

## COMPARISON OF INVERSE MODELS USED FOR THE FORECAST OF THE ELECTRIC DEMAND OF CHILLERS

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### ABSTRACT

This paper reviews different inverse modelling techniques used to forecast electric demand for chillers in large institutional buildings. Three such models are tested with measurements of electric demand of a chiller installed on a university campus.

### INTRODUCTION

The forecasting of operation and the electric demand could significantly contribute to the improvement of operation of HVAC systems. The forecasting could be done using calibrated forward models, however their development is time consuming; in addition, they need detailed data about the building and HVAC system. Inverse models present an alternative approach for forecasting. Most studies focused on energy consumption forecasting instead of electric demand. It should be noticed that very few studies have been performed on the short-term electric demand forecasting of one building.

This paper focuses only on the short-term forecasting of electric demand of chillers, with a prediction horizon going from a few hours to a few days. Section 2 presents the main types of inverse models used for energy consumption forecasting presented in the literature. Section 3 presents a numerical comparison based on previous case studies. In section 4, the results from three inverse models are compared with measurements from a cooling plant.

### A REVIEW OF INVERSE MODELS

#### **Statistical models**

##### *Regression models*

Regression models commonly used for building load forecasting express a relationship between the dependent variable (e.g. electric demand, thermal load) and some regressors (Feinberg and Genethliou, 2005), which are representative of the climate conditions, the season of the year, or the building and system characteristics. As stated in (Kyriakides and Polycarpou, 2007), the outdoor dry bulb temperature appears to be the preferred weather parameter. The PRinceton Scorekeeping Method (PRISM) estimates the annual energy consumption based on billing data and heating degree-days (Fels, 1986). Most used are

linear regression models, which could be simple or multiple, with one or several regressors. In (Reddy and Claridge, 1994), Multiple Regression Analysis (MRA) and Principal Component Analyses (PCA) methods are used to model daily energy use of a large institutional building. Polynomial regression models have also been used.

##### *Time series models*

Time series have a natural temporal ordering; they assume that there is an internal structure in the historical dataset, such as autocorrelation, trend or seasonal variation. Time series analysis has been used for decades in the forecasting field (Box et al., 1976). The stationary time series models are based on the assumption that the future load could be modelled as a linear combination of the previous ones. They involve autoregressive (AR) and moving average (MA) processes, which could be merged together into an autoregressive moving average (ARMA) process also known as Box-Jenkins model. As this assumption is invalid in most cases, the non-stationary time series models with autoregressive integrated moving average (ARIMA) processes are introduced. MA and AR processes have then been extended to take into account exogenous variables; these models are ARMAX (Auto Regressive Moving Average with eXogenous variables), and ARIMAX (Auto Regressive Integrated Moving Average with eXogenous variables).

##### *Kalman filtering technique*

This technique, also known as linear quadratic estimation, is a recursive estimator based on state-space representation. Kalman filter involves a set of inputs, outputs and state variables that are related by first-order differential equations. Kalman filter is combined with other regression approaches in (Al-Hamadi and Soliman, 2004; Markoulakis et al., 2006) to forecast the hourly electric load of a province over a prediction horizon of 1-24 hours.

##### *Nonparametric Regression models*

Kernel Regression belongs to this class that has been used for short-term forecasting of load and power demand (Agarwal et al., 2006; Brown et al., 2011; Le Cam and Daoud, 2012). This form of regression analysis contains physical information that black-box models do not have. The kernel bandwidths are more meaningful than the synapses, weights associated to

inputs in neural networks. This method can be automatically applied to different buildings: it does not require prior information on the building structure and equipment. Kernel Regression approaches retain the data and search through them; in case of large dataset they could be time-consuming.

#### **Artificial intelligence models**

(Zhao and Magoulès, 2012) performed a literature review on prediction methods applied to building energy consumption; details on neural networks and support vector machines are given.

##### *Neural network based models*

Artificial Neural Network (ANN) models were originally known as Parallel Distributed Processing (PDP) (Rumelhart and McClelland, 1986); they are also called connectionists approaches. ANNs have been widely applied to energy forecasting in the last twenty years. Recently published studies involve neural networks approaches for three main applications: whole building energy demand forecasting, heating and cooling load forecasting, and HVAC subcomponents modelling. In (Yang et al., 2005; Escrivá-Escrivá and Roldán-Blay, 2011), ANNs have been developed for whole building energy demand forecasting. ANNs are also widely employed for short term forecasting of cooling and heating loads (Li et al., 2009). ANNs have also been used to predict the fan motor speed of a HVAC system in (Soyguder, 2011).

##### *Support vector machines*

Support Vector Machines (SVMs) have been introduced by Vapnik in the 1960's (Vapnik, 1999). These models are based on the VC statistical learning theory. Around 3500 papers have been published during the last decade on the use of SVMs in predictions: they show promising results in solving non-linear problems even with a small amount of data available, and only a few parameters to be tuned. A few studies have been published on the application of SVM to hourly building thermal load forecasting (Li et al., 2009). In (He, 2008; Niu et al., 2010), SVR are employed for electric load forecasting. Studies used hourly, monthly or even yearly averages of electric demand for the forecasting of energy demand of office buildings, cities, provinces or even entire state. SVMs have also been employed in HVAC applications (Kumar and Kar, 2009; Haijun and Jingru, 2012).

#### **Hybrid models**

##### *Hybrid modelling using economist' and engineer's methods*

In (Giraudet et al., 2012), hybrid models are presented as a trade-off between economist's top-down and engineer's bottom-up techniques. A hybrid model was used to assess energy consumption of residential buildings (Swan et al., 2011), and building thermal load (Iino et al., 2009).

##### *"Grey-Box" modelling*

"Grey-box" or "semi-physical" models are physically based models with parameters identified from measurements. They are qualified as "grey box" because they are somewhere between the "white-box" models which are completely based on physical models and "black-box" techniques which learn from measurements without previous knowledge of physical laws.

The application of "grey-box" techniques to model chillers has been introduced in (Bourdouxhe et al., 1994). In (Lemort et al., 2009), a semi-empirical steady-state model of an air-cooled water chiller is presented. In (Zhou et al., 2008) a simplified model has been developed for building load prediction.

##### *Trade-off between statistical and/or artificial intelligence approaches*

Several hybrid models combining statistical and artificial intelligence techniques can be found in the literature. These hybrid models often involve ANNs and SVMs as support models; fuzzy logic or genetic algorithms are combined with the support models. In (Li et al., 2011) neuro-fuzzy network models are used for forecasting the building energy consumption. In (Nie et al., 2012), an ARIMA model is used to forecast the daily load and a SVM algorithm is applied to correct the deviation of time series model's forecasting.

## DISCUSSION ABOUT PUBLISHED APPLICATION OF MODELS

Linear regression methods have shown the advantage of being very easy and quick to implement. They do not require prior detailed information about technical characteristics of buildings; however, they need quite large datasets of measurements for training. Very accurate linear regression-based models are quite difficult to develop. These models suffer from performance deterioration when a sudden change occurs in the inputs. They are suited for predicting an average consumption over periods like days, months or even years.

As well as linear models, non-parametric regression models do not need any prior information; they present a useful generalization skill. They can perform more accurate forecasts than linear models and are as efficient as connectionist's methods. The approach is simple to set and requires only few parameters: the bandwidth's size of each explanatory variable. These parameters are physically interpretable and can give useful information for building energy analysis. Nevertheless, this technique could be time-consuming in case of large datasets, and hence inefficient for short-term estimation.

According to (Kyriakides and Polycarpou, 2007), time series models have a satisfactory accuracy in forecasting. Nonlinear time series can handle non-stationary processes that involve unexpected changes in exogenous variables. However, these techniques

require an important computational time when dealing with large data sets. They have many parameters to estimate which could be inefficient for short-term predictions.

Connectionist's approaches have been extensively used in recent works because of their ability to accurately capture the inherent relationship between inputs and outputs of any data set without using a physical model. They are able to learn by themselves from previous examples and then generalize to predict the future system state under new conditions. ANNs could be applied to complex systems; they could be non-linear, with multiple inputs and multiple outputs or even coupled variables. ANNs have shown high performance in the modeling and predicting field. However, they are not efficient if the amount of available data for the learning phase is insufficient. Static models cannot automatically adapt to changes, they need to be trained again; thus two models are used in (Yang et al., 2005): a sliding window and accumulative training. They found that when the training period was not stopped at the right time, the process led to reduction in accuracy or over-fitting. The design process of ANN's structure is another difficult task; it includes the selection of

number of layers and neurons in each layer, and type of activation function. Network's architecture is normally designed for one building and one application only.

SVMs provide promising results in solving non-linear problems even with a small amount of data available. They need only a few parameters to be tuned, which is advantageous in term of computation cost. They also present good generalization skills that allow the model to be applied to different buildings without any change. Compared to ANNs, SVMs require less measurements and parameters for the same accuracy.

A particular attention should be given to the selection of inputs, data pre-processing and training of all inverse models. Table 1 presents a sample of inverse models, the prediction horizon and statistics of the comparison with measurements. The prediction horizon time usually is from one hour to several days. The prediction accuracy depends on the specific case study, the prediction horizon and the type of forecasting target (instantaneous or average value). In most cases, the Mean Absolute Percentage Error (MAPE) is below 5% and the coefficient of variance (CV) is below 11%.

Table 1 Models predictions of electric load versus measurements from case studies

Model	Case studies	Training data	Prediction horizon	Difference	
				MAPE[%]	CV[%]
<b>Time series</b>	(Soares and Souza, 2006; Amaral et al., 2008)	Hourly or half-hourly	1 hour - 7 days	3.42 - 4.4	N/A
<b>Fourier series</b>	(Dhar et al., 1993; Ding et al., 2011)	Hourly or half-hourly	N/A	13.5	≤ 5.1
<b>Kernel Regression</b>	(Agarwal et al., 2006; Brown et al., 2011)	Hourly	1 - 48 hours	≤ 4.1	≤ 11
<b>Kalman Filter</b>	(Al-Hamadi and Soliman, 2004; Markoulakis et al., 2006)	Hourly	1 - 24 hours	1 - 13	N/A
<b>ANN</b>	(Yang et al., 2005; Escrivá-Escrivá and Roldán-Blay, 2011)	Hourly	1 - 24 hours	7	≤ 3
<b>SVR</b>	(He, 2008; Niu et al., 2010)	Hourly	1 - 24 hours	≤ 3	N/A

## COMPARISON BETWEEN PREDICTIONS AND MEASUREMENTS

This section presents the comparison of predictions of electric demand as given by three inverse models against measurements, which were collected at a 15-minute time-step through the Monitoring and Data Acquisition System of a central cooling plant of a university campus. They include historical electrical demand and operating conditions of two chillers, as well as the local environment variables over three cooling seasons (from April to September 2009 and 2010, and from April to June 2011). The chillers have a design cooling capacity of 3165 kW and electric demand of 550 kW. These monitored data have already been used in a study carried out by

other researchers (Monfet and Zmeureanu, 2012). Their results are used for comparison in this study.

### **Input data**

Four regressors are retained in order to forecast the electric demand of one chiller. They have been chosen because of their statistical correlation to the electric demand of the chiller: the hour of the day, outdoor temperature, and supply chilled water and condenser water temperatures. We consider that the outdoor air temperature at 15min time step is a better regressor for the forecast of electric demand than other variables such as cooling degree-day.

### **Data Pre-processing**

Data pre-processing includes data cleaning, integration, reduction and transformation. Focus is on

data cleaning that deals with missing values, noisy and inconsistent data. In this case study, different methods presented in (Han and Kamber, 2006), are employed depending on the number of missing values in a row. Environmental variables and electric demand of the chiller are continuous functions; the missing values are replaced by interpolation when the missing data is far less than half of a day. Otherwise, values of previous days are copied and used to fill in the data set. These techniques are known to bias the data. However, missing data of more than a day appears only twice over three years of data used. Ignoring these subsets was not considered as an option, and keeping the trend over the time was preferred.

### Inverse models applied on this case study

The following inverse models are applied to this case study, using the same inputs: model 1 Kernel Regression, model 2 dynamic ANN and model 3 SVR. These models have been selected because they are still recent in building energy modeling and they present promising abilities in the forecasting field.

The first two models could be qualified as dynamic in the sense that, at each time step, they use previous and current values of the regressors (e.g., at time  $t-1$ ,  $t$ ) as well as previous values of the dependent variable to forecast the dependent variable at time  $t$ ; they are called Nonlinear AutoRegressive models with eXogenous inputs (NARX). In a first approach, models 1 to 3 are compared to the Multi-Polynomial (MP) inverse model presented in (Monfet and Zmeureanu, 2012), a static model, where the regression coefficients are calculated once based on previous data of training set; the electric demand at time  $t$  is estimated based on the current values (at time  $t$ ) of regressors. Model 3 can also be considered as a static model. The comparison of predicted performance of those four inverse models is carried out on a 24-hour testing set with a training set size varying from 7 to 21 days.

#### Kernel Regression model

The estimated future electric demand is an average of previous demand values in similar conditions; their similarity is defined via parameters' bandwidth. The crucial point to get an accurate forecast is in defining each bandwidth. A cross-validation step is carried out to define bandwidths while minimizing the prediction error over a given training set. The model can then be used for electric demand forecasting using previous values of demand.

#### Dynamic ANN model

The Matlab Neural Network Toolbox 7 was used to develop a dynamic ANN composed of four input neurons, one hidden layer with ten neurons and a sigmoid transfer function; and one neuron in the output layer with a linear transfer function. The model also includes a 24-step delay for previous inputs and electric demand; it is trained over a given

period using the Levenberg-Marquardt algorithm and a closed-loop is set to use forecasts as delayed input. The Levenberg-Marquardt algorithm sets and optimizes the weight of each neuron over the training set.

#### SVR model

The Matlab interface of the software developed by (Chang and Lin, 2011) for SVMs application has been applied in this case study; an epsilon SVR model was used to forecast energy demand of the chiller. A radial basis kernel function is used to map the vector of regressors to a higher-dimensional space called the "feature" space. In this space a linear regression is performed, which corresponds to a nonlinear regression in the initial space. Parameters of linear regression are tuned by minimizing a loss function composed of two terms: one characterizes level of complexity and the other one describes model's accuracy. A balance between these two terms has to be determined; this is the principle of Structural Risk. Three parameters ( $C$ ,  $\epsilon$  and  $\gamma$ ) related to the loss function and kernel function are tuned using a cross-validation procedure over a given partitioned training set.

#### Optimization step

The parameters of inverse models 1 and 3 are optimized over the training set using a Genetic Algorithm (GA), that minimizes the following objective function:  $f_{min} = \sum_{i=1}^n (\hat{y}_i - y_i)^2$ , where  $\hat{y}_i$  and  $y_i$  are the forecasted and measured electric demand, respectively. The GA methodology is presented in (Le Cam and Daoud, 2012); it mimics the principles of natural selection; the first values of parameters or individuals are randomly chosen. Some individuals who gave the best results are kept and combined to create the next generation of individuals. The optimization process stops when the required prediction accuracy or a limit number of generations is reached.

An optimization process is not required by the ANN model; the parameters or neurons' weights of this model are already optimized.

### Discussion of results

Table 2 presents the performance of inverse models for the prediction of electric demand of the chiller at a 15-minute time-step, using training data sets of different sizes, from 7 to 21 days. The testing data set covers the next 24 hours. Figure 3 shows the predicted and measured electric demand profiles of the chiller over the testing set. The Coefficient of Variation (CV) and Root Mean Square Error (RMSE) over the training and testing set are displayed.

$$RMSE = \sqrt{\sum_{i=1}^n (\hat{y}_i - y_i)^2 / n} \quad (1)$$

$$CV(RMSE) = RMSE / \bar{y} \quad (2)$$

where  $\hat{y}_i$ ,  $y_i$  and  $\bar{y}$  are the forecasted, measured and average of measured electric demand, respectively.

These models can catch the general shape of electric demand profile but some phenomena remain hard to predict. SVR and Kernel Regression show a CV(RMSE) of less than 5% over the 24-hour testing set, regardless of the training set size. The CV(RMSE) of dynamic ANN varies from 3.8% (for 21 days training data) to 6.6% (for 7 days data). The lower CV(RMSE) value over the testing set compared to the training set could be explained by their respective size: the testing set is only over 24 hours and the training set size is from 7 to 21 days.

Models 1 and 2 use current and previous values of regressors and dependent variable to make estimations; the more historical values they have, the better they perform. Indeed the variations range of the dependent variable to predict will be better described and so the predictions more accurate. Model 1 shows an improvement of its performance with the increase of the training set size. The issue is in defining the number of previous values that are relevant; average of regressors or peak values over previous hours or days could be involved as relevant variables to describe the future electric demand.

Figure 1 displays evolution of CV(RMSE) for the three inverse models, when using a training data set of 14 days, and a larger prediction horizon of 7 days, rather than 24 hours. The three models present forecasts with a CV(RMSE) of less than 10% over the following week. A noticeable increase of CV(RMSE) appears after the first day. In terms of RMSE, SVR and Kernel Regression models have values of 15.1-16.4 kW, over the 24-hour testing set, regardless of the training set size. The RMSE of dynamic ANN varies from 12.5 kW (for 21 days training data) to 21.6 kW (for 7 days data). The MP regression model has smaller RMSE values, of about 50% less.

It should be noticed that, in the summer, when the cooling load is high, both chillers 1&2 are operated

in the same time at part load (Figure 2). Rest of the time, depending on the load required, only one chiller is operated at part or full-load. The models give better forecasts of the electric demand of both chillers 1&2 considered together; the relationship between the dependent variable and the outdoor temperature is easier to define.

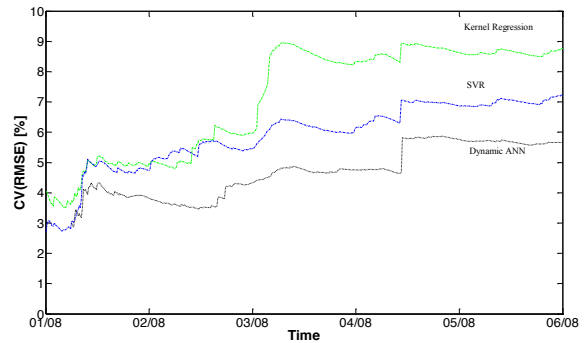


Figure 1 Evolution of CV over the prediction horizon for chiller's electric demand forecasting

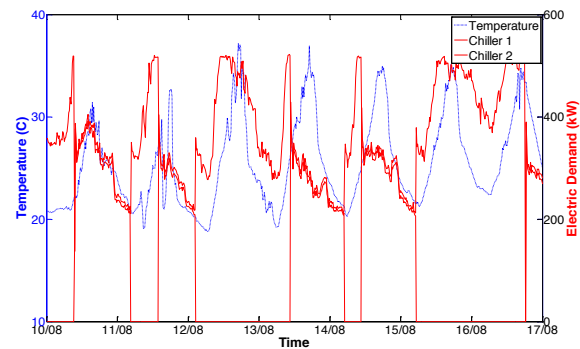


Figure 2 Measured chiller electric demand and outdoor air temperature over a week

Another point that should be involved in the methodology is the data normalisation; this step could help to improve the model accuracy.

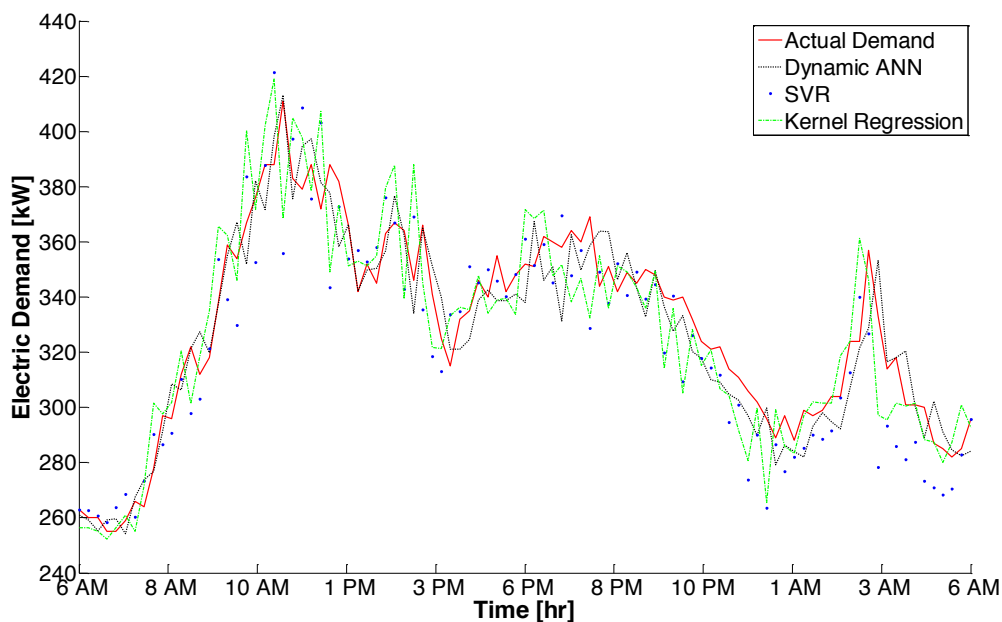


Figure 3 Chiller's electric demand forecasting over the next 24 hours with a 2-week training set

Table 2 Comparison of inverse models on case study

Model	Training set Size	Training set		Testing set (next 24h)	
		CV (%)	RMSE (kW)	CV (%)	RMSE (kW)
<b>Model 1.</b>	7 days	8.9	26.5	4.9	16.2
<b>Kernel</b>	10 days	8.7	26.6	4.9	16.4
<b>Regression</b>	14 days	10.9	31.3	4.9	16.2
	21 days	14.1	33.9	4.9	16.4
<b>Model 2.</b>	7 days	7.4	22.1	6.6	21.6
<b>Dynamic ANN</b>	10 days	6.4	19.8	4.1	13.5
	14 days	8.9	26.0	5.4	17.9
	21 days	11.6	28.1	3.8	12.5
<b>Model 3.</b>	7 days	6.2	18.4	4.8	15.6
<b>SVR</b>	10 days	6.2	19.0	4.7	15.4
	14 days	7.2	20.5	4.7	15.3
	21 days	9.2	22.1	4.6	15.1
<b>MP</b>	7 days	3.9	12.4	3.7	8.8
<b>Regression*</b>	10 days	3.8	11.1	4.0	9.7
	14 days	3.9	10.9	3.8	11.8
	21 days	3.7	10.8	2.9	9.7

\*(Monfet and Zmeureanu, 2012)

In a second approach, the idea is to modify the inverse models to perform “real” predictions; i.e. using regressors whose future value can be known such as the time of the day, day of the week and the forecast of outdoor temperature. The number of regressors has then been reduced to the previously presented three variables; the inputs specific to chiller operation (supply chilled and condenser water temperatures), as used in Table 2 were removed. The three studied models have been trained using a 14-day training data set; the optimized parameters are given in Table 3 and Table 4. These parameters have been obtained by minimizing the residual between the measured and predicted profile over the training set. An improvement of parameters’ optimization would involve multiple rounds of cross-validation steps in which the training set itself is successively and randomly partitioned into complementary subsets: training and testing sets.

The comparison of predicted and measured electric demand over the week following the training period is presented in Figure 4 to Figure 6. SVR and Kernel Regression models present a CV(RMSE) of about 15% in the first day and converges at about 20% over the complete testing set. The dynamic ANN presents a bigger CV(RMSE) of 24.9% over the next 24 hours and reach 22.4% for a one week prediction horizon.

Table 3 Optimized parameters for Model 1 - Kernel Regression

Parameter	Kernel bandwidth	Optimized value
<i>h</i>	Hour of the day	3.33
<i>d</i>	Day of the week	3.33
<i>t</i>	Outdoor air temperature	3.33

Table 4 Optimized parameters for Model 3 - SVR

Parameter	Description	Optimized value
$\gamma$	Kernel bandwidth	6.75
$C$	Penalty parameter of Kernel function	50
$\epsilon$	Penalty parameter of loss function	20.06

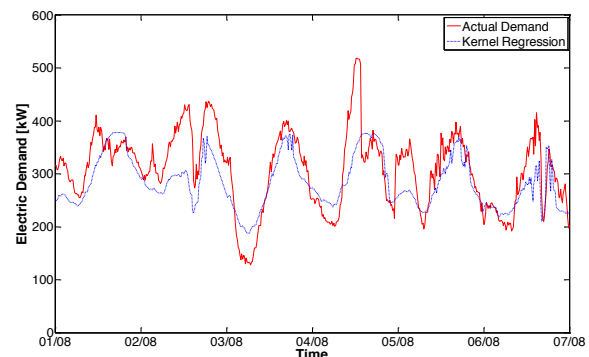


Figure 4 Forecast of electric demand over the first week of August 2009 using Model 1 - Kernel Regression

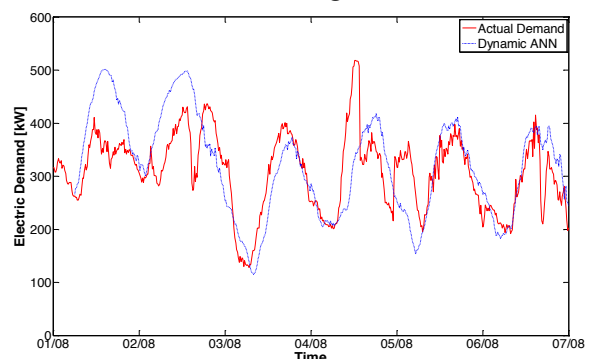


Figure 5 Forecast of electric demand over the first week of August 2009 using Model 2 - dynamic ANN

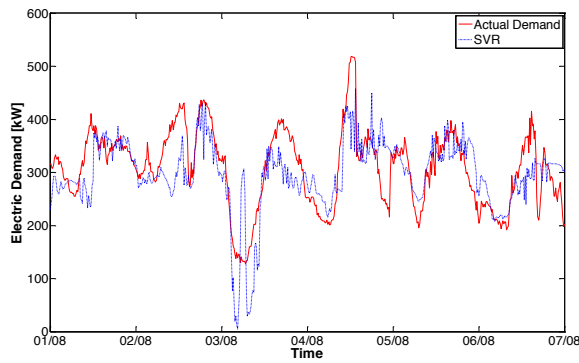


Figure 6 Forecast of electric demand over the first week of August 2009 using Model 3 - SVR

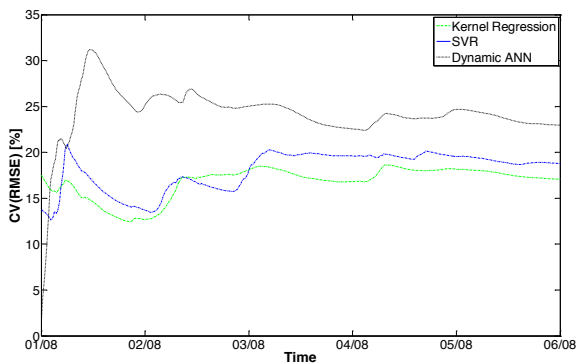


Figure 7 Evolution of CV over the prediction horizon for chiller's electric demand forecasting using the 2<sup>nd</sup> approach

## CONCLUSION

This paper started with the authors' analysis of the current trends in inverse modelling applied to the forecast of building energy use. Three inverse models have been tested with actual measurements of electricity demand of a chiller installed on a university campus. Inverse models applied on this case study showed good ability in electric demand forecasting and SVR model presents interesting generalization aptitude.

Further work will focus on multiple rounds of cross-validation for a better optimization process and the addition of other regressors to better describe the dependent variable. The optimization of SVR models will help to exploit their generalization ability, especially for sudden changes in the operating conditions of chillers or other components of HVAC systems.

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