating equipment, covered area of property, etc.

However, this data in the existing STLF modeling method does not produce any better forecast than the statistical methods. Columns 4–5 of Table 1 shows results of STLF techniques which can incorporate higher order data for forecasting energy loads. Here, statistical technique (MLR) and standard AI technique (ANN) are used for this forecasting. But it can be observed that merely adding more data to the existing STLF model does not result in improvement in forecast accuracy.

3. STMLF model

The need for STMLF is born out of the inherent short comings of existing short term load forecasting models when forecasting for household loads. These short-comings stem from the fact that till recently, the control of energy in grid did not provide a detailed control of the demand side. The demand side, although made up of individual loads with their own profiles, was considered as a single large chunk. Some researchers acknowledged this diversity of patterns in load data but they only used the sub-pattern to forecast the total load of the system and were less concerned with forecasting individual loads. For example, [28,23] leveraged this fact by identifying these patterns through wavelet transform and forecasted the more crisp sub-patterns rather than a complex combined pattern. These sub-patterns were then combined to form a single forecast for the entire system. The break-down of the wavelet in [23] was also to a degree where it was needed for large system forecast and not to forecast independent components of the load.

However for our proposed ADSM (Appendix A) in micro-grids the need is no longer for an aggregation of all loads, rather our interest is to find the individual load value for each house for DSM. But the existing methods which are used for STLF are explicitly limited to single time series. There are two options, either we use existing STLF for each house or we appropriately transform the STLF model to work for forecasting multiple loads. As shown in the previous section, STLF for single loads has low accuracy for such forecasting. We found that transforming STLF to a succinct multi-load model not only increase efficiency of running time but also increase the accuracy of forecast as well. To understand this transformation we will first define STLF as an abstract system and then use this abstract model to explain the transformations to realize the multi-load model we call STMLF.

3.1. STLF operations

To understand the working of STLF and reason about the need for STMLF, we will first diverge for a brief discussion on STLF's working at an abstract level. STLF is usually a two step process. First an STLF modeler builds a model based on the time-series of consumption. This time-series in most cases is complemented by other environmental variants which effect energy load. These may include temperature, time of day, season, day of week, etc. In addition each model requires some tuning parameters and constants such as weights for algorithms which are specific to the algorithm and the input data. These are the invariants, or variable which do not change over time.

Formally we can say that STLF modeler is a function given by:

$$\mathrm{STLF}(T_{(1..j,0..t-1)}, P_{0..t-1}, E) = M \tag{1}$$

where $T_{(1..j,0..t-1)}$ is the time-series for j environmental variants such as temperature, wind, and solar radiance, $P_{0..t-1}$ is the historical time series data of load and E are the local invariants and tuning parameters such as weights given to parameters.

For most forecasting engines the input is usually streamed as series of tuples of data. Each tuple is made of $j + 1 + |E|$ values, j values for j environment variables, 1 value for the load and $|E|$ values for the number of invariants. For example, for fifth time quantum there will be four tuples representing readings from first four time quanta and so on.

Based on this input STLF creates a model M. M can be simulated such that effects of environment variants $T_{(1..j,t)}$, and invariants E for a specific time t over this model produce load P_t. That is:

$$\mathrm{simulate}(M, t, T_{(1..j,t-1)}, E) = P_t \tag{2}$$

Here P_t is the forecast for the system for time $T = 1$. The modeler usually associate the variants with specific load values. This creates a model of the system to be forecasted. When a new forecast is required the model is simulated by providing it with variant and invariant data for forecasting period and model simulation produces the load value which is associated with the input data.

3.2. STLF for independent house forecast

STLF forecasts are for a single system. To forecast for a number of houses, this translates to having an STLF modeler and simulator for each house. For such, following the general convention of STLF, the input to each modeler will be series of t tuples where t is the length of training period. Each tuple will contain the environment variable value, the load of the house and invariants for the modeler. There are two problems with this method of forecasting which we have discussed briefly before and will delve in more detail here.

First, such a large number of modelers will require large computational resources. Either each house will require computing resources to store data of the house and run a computationally complex model for every forecast or the utility will require numerous computing resources to achieve this goal.

Secondly, as we have pointed out in the previous section, the load curve of a house is order of magnitude more volatile than any other system that STLF has been applied on. There are further two issues with modeling such volatile systems. First, sufficient data attributes should be there to discriminate the root causes of volatility and second sufficient data should be provided to avoid over-fitting. Over-fitting is the phenomenon when a forecaster captures outliers, or out of ordinary incidences and considers them part of the normal operations, thus increasing the error of forecast. First issue is related to the number of attributes of data and second issue is related to number of good examples for each attribute combination.

Application of STLFs over house loads with existing data suffer from both of these problems. As we will show in our experiments the existing global variants are insufficient to discriminate house loads. This is because the house data is too volatile and the environmental variants of system are insufficient to associate a load value to the input. This is evident from our evaluation results later which show STLFs as ineffective in forecast loads of houses.

To illustrate this point further let us take the example discussed in Section 1. If each house has its own forecast then the model will have insufficient data to avoid over-fitting. Even increasing the training window will not have much effect. Secondly, we do not gain any information from cross cutting patterns in the society since each model is independent of other houses. If we move this STLF to neighborhood level then we will have sufficient data to avoid over fitting but this model will not be able to capture the differences in load variations since it does not have the discriminating attribute to capture the volatility of sub-systems. Input vector to this modeler will be the total (or average) load value, global variants and system invariants. The result will be a forecast for average load of all the houses. This will be an inaccurate forecast for both the house with school-going children and for those who do not have this peculiar characteristic. Thus we need a forecast which has considerable size of data to avoid over-fitting and sufficient attributes to differentiate between different load patterns.

3.3. STMLF$_1$

To ameliorate this problem we propose STMLF, a modeling framework for combining multiple time-series. We propose two paradigm shifts from STLF for this model.

First, instead of creating load model from a single time-series, we use all the available time-series as training data. This is different from sum of loads where all the loads are summed and STLF forecasts the sum (or average) of loads. Rather each load and its attributes are passed to the modeler as a tuple. That is instead of providing one value for each time-period, we provide n tuples for each time-period. Here n is the number of houses. This resolves the issue of over-fitting since sufficiently diverse data smooths the out of ordinary events.

But just combining time-series in a single system is not sufficient. As we have discussed above, we need to provide discriminating attribute for the modeler to associate the learning output value with the input values.

Our first attempt was to use houseIds as the discriminating attribute. Such a model can be expressed as:

$$\mathrm{STMLF}_1(T_{(1..j,0..t-1)}, P_{1_{(0..t-1)}}, .., P_{n_{(0..t-1)}}, E, \mathrm{houseId}) = \mathbb{M}_1 \tag{3}$$

Here T and E are same as in single load forecasting but for each load i a time series P_i is also considered.

The resultant model $\mathbb{M}$ can be simulated to map time t, environmental variants T, invariants E, and the index of load i to predicted load for $P_{(i,t)}$. That is:

$$\mathrm{simulate}(\mathbb{M}_1, t, T_{(1..j,t)}, E, \mathrm{houseId}) = P_{i,t} \tag{4}$$

In this model an input tuple in addition to load value, environmental variants and system invariants also contains the houseId flag. For house number x the xth flag is set as one and the rest as zeros.

This scheme has two drawbacks. First houseId is too vague for the modeler to associate load patterns with. We will show this in the discussion of results where it is evident that most of the forecasts of STMLF$_1$ are in a narrow band of values. Second, this scheme is computationally complex and not scalable as we will discuss later in this section. A graphical representation of STMLF using houseId as discriminants in a neural network is shown in Fig. 4b.

3.4. STMLF$_2$

Instead of this complex and inaccurate model, our second paradigm shift is to consider richer data for forecast. This richer data incorporates the anthropologic and structural data discussed in Section 2. This resolves both the problems we faced in using independent STLFs and in using a combined model using houseIds.

In this methodology, the modeler is provided with the local invariants in addition to the global variants to construct its model. An input tuple for STMLF$_2$ consists of the j environment variants, the load data for the house, the system invariants and in addition local invariants of the house which correspond to the load P.

STMLF$_2$ considering this richer data is expressed as following:

$$\mathrm{STMLF}_2\left(T_{(1..j,0..t-1)}, P_{(1..n,0..t-1)}, E, E'_{(1..n,1..k)}\right) = \mathbb{M}_2 \tag{5}$$

Here $E'_{(1..i,1..k)}$ are the invariants of house to the load time series. A forecasting engine will create a model which will associate T, P, and E' with the outout. Simulating this model is a bit different. Instead of providing the house flag, the invariants of houses with $E'_{1..m}$ values are used, in addition to t and T, to construct a forecast for all the houses with $E'_{1..m}$ characteristics.

$$\mathrm{simulate}\left(\mathbb{M}_2, t, T_{(1..j,t)}, E'_{(1..m)}, E\right) = P_{(1..m,t)} \tag{6}$$

We will first discuss its graphical representation in neural network model and then discuss why it is better than STLF and STMLF$_1$. A graphical representation of STMLF using richer data as discriminants in a neural network is shown in Fig. 4c. Each training record of our model is a tuple consisting of global variants (hour of day, day of week, temperature, etc.), house variants (number of occupants, number of school going children, wall types, etc.), and load value for that houseId under the variants. Each input attribute corresponds to a neuron of first layer. The trainer associates weights with each neuron.

In this model different input parameters or their combinations are assigned according to the training data. Temperature and time of day may have higher weights but statistics such as number of children will add their weight to the output as well. This weight can be positive or negative and modulates the temperature driven load on the basis of local characteristics.

To explain this further let us consider the example we discussed above. In such a case, when input for number of school going children is positive and time and date is early in the morning and weekday then the internal node connected with these input neurons will add positive weight to the output. So for all the houses with these characteristics, in addition to the load forecasted due to weather conditions, an additional load will be added. In comparison, houses with no school going children will only be affected with weather conditions. We add another twist to this example. For the houses with senior citizens, the consumption may be low early in the morning but will be high around 10 am. For the houses which contains senior citizens, a load will be added to the base load at 10 am. For those with school going children, the addition will be for 7 am. But if a house has both then it will borrow from both models and will register specific consumption patterns for both 7 am and 10 am. in this way we can potentially construct a model from a subset of houses and use this model to forecast houses with similar trends and traits for forecasting.

3.5. Model complexity

We have discussed three models. First is an STLF for each house, second is the STMLF using houseId as discriminant and last is STMLF with house attributes as discriminant. Complexity of a modeler is generally expressed in terms of the extra time system will take with addition of input parameters. Traditionally O() (big oh) analysis considers the worst time, that is the most time that algorithm can ever take and is taken as the academic and industrial standard in computational sciences. Here we would like to clarify that $O(1)$ does not mean a small execution time. Rather it means that as we increase the number of houses, the expected worst time of completion of algorithm remains unchanged for a single mod-

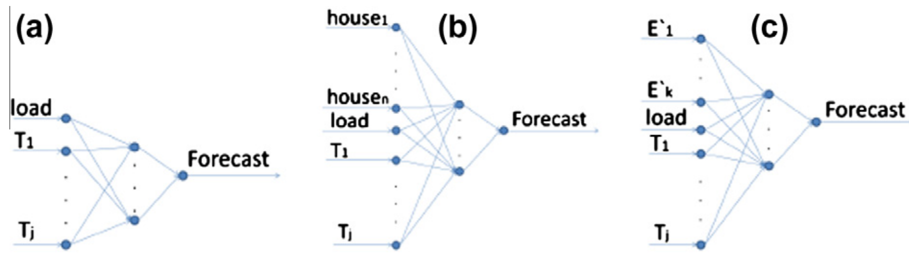

Fig. 4. ANN models for three forecasters. (a) Is ANN model is for a single house where only load and global invariants are provided for forecast. (b) Is the ANN model for $STMLF_1$. (c) Is the ANN model for $STMLF_2$

eler. Scalable modeler is one which is at the most some polynomial function of input variables since power series or exponential series are intractable for large data sets. Without loss of generality we can assume the complexity, or efficiency, of a modeler as $O(x^\gamma)$ where x is the number of input parameters and γ is modeler efficiency. In other words, $O(x^\gamma)$ is the order of the time in which the modeler is able to make a model of a system with γ input parameters.

Considering the complexity of our modeler, STLF for each house will have the complexity of:

$$O_{STLF} = n \times O(j^\gamma) = O(n) \times O(j^\gamma)$$

That is, we will have n STLFs and for each STLF we will require $O(j^\gamma)$ computations. Here j are the number of environment variables.

Since j is not dependent on the number of houses, E^γ is a constant for a system with fixed E and γ thus $O(E^\gamma) = O(1)$:

$$O_{STLF} = O(n) \times O(1) = O(n)$$

In comparison $STMLF_1$ with houseId as discriminant will have

$$O_{stmlf_1} = O((j+n)^\gamma)) = O(j^\gamma + n^\gamma) = O(1) + O(n^\gamma)$$

Here the number of input parameters are j environment variables and n houseId flags. Although we require only one algorithm but since houseId flags increase with time the complexity of the system is worst than STLF as long as *gama* > 1.

The third model is STMLF with k house attributes used to model the load. The worst case analysis for this model is:

$$O_{stmlf_2} = O((j \times k)^\gamma)$$

That is the forecasting engine's time increases with increase in number of house parameters and environment variants but the number of houses do not effect the running time of the algorithm. Since both k and E are constant for a system:

$$O_{stmlf_2} = O((j \times k)^\gamma)$$

This means that this model is not affected by number of houses in the system. As can be seen from the ANN illustration in Fig. 4, STMLF modeler builds a model using the k attributes. If we increase the number of houses, the modeler will still have only k parameters to learn. On the other hand if we have only one house even then the modeler will have k attributes to learn. This means that the modeler will have similar complexity of learning irrespective of the number of houses.

4. Experimental setup

This section discusses the experimental setup for our experiment. First our forecasting engine is described followed by the measures used to assess the effects of STMLF and richer data for forecasting. We will then discuss anthropologic and structural data that was collected for this experiment.

4.1. Forecasting engine

We discuss in Appendix B in detail the issues with existing forecasting methods for forecasting in a multivariate environment. The issue is with building a multidimensional model in higher dimensions. Secondly, our focus in this paper is to show the efficacy of our modeling paradigm and effects of richer data on forecast. For this reason we select the two base forecasting algorithms which are used for forecasting namely regression and neural networks. It is easy to see that since most of the state of the art forecasting engines are extensions of these two basic engines a proof of increased on the archetypical engine implies effectiveness of STMLF with richer data for the enhancements as well. For neural networks we use the basic resilient back propagation algorithm of ANN proposed by Riedmiller and Braun [27].

The forecasting engine is constructed in Matlab. A three layered back propagation neural network is trained on three weeks of data. ANN consists of three layers, input layer consisting of 60 neurons representing the input in layer 1(L1). Second layer (L2) consists of 20 neurons. The output layer only consists of single neuron representing the forecast. The trained model is used to forecast the power load for each hour for the next day.

4.2. Measurements

Measuring success for multiple individual forecasts is more involved than measuring success of a single system. There are three measures that are usually used for such systems. (1) precision, (2) accuracy and (3) stability or certainty. These measurements are more appropriate when measuring forecasts for multiple objects. Traditional measures such as percentage error and even MSE is not considered the most appropriate measures for numerous forecasted data as they can be over-influenced by some very bad examples and can overshadow a good forecast for majority of population. For example, if consumption for a house is zero for a particular hour then any forecast other than zero will be infinitely erroneous if we consider percentage error. Similarly a forecast of 0.2 for a consumption of 0.1 will be hundred percent inaccurate though the actual miss-forecast is 0.1. When we consider numerous forecasts, the more appropriate measure is accuracy which measures the number of wrong forecasts against the number of correct forecasts. This will be discussed in more detail below.

4.2.1. Precision

Precision is the measure of how close we are able to forecast to the actual load. To measure precision we use mean squared error given by the following function:

$$MSE_t = \frac{\sum_{i=0}^{n} |L_{i,t} - P_{i,t}|}{n} \quad (7)$$

where L_i is the observed load and P_i is the forecasted load.

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4.2.2. Accuracy

Accuracy is the measure of how many correct forecasts the forecasting engine makes. Correctness is a user defined parameter. It is preferred to define correct forecast as a value within a percentage range of actual load. However, for low loads, a percentage range becomes insignificant. For a load of 0.1 kW h, a 20% range would be 0.08–0.12 and a forecast of 0.2 will be considered extremely wrong. However, practically a forecast of 0.2 will not be very unsuitable provided that such loads are not majority of population. To avoid this false loss of accuracy we have two scales to measure accuracy. We set a 15% range of error for accuracy, but if load is smaller than 3 then we consider range of ±0.5 kW h as range of acceptable forecast.

So accuracy for time t is given as:

$$Acc_t = \sum_{\substack{\{\forall P_{i,t} > 3\ \& \\ |L_{i,t} - P_{i,t}| > P_{i,t} * 0.15\}}} 1 + \sum_{\substack{\{\forall P_{i,t} \leqslant 3\ \& \\ \{|L_{i,t} - P_{i,t}| > 0.5\}}} 1 \tag{8}$$

Accuracy is specifically important measure for measuring success over multiple forecasts.

4.2.3. Stability

The third measure of correctness is certainty or stability, that is the variance in error. It is given by

$$\mathrm{var}_t = \frac{\sum_{i=1}^{n} (\overline{P}_t - P_{i,t})^2}{n - 1} \tag{9}$$

Here $\overline{P}_t$ is the average forecasted load for time t.

4.3. Experimental data source

A survey over 204 houses was conducted in Eskistuna, a small town 100 km from Stockholm, Sweden. The main goal of the survey was to collect structural data of the house and anthropologic data of its occupants. In addition, these 204 houses were fitted with AMR which collected power consumed at each hour. Weather data was collected from local meteorological department for forecasting as well. The questionnaire collected from occupants contained the questions discussed in Section 2. To represent the seasonality and season specific patterns we conducted our experiments over a 7 day period in each season. That is, forecasts were made for a week of January, April, July and October to represent the four seasonal variations.

4.4. Experimental environment

The simulations for the experiments described below were run on a Intel core2 duo processor. The clock speed was 1.3 GHz with

Table 3
Results of three measures of forecast through multiple STLFs and STMLF. In addition average load of load for that week is provided to show a relationship between MSE and average load in that week.

Month	STLF (with richer data)			$STMLF_1$			$STMLF_2$ (with richer data)			Average load
	Var	MSE	Acc (%)	Var	MSE	Acc (%)	Var	MSE	Acc (%)	
Jan	5.53	2.29	51.2	7.31	3.39	36.4	4.23	1.59	59.9	4.21
April	3.08	1.10	49.0	3.69	1.57	35.2	2.7	0.93	52.5	2.21
July	2.62	1.12	62.1	4.86	1.12	49.5	1.93	0.62	65.0	1.12
October	3.39	2.61	48.9	5.26	1.92	37.6	2.69	0.95	54.7	2.61

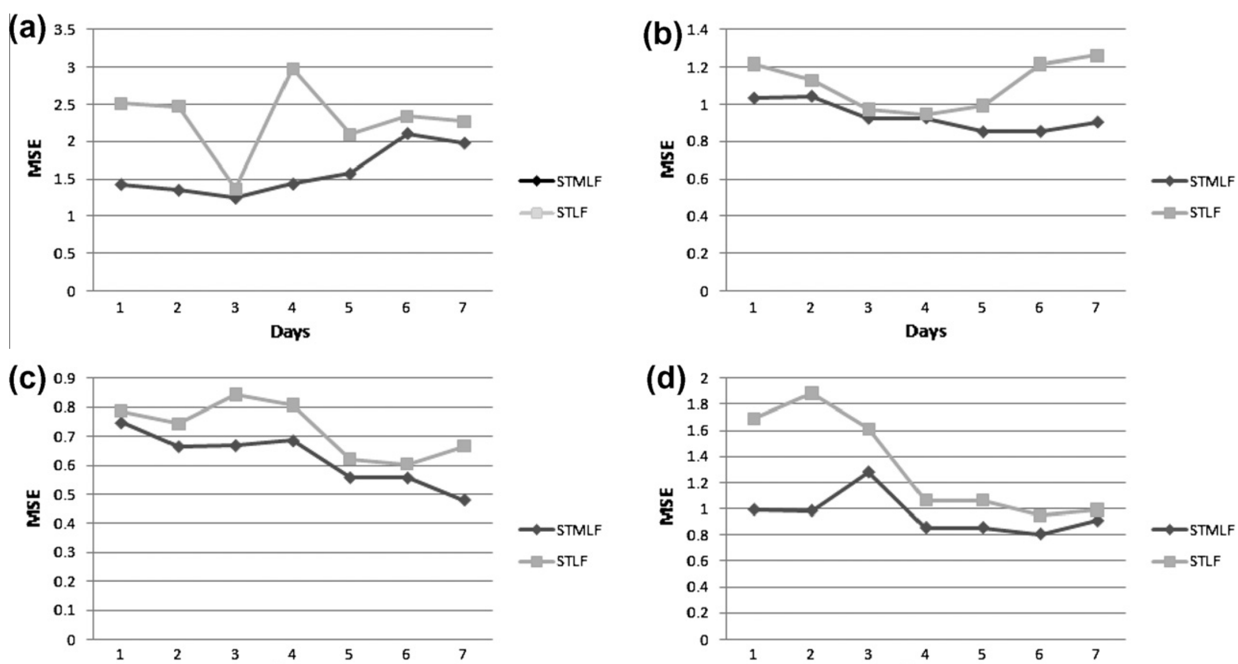

Fig. 5. Mean squared error for four test weeks ((a) week of January, (b) week of April, (c) week of July and (d) week of October) comparing STMLF with multiple STLFs. Blue line is STMLF and red line is average MSE of all STLFs. Days of week are on X axis and mean squared error is on Y axis.

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2 GB of memory. Matlab's Neural Networks Toolbox was used to implement the ANN.

5. Results

The results in this section show the effectiveness of our proposed modeling framework in combination with richer data against the traditional modeling method with richer data and multi-load forecasting without the richer data. That is, it is a three way comparison between STLF with anthropologic and structural data, STMLF with global parameters only and STMLF with anthropologic and structural data. Our claim is that STMLF with anthropologic and structural data is a more robust technique and has a higher accuracy than the other two methods.

To validate this claim we present here application of the three techniques for forecasting house energy load using two different forecasting engines: artificial neural networks and multiple linear regression. These two algorithms represent the archetype algorithms for artificial intelligence and statistical analysis based load forecasting. Furthermore, these algorithms satisfy the requirements for STMLF. Detailed discussion on the needs of STMLF and its implication for selection of algorithms is discussed in Appendix B.

5.1. Measurements

We will first provide the measurements that we collected for ANN experiments followed by discussion on interesting observations about our proposed method in comparison to the other two methods.

5.1.1. ANN output measurements

For the three comparisons we use the artificial neural network as shown in Fig. 4. The results in Table 3 lists the results of the three measurements for correctness of algorithms. Here STLF with richer

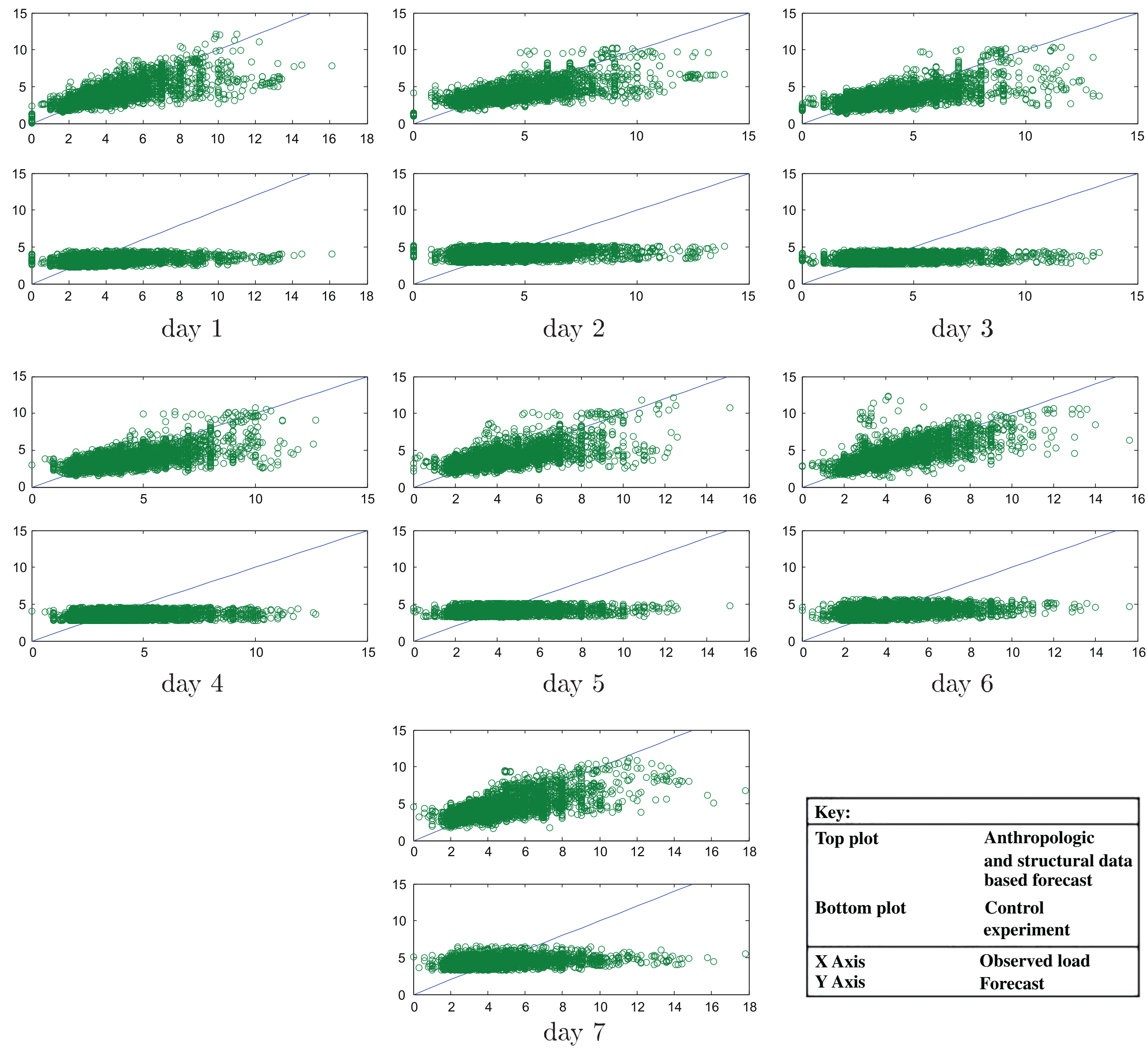

Fig. 6. Scatter plot of forecast against actual load for 7 day test period of January. The top plot in each figure is forecast through structural and anthropologic data and bottom one uses house-Id as discriminant. In all figure actual load is on *X* axis and forecast is on *Y* axis.

data is the application of STLF for each house independently with the anthropologic and structural. $STMLF_1$ is the model where multi-load model is used but without the anthropologic and structural data and $STMLF_2$ is the multi-load model with the anthropologic and structural data. As can be observed, $STMLF_2$ outperforms STLF and $STMLF_1$. $STMLF_2$ is as much as 10.8 percentage points more accurate than STLF. In comparison to $STMLF_1$ the difference is even more pronounced. The difference in MSE for $STMLF_2$ against STLF is also significant particularly in seasons when average load is more.

5.2. Discussion

So far we have presented results of the three modeling paradigms using two different forecasting engines. In this section we will discuss some of the interesting results and show the effectiveness of $STMLF_2$ over other two methods through these results.

5.2.1. Stability of $STMLF_2$ against STLF

Fig. 5 shows the daily MSE values for STLF and $STMLF_2$ for each of the 4 weeks. The graph shows interesting trend in that $STMLF_2$ results are more stable than STLF. Over the same week STLF can be as accurate as $STMLF_2$ or can have MSE twice to that of $STMLF_2$. For critical energy systems such volatility in forecast is highly undesirable since it becomes difficult to reduce error if the error itself is highly unpredictable.

5.2.2. Adaptability of $STMLF_1$ against $STMLF_2$

Fig. 6 shows scatter plot of $STMLF_1$ and $STMLF_2$ against the actual load for the week of test in January. As can be seen, the forecasts of $STMLF_1$ are in a narrow band. This validates our original claim that house Id is insufficient for discriminating loads. Since $STMLF_1$ does not have sufficient measures for discriminating house loads, it forecasts close to average for all the houses as can be seen in the scatter plots providing the benefit of using anthropologic and structural data for house load forecasting.

6. Conclusion and future work

In this paper we have first introduced autonomic demand side management (ADSM) as a paradigm to provide DSM and DR in micro-grids. We have identified forecasting of individual user's load as an important cog for ADSM and have attempted to answer two important questions for making this forecast. The first question is:

Do current STLF models and techniques work appropriately for forecasting individual households or are adjustments needed in modeling paradigm for forecasting individual consumer loads?

We found that the STLF model has some shortcomings in forecasting loads of individual consumers. STLF models are built to forecast for monolithic or single load forecasting. To forecast for hundreds of thousands of loads, an STLF will be required for each load. This posses a scalability problem. To overcome this shortcoming, we proposed a short term multiple load forecasting (STMLF) model which combines individual load time-series into a succinct model for forecasting many loads with a single model. Even more so we showed through our results that STMLF is up to seven percentage points more accurate than individual short term single load forecasts for each load. Furthermore, we identified techniques (ANN and SVM) which can compute forecasts based on STMLF model. For our experiments we used a basic ANN algorithm to prove the effect of anthropologic and structural data over STMLF. As future work this ANN engine can be replaced with more sophisticated ANNs to increase efficiency of forecast. Our second question was:

Do the anthropologic and structural variables enhance the forecasting accuracy of individual consumer loads?

We showed through experiments that a combination of anthropologic data and structural data of houses can greatly enhance forecasting of individual consumer's load when used with STMLF. This richer data within STMLF framework can reduce error by up to 50% in some cases. However, we did not co-relate the specific questions with the efficiency of the system. A more detailed analysis of effect of anthropologic and structural data over forecast accuracy is required.

As future work we outline three direction. First is to study use of other forecasting engines within our framework. Second is to study in detail the impact of data over the forecast. Third is explore the relationship of price and demand as correlated with house level DSM and DR within the ADSM architecture.

In conclusion, we recommend short term multiple load forecasting and use of anthropologic and structural data for smart grid applications where highly accurate behavior of individual consumers is required such as in demand response and demand side management.

Appendix A. Motivation and need: autonomic demand side management

In the traditional grid, short term load forecasting for a complete aggregated system is sufficient. The demand in grid is an aggregation of consumptions and individual loads within this aggregated demand tend to average out the total demand. Thus there are usually no sharp variations in demand when the grid is considered as an aggregated load. However, smart grids, particularly the concept of micro-grids opens up many avenues for efficient energy management. It was anticipated that within micro-grids demand response or other demand side management techniques will be very helpful if implemented at a finer granularity level. To this end, demand side management (DSM) at one time had been dubbed as a revolutionary measure for energy saving. But it has not delivered much. It is estimated that maximum saving through DSM is no more than 5%. Some of the reasons identified by Kim and Shcherbakova are response fatigue, availability of technology, satisficing behavior in switching patterns, and consumer knowledge [20]. Here we will discuss how concepts of micro-grids when entwined with autonomic computing can mitigate the issues of demand response in an efficient and accurate manner.

Autonomic computing is the vision of a class of computing systems which will manage themselves in accordance with high-level objectives specified by human. The goal is to make systems intelligent enough to handle their optimization, configuration, healing and protection mechanisms on their own. This is to mostly relieve the human operator from the mundane administrative tasks. Additionally, research in autonomic system has realized systems which go beyond just helping the human administrators. The state of the art autonomic systems through their intelligence provide solutions which were not possible with human operators. We see application of autonomic computing for DSM as an obvious choice. For example colorpower proposed by Ranade and Beal [26] implements a demand response program in which users mark their devices according to their priority. The proposed system then implements the demand response program over the entire population according to its calculations in such a way that the energy usage is fair and reduction in load corresponds to the shortage of energy. Similarly Javed and Arshad proposed AdOpt which manages usage of air-conditioning units to reduce supply–demand gap whilst maintaining service level guarantees promised to users [18]. Both of these systems allow a more crisp control of device usage by user and energy modulation by utility provider. This is a marked improvement over user driven DSM program or automated blanket load shedding programs are not possible without explicit computing support.

However, such autonomic applications for DSM in micro-grids are very rare. There are a few autonomic applications being devel-

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oped for controlling energy of a house [22]. But the scope of these applications is limited to a house and do not span to the micro-grid level. Though managing energy of a house is a valid goal, our results and practical concerns show that managing of energy at micro-grid level can be much more effective. Renewables and distributed generation integration at a micro-grid level is much more feasible. Also, DSM within a house has very little elasticity to play with. All one can do is make sure that most energy is coming from renewables of the house. Integrating energy needs and supply across a neighborhood-level micro-grid would increase the flexibility and thus result into better optimization of energy demand and supply.

Autonomic DSM architecture: implementing autonomic behavior is more involved than proposing a planning technique alone. This was found by researchers in autonomic computing as well and to mitigate this problem a comprehensive MAPE-K architecture was proposed to control the managed element [19]. This architecture has four modules: Monitoring, to monitor the managed element, Analysis to analyze if the managed element requires some correction, Planning to plan the corrects and Execute to implement the plan. A knowledge base spans the four modules.

We incorporate autonomic computing for DSM using this traditional autonomic computing architecture. Fig. 7 shows a MAPE-K loop over a managed micro-grid neighborhood. Here the neighborhood is the controlled element. The task for each module is shown in the box.

The aforementioned techniques of colorpower and AdOpt form the planning module. But both these techniques require an analysis of the managed system. This analysis at the least entails a forecast which can be used to construct the plan. Without this forecasting the autonomic system would not be able to plan for better optimizations. In this paper we present our experiments to construct such a forecast which can be used by colorpower or AdOpt or any other autonomic planner for constructing a plan for targeted DR or DSM in a micro-grid.

Appendix B. Short term forecasting techniques for STMLF

There are three concerns that we have for using a forecaster for STMLF. First it should be able to handle at the least *k* input parameter. Our results show that this *k* should be significantly large to distinguish between house characteristics. Second, as is shown in Section 2, significant portion of our forecasted data is far from mean. Therefore, the forecasting technique should not ignore or suppress outliers. Third, the technique should be able to handle a highly volatile system since consumers loads are highly volatile as discussed earlier.

Now we will discuss various STLF techniques in light of STMLF requirements stated above and discuss which techniques can be used for STMLF. This discussion is important in identifying the forecasting engine that we use for STMLF since many existing forecasting techniques do not support the computation required for STMLF.

Load forecasting historically has been used to forecast large scale monolithic systems such as power loads of a city or region or cost of energy in a market. There are three fundamental techniques which have been applied for such forecasts for a single system: (1) statistical techniques focused on smoothing and averaging such as regression [24], exponential smoothing [8], Kalman filters [17], and stochastic models [29], (2) time series methods such as linear univariate model [9], ARIMA [3], Hagan and Behr [15], in combination with econometrics model [10], GIGARCH [12], GARCH [13] and hybrid models such as combination of ARIMA and GARCH using wavelet transform [28], and (3) AI techniques such as ANN [16], ANN with radial basis function [21], pattern recognition-based techniques [11], expert system-based techniques [25], particle swarm optimization [2] and fuzzy system-based techniques [30].

Recently due to prevalence of smart grid ideas research has been focused on STLF for small scale systems. STLF for small scale systems is proven to be a much harder problem than for a large scale system as has been explained by Amjadi and colleagues [4]. Amjadi and colleagues and [4] and Gurguis and Zeid [14] have proposed solutions which work better than the standard STLF for a micro-grid or building level granularity. However, the accuracy of the system still does not match those of a large scale STLF due to volatility of underlying system.

We will look at each of the three classes of algorithms to identify methods which can be used for STMLF and also point out the reasons why an algorithm is not usable for STMLF.

We see that most of statistical techniques are not applicable for STMLF for two reasons. First, these techniques are based on

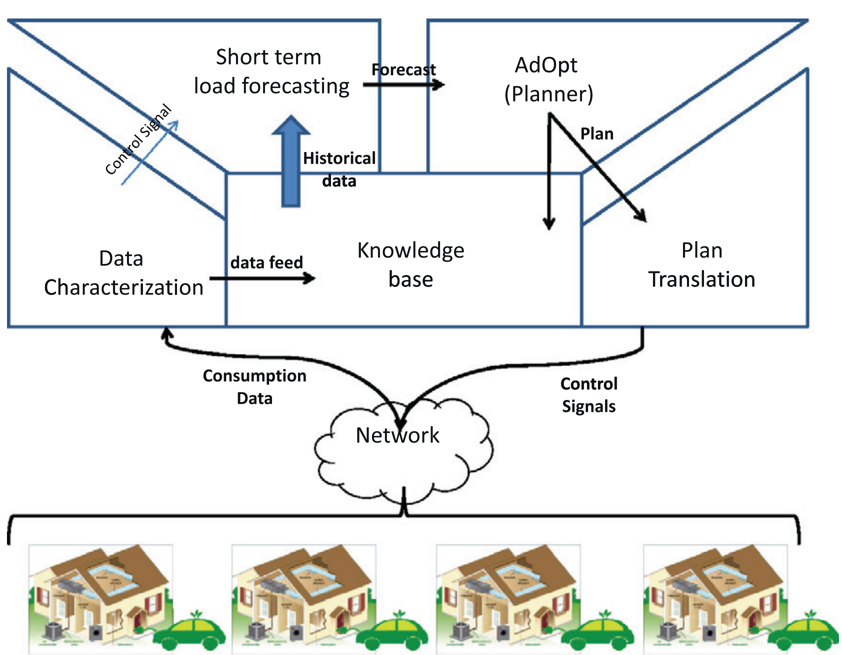

Fig. 7. Autonomic demand side management architecture for intelligent DSM in micro-grids.

Table B.4
Mean squared error (in kW h) for 9 day STMLF using multiple linear regression.

Day	Mean squared error
1	2.72
2	2.70
3	2.51
4	2.43
5	2.53
6	2.53
7	3.23
8	3.42
9	2.56

smoothing data around mean. As we have shown in Section 2, for large, highly volatile data-set, mean is not a good forecast. Regression, exponential smoothing and Kalman filters thus are not appropriate for such forecast. Secondly, most of the techniques are not capable of handling higher input dimensions required for the forecast. This is true for the above methods and the stochastic technique presented in [29]. To prove our first claim we used multiple linear regression (MLR) for STMLF since MLR is able to cater the k dimensions in its model. As expected, the forecast has a high error rate. Table B.4 shows the mean squared error (MSE) value for each of the 9 days of experiment. The results showed a high MSE with average MSE of 2.73 and for some day as high as 3.42. For a value in the range of zero to fifteen, such a value is relatively very high.

It is well known that time series analysis techniques are neither scalable to higher dimensions nor are effective in highly volatile data [6]. Usually time-series analysis are limited to 4 or 5 input variables which is insufficient for our requirements. For this reason time series methods such as linear univariate model [9], ARIMA [3], Hagan and Behr [15], in combination with econometrics model [10], GIGARCH [12], GARCH [13] and hybrid models such as combination of ARIMA and GARCH using wavelet transform [28] were not considered for STMLF.

In comparison, AI technique such as artificial neural networks through their hidden layers and SVMs through their projection into hyper-dimensions, seem much more capable of solving an STMLF model. These techniques are able to identify hidden trends thereby finding the similar trends in different time series. Furthermore, ANN and SVMs are proven to be scalable to the dimensional needs of STMLF. However, their ability to handle such a volatile data set is still unknown. In next section we will discuss use of ANN for experimentation comparing STLF with STMLF and quantifying effect of anthropologic and structural data over consumer load forecasting. In summary we believe that from the existing short term forecasting techniques only AI methods with ability to scale in input dimensions are applicable for STMLF.

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