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Short-term load forecasting for non-residential buildings contrasting artificial occupancy attributes

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ABSTRACT

An accurate short-term load forecasting system allows an optimum daily operation of the power system and a suitable process of decision-making, such as with regard to control measures, resource planning or initial investment, to be achieved. In a previous work, the authors demonstrated that an SVR model to forecast the electric load in a non-residential building using only the temperature and occupancy of the building as attributes is the one that gives the best balance of accuracy and computational cost for the cases under study. Starting from this conclusion, a simple, low-computational requirements and economical hourly consumption prediction method, based on SVR model and only the calculated occupancy indicator as attribute, is proposed. The method, unlike the others, is able to perform hourly predictions months in advance using only the occupancy indicator.

Due to the relevance of the occupancy indicator in the model, this paper provides a complete study of the methods and data sources employed in the creation of the artificial occupancy attributes. Several occupancy indicators are defined, from the simplest one, using general information, to the most complex one, based on very detailed information. Then, a load forecasting performance discrimination between the artificial occupancy attributes is realized demonstrating that using the most complex indicator increases the workload and complexity while not improving the load prediction significantly. A real case study, applying the forecasting method to several non-residential buildings in the University of Girona, serve as a demonstration.

1. Introduction

In order to build a fair and more sustainable society, new approaches and initiatives have appeared in all areas. Energy resources are limited, and there is the need to generate new technologies and legislation that allows to achieve a certain environmental balance. The Lisbon Treaty [30] and the Kyoto Protocol [10] are examples of legal initiatives that have the aim of reducing consumption and emissions. To reduce the consumption, it is necessary to improve the existing electricity grid making it more efficient and robust. The smart grid, in conjunction with decentralized power generation, could avoid many of the shortcomings of the classical electrical grid.

Thus, to increase the efficiency of the electricity grid, a balance of power generation is required such that there is no waste or lack of resources. Due to the apparition of micro-grids, there is a balance between the generation of power and the users' consumption. Given that buildings are responsible for a large part of the electricity consumption, having tools to predict their consumption is key in the adjustment process. Predicting the consumption of a city is different from predicting the consumption of a building, in that in the case of buildings there is much variability. Disaggregated environments are more difficult to predict. Thus, short-term load forecasting (STLF) methodology is used to reduce the building's consumption since it must deal with non-linearities and noise.

Recent research on energy efficiency in buildings include optimal decisions and an overall improvement in human behaviour, not just technology. The International Energy Agency's Energy in Buildings and Communities Programme (IEA-EBC) has recently completed a project related to strengthening the robust prediction of energy usage in buildings, with the goal of enabling the proper assessment of short and long-term energy measures, policies and technologies. The results of this project are collected in Annex 53 [15]. The analysis methods, developed models and results of Annex 53 were taken as the starting point for other several working areas. In particular, and due to the important effect of occupancy in energy

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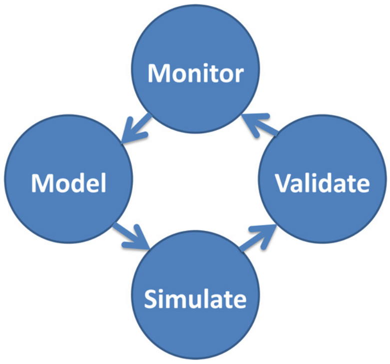

Fig. 1. Technical framework used in occupancy behaviour.

prediction, the IEA-EBC is working on Annex 66 [16]. On this annex they are trying to define and simulate occupant behaviour in a consistent and standard way. Based on these works, some new proposals have arisen, as is shown in [13]. The ontology represents energy-related occupant behaviour outlined as a DNAS (drivers, needs, actions and systems) framework, providing a systematic representation of energy-related occupant behaviour in buildings. Generally, researchers working on this topic follow a methodology that consists of monitoring, modelling and simulating, such as [13,14], as seen in Fig. 1.

These models are built after monitoring and collecting enough data about occupancy of the building. As stated in [14], this data is obtained from observational studies, occupant surveys and interviews, laboratory studies and unresolved issues in occupant monitoring, such as contextual factors. The occupancy models take into account the actions that occupant can do on the building, such as open the light, close the window, track or predict the occupant movements, and so on. It can be seen that the building must be sensorized to some extent to have this information available, a fact that is not always possible.

Although computing technology continues to develop, some forecasting models training on databases with dozens of attributes and millions of instances, may lead to high computational cost. Therefore, reducing the database is still necessary, always taking care to ensure that performance does not deteriorate. Most of the papers that propose the use of STLF methods in non-residential buildings often use weather data and, in some cases, occupancy information. Other works, such as [17,19,22], conduct comparison studies using similar models and arrive to a different conclusion, selecting other model as a best approach. The type of building and the test and training conditions can greatly affect the results. So, it is important to study different type of models in order to choose the best option in each case. According to [24], a model predicting consumption with minimal instances using support vector regression (SVR) with temperature and occupancy attributes provides excellent results for our buildings under study.

Obtaining predictions of temperature, in order to know the temperature of a particular place, is normally possible, although acquiring information of future occupancy remains difficult. In [24], occupancy information collected from passive infra-red (PIR) sensors was used. However, this information is not available in advance. The non-residential buildings usually dispose of work or scholar schedules, or other information about their occupancy. A technique designed to generate this information beforehand is needed. The goal is to obtain a model that is not dependent of any information unavailable months ago, such as previous consumption or temperature. This model can perform consumption predictions months ahead. Perhaps resulting accuracy level of the model may not be as good as the other works in this topic, but this is only a first step in this new direction.

Table 1
Occupancy related methods.

Method	Sources	Works
Calendar	Day types, months, etc.	[2,5,7,17,28,29,31,37]
Schedule	Work, student or use schedules.	[6,20,21]
Sensors	Motion, CO_2, noise, light, etc.	[8,18,23,24,26,27,33]
Expert knowledge	Surveys, interviews or inspections.	[19,25,35]

The aim of the work is to test the load forecasting accuracy using several occupancy indicators. It is not centred on occupant behaviour modelling, but estimating the occupancy is necessary, as it is one of the main factors that contributes to the accuracy of the SFTL. Concerning the occupancy estimation, we deal with buildings that are poorly sensed. That means there is not information about occupant actions, such as open/close the window, switch on/off the lights or plug a device, even if the actions are taken. There is information about scholar and working schedules, classrooms dimensions, expert knowledge, etc. Furthermore, there is only one of the buildings under study having sensors to estimate the amount of occupants inside the building by means of PIR sensors. Due to this limitation, several occupancy indexes have been defined using the available information.

In the first part of the paper, artificial occupancy indicators for the buildings are generated using different techniques and information available in advance such as academic calendars and work schedules. Then, SVR model is trained to forecast the consumption of the respective buildings, using these indicators of occupancy. Subsequently, an analysis of the relationship between the forecasting performance and the workload based on occupancy indicators, is performed. The idea is to show that there is a balance point in the artificial occupancy indicators, between forecast accuracy and workload. From a certain point on, increasing the complexity of the indicator does not improve significantly the prediction.

The paper starts with related works and follows with background material. Then, the dataset is explained. This is followed by a presentation of the methodology, where the several occupancy indicators are defined, and the test process explained. Next, the results are presented and the method is discussed. Finally, conclusions are shown.

2. Related works

There have been a large number of papers on the topic of STLF with regard to residential and non-residential buildings. The non-residential buildings are basically malls, schools, universities, hospitals and offices. Assuming that the use of information concerning the occupancy of buildings is key for improving prediction, the present state of the art focuses on the following topic: STLF in non-residential buildings based on occupancy data.

In the present state of the art, the advantages and disadvantages of the several methods associated with using the building's occupancy information in a prediction model are evaluated. The methods can be grouped into 4 blocks, as seen in Table 1.

In the first block, there are eight works that use calendar information. The first [2], is the case of a campus in Los Angeles that uses temperature and occupancy information, based on calendar data such as day of the week and holidays, with a regression tree model. In the paper [17], based on synthetic data and a non-residential building located in Athens (Greece), using meteorological data including temperature, solar flux, relative humidity and wind speed and the profile of the days of the week, the consumption is predicted using an ANN model. The work [28,29], in