Forecasting Techniques for Energy Optimization in Buildings

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INTRODUCTION

Energy efficiency is one of the most important elements in resource management and control for institutions and individuals, since it may affect several factors, such as economic (savings, competition, crisis), social and cultural (environment), and political (energy independence, etc.). Many governments are making great efforts to issue a series of recommendations and even promote energy efficiency related business with the aim of moving towards a sustainable energy model (U.S. Department of Energy, 2010).

For instance, the energy consumption in residential and commercial buildings accounts for about 40% of the final energy consumption, with a significant portion related to heating, ventilation and air conditioning systems (HVAC), according to the Building Energy Data Book (U.S. Department of Energy, 2010) and the IEA (International Energy Agency) (IEA, 2010). Obtaining a good set of rules and policies for building management systems (BMS) is necessary for an optimal tuning of HVAC systems (Gacto et al., 2012). There exist several factors that have a significant impact on energy efficiency optimization in buildings. Two of them are temperature and electric load consumption. An accurate prediction of these magnitudes is vital for HVAC systems to optimize energy usage in buildings while keeping good comfort conditions (Mateo et al., 2012).

BACKGROUND

Forecasting applications often rely on classical linear statistical modeling techniques like Multiple Linear Regression (MLR), Robust Multiple Linear Regression (RMLR) (Weisberg, 1985) and ARMA models (Makridakis et al., 1998). More recently, machine learning methods such as Artificial Neural Networks (ANNs) (Eynard et al., 2011) or Support Vector Machines (SVMs) (Li et al., 2009), have emerged as a robust alternative to classical models, generally enabling a better approximation of complex, non-linear relationships between the system inputs and outputs.

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ANNs cover a wide range of forecasting problems, and they are known for their flexibility and high predictive accuracy (Haykin, 2008). Therefore, they have a widespread use in the field of building indoor temperature prediction (Gouda et al., 2002; Mustafaraj et al., 2011; Ruano et al., 2006).

In the literature it is possible to find comparisons of linear models with ANNs applied to daily temperature profile forecast (Hippert & Pedreira, 2004) and indoor temperature forecast in buildings (Mechaqrane & Zouak, 2004; Thomas & Soleimani-Mohseni, 2007; Mateo et al., 2012). These studies conclude that ANNs are more advantageous than linear models. In the field of power load forecasting, one can find time series approaches (Paarmann & Najar, 1995), regression analysis (Goia et al., 2010), ANNs (Wang et al., 2012) and, more recently, SVMs (Zheng et al., 2011).

In this article, we introduce a variety of advanced forecasting techniques like Extreme Learning Machines (ELMs) (Huang et al., 2006), Multilayer Perceptrons (MLPs), Least-Squares-Support Vector Machines (LS-SVM) (Suykens et al., 2002), General Regression Neural Networks (GRNNs) (Specht, 1991) and a combination of MLPs with Non-linear Autoregressive Exogenous techniques (NARX) (Lentaritidis & Billings, 1985a; Lentaritidis & Billings, 1985b). These methods are going to be evaluated on two applications related to energy optimization in buildings, more precisely:

- Forecast of the next-hour indoor temperature fluctuation from data obtained from a building simulator. For this we use the record of past temperatures and other environmental variables.
- Short-term (next hour) electrical load consumption forecasting from data acquired from a set of buildings in the University of León (Spain).

In both cases, the variables are acquired for a time span of one full year with a frequency of one hour.

OPTIMIZATION IN BUILDINGS

This section describes the proposed methodologies to carry out the temperature and load consumption forecast with the final goal of optimizing the use of energy.

Data Description

Temperature predictions were obtained by simulating a real building in the CAD software TeKton 3D (Procedimientos Uno S.L., 2008). The building, located in the city of Málaga (Spain), is intended for educational purposes. The dataset contains outdoor climate variables of the building and climate variables and thermal loads of four different areas inside the building. The data collection frequency is one hour and the data set contains a total of 8760 samples per year. The variables are: month, day of the week, day of the month, official time, relative humidity (%), outside temperature (°C), setpoint temperature of the four zones (ºC), total thermal power in each zone (W), current temperature in each zone (°C) and predicted temperature in each zone (°C). The high setpoint temperature is 24 °C and the low setpoint temperature is 22 ºC. Thermal power represents the value consumed by the air-conditioning systems for one hour. Positive values represent the use of cooling mode and negative values the use of the heating mode. Figure 1 shows the monthly average of the temperature in each zone.

Additionally, to carry out the power consumption prediction, a set of real data from 32 buildings in the University of León (Spain) has been acquired. The registered variables are: day, month, official time, outside temperature (°C), relative humidity (%), solar radiation (W/m^2), working day, active power (kW/h), standard deviation of the active power (kW/h) and predicted active power (kW/h). All variables have been registered from March 2011 to March 2012 (13 months). The hourly and weather variables are common to all buildings. The frequency of data collection is two minutes, accounting for a total of 280800 samples. To reduce the size of the data, an averaging every 30 samples is performed, leading to a sample per hour. To evaluate the performance of the models, we have chosen five buildings with different characteristics. Table 1 lists the selected buildings, their floor space and the basic statistics of the active power.

FORECASTING METHODS

In this section, classical and advanced short-term forecast methods, which are based on the concept of time series, are presented.