Short-term thermal and electric load forecasting in buildings

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SHORT-TERM THERMAL AND ELECTRIC LOAD FORECASTING IN BUILDINGS

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ABSTRACT

Increasing environmental awareness and energy costs encourage the increase of the contribution of renewable energy sources (RES) to the energy supply of buildings. However, the integration of RES and energy storage systems introduces significant challenges for the energy management system (EMS) of complex building energy systems. An energy management strategy based on fixed control rules may fail to efficiently operate such systems. These circumstances raise the need to apply advanced control strategies. A promising approach is model predictive control (MPC), which allows the consideration of the expected dynamic system behavior as well as of forecasts of the loads and of the renewable energy generated. Obviously, the performance of an MPC-based EMS crucially depends on the accuracy of the load forecasts.

The goal of this paper is to compare the capabilities of neural networks (NNs) and of the least squares support vector machine (LS-SVM) in forecasting the hourly thermal and electric load of buildings. Two short-term load forecasting algorithms are evaluated which treat every hour of the day separately by an individual forecasting model. Additionally, the algorithms also distinguish between working days, weekends and holidays. In order to adapt to changing load patterns, the algorithms use the sliding window training approach. Both algorithms are tested using the measured thermal and electric load data of a large office building and of a small building which houses a kindergarten.

In the tests conducted, in general, the forecasting algorithm based on the LS-SVM shows a better performance than the forecasting algorithm based on NNs. In addition, the LS-SVM involves fewer free parameters to be determined than a NN, which makes the former easier to apply.

The results reported further indicate that the accurate forecasting of the load of a small building is the more challenging task compared to the load forecasting of a large office building. Furthermore, using a training window size of more than 20 days does not significantly improve the performance of the algorithms examined.

Keywords: short-term load forecasting, neural networks, least squares support vector machine

INTRODUCTION

Due to sustainability concerns, fossil energy sources in the energy supply of buildings are increasingly being substituted by renewable energy sources (RES). However, if RES and energy storage devices are added to conventional building energy systems, the complexity of the complete system increases considerably. An energy management strategy based on fixed control rules may fail to efficiently operate such a complex energy system [1]. These circumstances raise the need to introduce advanced control strategies. A promising approach is model predictive control (MPC), which is based on solving at each sampling interval a constrained optimal control problem for the current state of the system. Thus, MPC allows the consideration of the expected dynamic system behavior as well as of forecasts of the loads and of the renewable energy generated. Obviously, accurate load forecasts are essential for the successful performance of an MPC-based energy management system (EMS).

Typically, an MPC-based EMS requires load forecasts with a prediction horizon of up to a few days, which in the literature is often referred to as short-term load forecasting (STLF). Especially for the forecasting of the electric load of large territories, various approaches have been proposed for that purpose [2]. In general, these approaches are divided into two categories [3]. Classical approaches include methods such as time series models, regression models and techniques based on Kalman filtering. Newer approaches apply methods from the research field of artificial and computational intelligence such as artificial neural networks, fuzzy inference and fuzzy-neural models, expert systems, and support vector machines (SVMs). Although there is a large volume of literature on this topic, almost no applications of STLF to the thermal and electric loads of buildings have been reported [4]. Forrester and Wepfer [5], for instance, proposed a method based on multiple linear regression to provide forecasts of the energy demand of a large, commercial building. Dhar et al. [6] applied a Fourier series model to predict the hourly heating and cooling energy use in commercial buildings. Several researchers studied neural networks (NNs) to develop a building STLF algorithm [7, 8, 9]. Hou and Lian [10] studied in their work the feasibility and applicability of the SVM for the specific case of building load forecasting. In [4], the performances of an autoregressive model, an autoregressive integrated moving average (ARIMA) model, a NN and a Bayesian model for the forecasting of the electric load of an air-conditioned non-residential building are examined.

In this paper, two building STLF algorithms providing hourly load forecasts are presented and evaluated. The first algorithm is based on NNs and the second one uses least squares SVM (LS-SVM) regression models. The performances of the two building STLF algorithms are tested using the measured thermal and electric load data of a large office building and of a small building which houses a kindergarten.

INTRODUCTION TO NEURAL NETWORKS AND LEAST SQUARES SUPPORT VECTOR MACHINE

This section provides a brief introduction to NNs and the LS-SVM.

Neural Networks

NNs have received much attention in the field of STLF [11]. They mimic the behavior of the human brain in order to provide an approximation of the nonlinear relationship between input and output variables [8]. The basic unit of a NN is the artificial neuron, which receives information through a number of input nodes, processes it internally, and outputs a response [11]. Typically, the neurons in a NN are organized in layers. For more information about NNs, the interested reader is referred to, e.g., [12].

Least Squares Support Vector Machine

LS-SVM, as proposed by Suykens and Vandewalle [13], is an algorithm based on the standard SVM method developed by Vapnik [14] for classification and regression. The basic idea of the standard SVM method applied for regression is to map the original input vectors into a feature space with higher dimensionality using a nonlinear mapping function, and then to perform a linear regression in the feature space [14]. Instead of using inequality constraints as in SVM regression, the LS-SVM uses equality constraints and a least squares error term to determine the weight vector and the bias of the regression model. Therefore, training the LS-SVM regression model is equivalent to solving a set of linear equations instead of solving a quadratic programming problem as in SVM regression [13].

BUILDING STLF ALGORITHMS PROPOSED

In this work, the load forecasting problem is regarded as being equivalent to describing the relationship between the load and the factors most likely to influence it. Since the electric and thermal loads of a building strongly depend on the activity in the building, it is proposed to distinguish between working days, weekends and holidays, and therefore, to treat each day type individually. This approach avoids much of the non-linearity of the forecasting process [4]. Furthermore, on days of the same day type, building loads typically exhibit a similar daily pattern. Hence, the building STLF algorithms evaluated in this work treat each hour of the day separately by an individual forecasting model, so that a total amount of 24 different models have to be trained for each day type. The variables chosen as input variables of the individual hour-by-hour models are the ambient air temperature and the vertical solar radiation on the south-east and south-west oriented facades of the building in the corresponding hour. A variety of methods exists to describe the relationship between these input variables selected and the load. In this work, the NN model and the LS-SVM model are tested for that purpose. In order to adapt to changing load patterns, the models are trained with the sliding window approach, i.e., as soon as new measurement data is available it is added to the training data set and the oldest data is removed. In doing so, the size of the training data set is kept constant [8].

EXPERIMENTAL RESULTS

To test the building STLF algorithms proposed, the electric and thermal (including domestic hot water) load data of two different buildings are used. These buildings are located next to each other on the Science City Hönggerberg campus of the ETH Zürich. The first building is a large office building built in 2008. It is equipped with a heating, ventilation, and air conditioning (HVAC) system. The second building is a small one which houses a kindergarten. Both buildings have a south-east and a south-west oriented facade. The two buildings are shown in Fig. 1. Figure 2 depicts the hourly electric and thermal loads of these buildings on January 29, 2013.

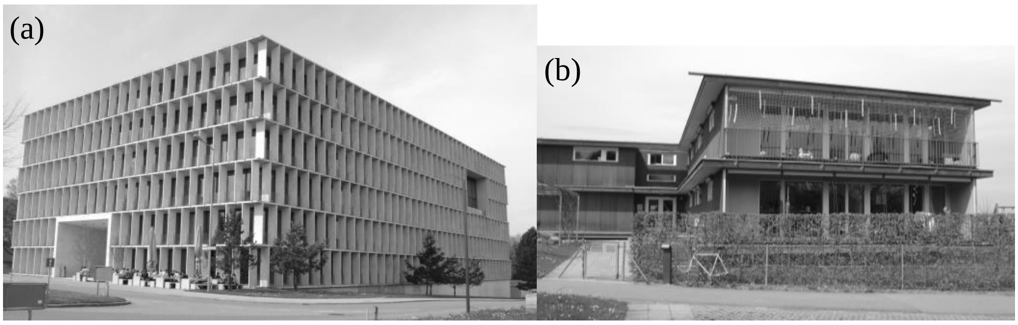

Figure 1: The two test buildings: An office building (left) and a kindergarten building (right).

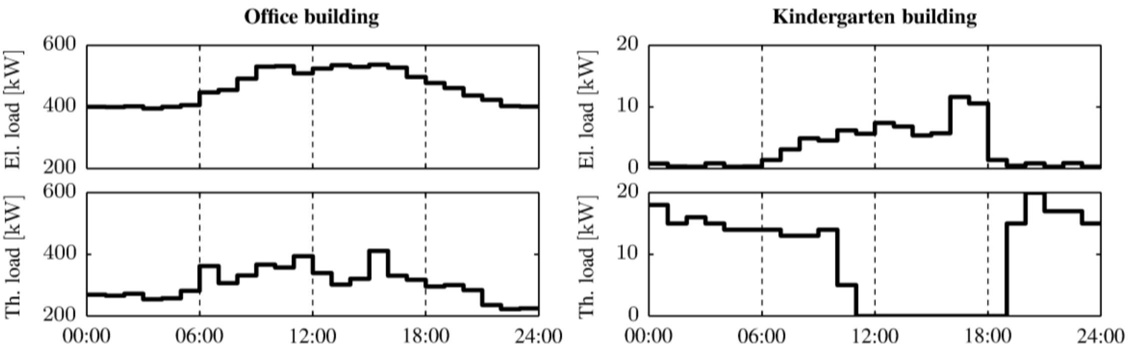

Figure 2: The hourly electric and thermal loads of the test buildings on January 29, 2013.

A weather station located in the neighboring village provides measurement data of the ambient temperature and the global horizontal solar radiation. The Erbs et al. correlation [15] for the estimation of the diffuse component of the horizontal solar radiation and the Perez et al. sky model [16] are used to compute the vertical solar radiation on the building facades from the horizontally measured global solar radiation data. The training of the hour-by-hour models is performed using these measurement data of the input variables. However, the load forecasts are generated using COSMO-2 and COSMO-7 weather forecasts provided by the Swiss national weather and climate service [17].

To test both building STLF algorithms, one-day-ahead forecasts generated at midnight are used. The training data is always updated before a new forecast is generated. Three different training window sizes are examined: 20, 50 and 100 days of the same day type. The analyses are performed using data acquired in the period November 2011 – March 2013, whereas in this work only the results for working days are presented.

The building STLF algorithms evaluated are implemented in MATLAB. The results for the hour-by-hour models based on NNs are obtained using the MATLAB Neural Network Toolbox which applies a feedforward NN [18]. The NNs are trained using the Levenberg-Marquardt backpropagation algorithm. Both, NNs with one hidden layer with two neurons and NNs with one hidden layer with four neurons were examined. Since the NNs with two hidden neurons performed better, only these results are reported. The hour-by-hour models based on the LS-SVM model are implemented using the LS-SVMlab toolbox [19]. The radial basis function is chosen as the kernel function.

The accuracy of the load forecasts are measured by the root mean square error (RMSE) and the coefficient of variation of the RMSE (CV-RMSE), which are computed as

$$RMSE = \sqrt{1/N \sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2} \;, \qquad CV - RMSE = \frac{\sqrt{1/N \sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2}}{1/N \sum_{i=1}^{N} y_i} \;, \tag{1}$$

where y_i is the real value, $\hat{y}_i$ is the value forecasted, and N represents the number of samples in the data set.

The results of both building STLF algorithms in the case of the office building are depicted in Fig. 3, whereas Fig. 4 shows the results for the kindergarten building. In general, the LS-SVM-based STLF algorithm performs better than the NN-based STLF algorithm. It is also noticeable that the CV-RMSE values of both the electric and thermal load forecasts are significant larger for the kindergarten building than for the office building. Obviously, the load forecasts for a large office building can be generated more accurately since its load profiles are less sensitive to the behavior of individual occupants.

The performances reported further show that for both buildings the accuracy of the electric load forecasts is slightly improved by increasing the size of the training window. On the other hand, the accuracy of the thermal load forecasts decreases with increasing training window size. The reason is that the thermal load of both buildings varies much more with the season than the electric load. Therefore, in the case of a large training window size, the training data contains data from another season deteriorating the training of the models.

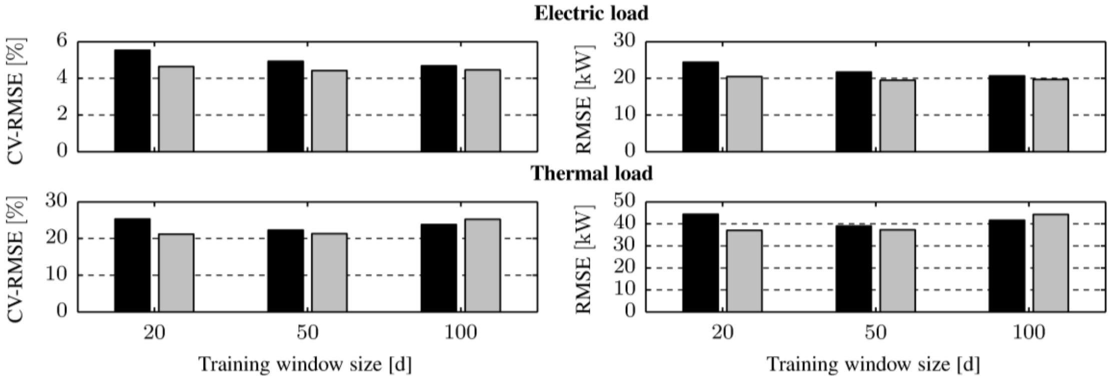

Figure 3: Performances of the NN-based STLF algorithm (black) and the LS-SVM-based STLF algorithm (gray) in the case of the office building.

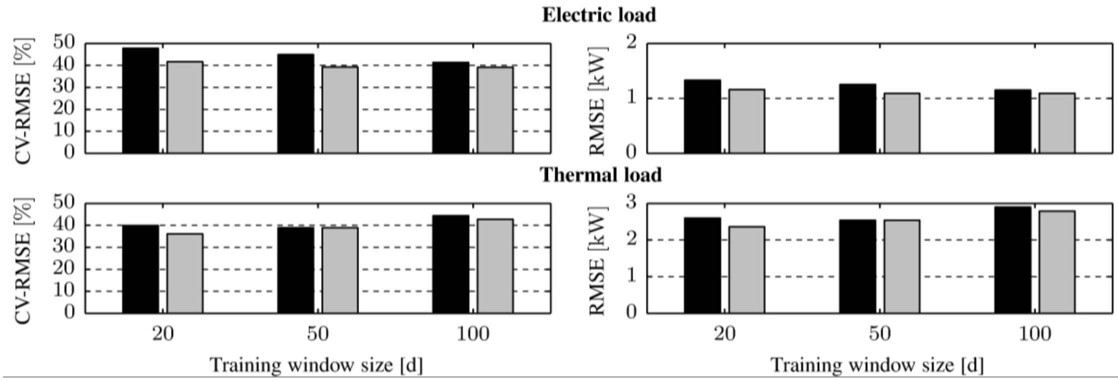

Figure 4: Performances of the NN-based STLF algorithm (black) and the LS-SVM-based STLF algorithm (gray) in the case of the kindergarten building.

CONCLUSION

In this paper, the capabilities of neural networks and of the least squares support vector machine in thermal and electric load forecasting in buildings are examined and compared. The following conclusions are drawn from the tests conducted using the measured thermal and electric load data of a large office building and of a small kindergarten building:

- The least squares support vector machine performs better than neural networks in building load forecasting.
- The least squares support vector machine involves fewer free parameters than a NN. This circumstance makes the application of the forecasting algorithm based on the least squares support vector machine easier compared to the forecasting algorithm based on neural networks.
- Compared to the large office building, the accurate load forecasting of a small building is a more difficult task.
- Using training window sizes of more than 20 days provides no significant benefit.

Future research will focus on the systematic selection of the input variables of the hour-by-hour models.

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