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Occupancy based fault detection on building level – a feasibility study

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ABSTRACT

Buildings rarely perform as designed. Improving building functioning could be of great value for different stakeholders as building users, building owners and maintenance companies. In this study, a prototype procedure is developed for an on-line, self learning fault detection tool on building level. Taking passive user behavior into account, the tool aims to distinguish real faults from unexpected user behavior. An artificial neural network model is used to predict building energy consumption based on real time weather conditions and occupancy. Fault detection is performed by comparing this predicted consumption with measured values. The prototype procedure is currently tested in an office building in the Netherlands, the first results are promising.

INTRODUCTION

Published research shows that buildings rarely perform as designed. Results show that 81% of building owners experience problems using the heating ventilation and air conditioning (HVAC) system [Baily 1998], 50% of (researched) buildings experience control problems [Piette 1994], 40% of buildings experience HVAC equipment problems [Piette 1994] and 85% of buildings do not function properly because of wrong use and no proper building management [Elkhuizen and Rooijakers 2008].

To maintain building functioning as designed, prevent failures in the technical system and to maintain the required comfort level or even improve the comfort, commissioning is important. Research on on-going commissioning and fault detection and diagnostics (FDD) has been performed to improve the current situation of building problems by comparing measured building performance with design predictions [Portland 2003].

For fault detection, different methods for HVAC systems have been developed over the last 20 years. Approaches vary on nature of knowledge used, analysis technique and the level of fault detection [Katipaluma and Brambley 2005; Bing 2003]. Within different approaches assumptions have to be made which can cause uncertainties in FDD predictions.

One commonly made assumption is about the building user. By assuming a constant pattern for the presence, number of people and their distribution through the building (passive user behavior), the exact influence of the user on the system performance and building energy consumption is neglected.

In general, the available capabilities for user behavior modeling in connection to first principle system models (models based on energy-, mass- and momentum balances) are highly simplified. To make a first principle model including building, system and user details is complicated and time consuming. On the other hand, self learning approaches as artificial neural networks (ANN) have proven to be of great value in predicting complex system behavior [Kalogirou 2000]. The use of an ANN model to take user influence into account for building performance predictions will be tested in this research.

The objective of this research is to develop a new, self learning method to continuously check building performance and which will distinguish deviations of the building performance as designed, caused by unexpected passive user behavior from the faulty system behavior.

RESEARCH METHOD

This research project involved several stages:
- The development of a prototype procedure to meet project objectives.
- As part of the prototype procedure: the development of a method to take passive user behavior into account.
- The collection of measurement data of a testcase building.
- A test of the prototype procedure based on the testcase measurements.

The research is still ongoing and currently the ANN performance of the prototype procedure is tested. The prototype procedure, the method to take passive user behavior into account, and the testcase building are described in more detail in the next paragraphs. In the result chapter, the first results from the testcase measurements are presented.

Prototype Procedure

The basic principle for the fault detection in the prototype procedure is to continuously compare real time measurements with simulation data. Depending on the result of this comparison, measures might be needed to improve the building performance (Figure 1).
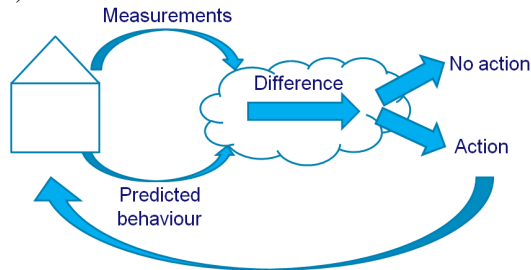

Figure 1.   Fault detection principle

Predicted behavior: the ANN model.

To predict building performance, an artificial neural network model will be used. The principle of an ANN model is a simplification of the functioning of the human brain. The brain consists of a network of neurons, which can be trained to learn.

An ANN model consist of an input, output and one or more hidden layers of neurons. All neurons of one layer are connected to the ones in the next layer (Figure 2).

By using a set of training data, an ANN model can be trained for that specific set of data by adapting the strengths and weights of the neurons and their connections, so that each input produces the correct output.
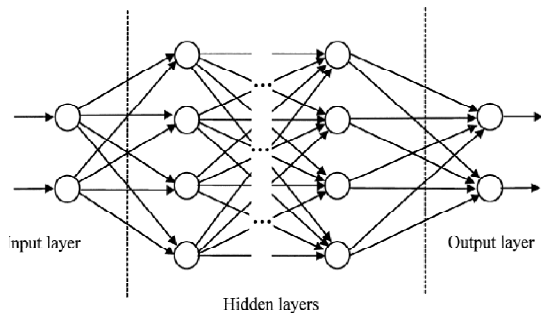

Figure 2.   Schematic view of artificial neural network [Kalogirou 2000]

ANN models are particularly suitable to model complex systems. Difficult relations can be learned. After learning, ANN can be a fast simulation tool. Because of the self learning principle there is no need to insert system characteristics (parameterize) manually and the ANN model can be adaptive to different situations.

The main disadvantage of an ANN model is the need of good training data. An ANN model can only be used within the range of learned input/output. Thus, a continuous updating of the ANN model by extending the range of input/output data is required. Also, faults in training data need to be filtered out. If not filtered out, the faults will be learned as normal (good) behavior reducing the usability of the model.

In the field of commissioning and FDD in building systems, ANN models have shown to be suitable in all kind of projects, from building level [Kalogirou 2000; Kalogirou and Bojic 2000] to component level [Kalogirou 2000, Morisor and Marchio 1999].

The ANN approach in this project is based on the assumption that with a well functioning technical installation and constant comfort requirements, energy consumption only changes due to the outdoor conditions and building use (passive user behavior).

We assumed that for a specific situation, users behave in a learnable way. Thus, the building performance will only change in time due to changes in outdoor conditions, the number of users, and faults in the system. To predict the range of expected building performance we measured outdoor conditions and the delta CO_2 over the supply and exhaust air. This ΔCO_2 will be used as an indicator for the number of building users. Both measurements are used as an input for the ANN model to predict the range of expected building performance.
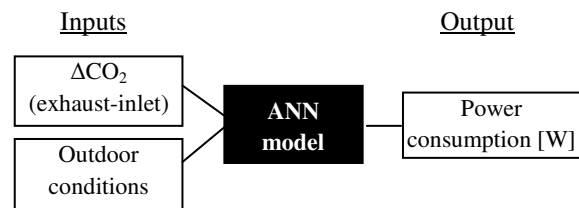

Figure 3.   ANN model in-/output for prototype procedure

As shown in Figure 1, predictions and measurements will be compared to detect faults in system functioning. By taking occupancy and outdoor conditions as an input for ANN model, predicted building performance is adapted to the current number of users and outdoor conditions. Figure 4 shows an impression of the fault detection principle of the prototype procedure.
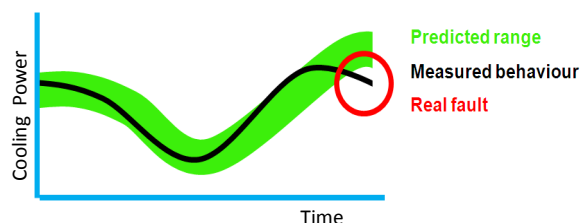

Figure 4.   Impression of fault detection principle: comparison of model predictions and measurements

The ANN model divides power consumption in three parts: cooling-, heating- and other electrical power consumption. Fault detection will thus be based on comparing these predicted values with the real power consumption.

<u>User based fault detection: CO_2 measurements.</u>
As described in the introduction, the number of building users is used as an input for the performance predictions to be able to distinguish real faults from unexpected user behavior.

On a building level it is not feasible to measure exactly how people behave and what they are doing. In relation to installation performance and energy consumption, continuously knowing the number of people in the building (or per floor) can already provide useful information. Internal gains for example are highly related to the occupancy.

To develop a widely usable method to measure the number of people in a building, CO_2 measurements are used.

Research about the relation between occupancy and indoor CO_2 concentrations has been done before but particularly on room level in the field of demand controlled ventilation [Lam et al 2009; Lawrence and Braun 2007; Persily et al 2003]. A study to estimate moisture production and capacity loads in museums used CO_2 measurements to estimate occupancy based on a wide range of generation rates [Schijndel 2008], in other research is tried to estimate these source generation rates [Lawrence and Braun 2007].

In this project the difference between CO_2 concentration in supply and exhaust air is used as an indication for the number of people within the building, therefore, this difference, ΔCO_2, will be used as an input for the ANN model.

There is few evidence of the similar approach (to use CO_2 measurements on a building level to estimate the occupancy) in literature. To gain initial confidence into the prospect of the approach, we have performed an experiment in a 60 m² office space occupied by six people to justify the concept idea based on ΔCO_2. The experiment was performed during one day and present people where counted on a minute base. Figures 5 and 6 show the similarity between the ΔCO_2 measurements and the occupancy.
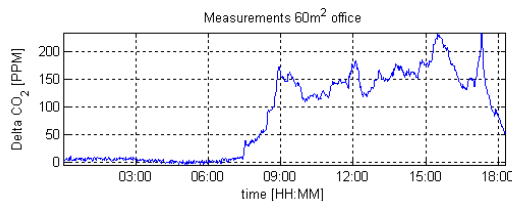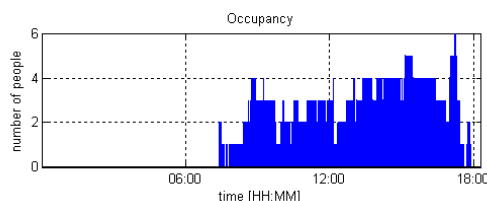

Figure 5. Measured $\Delta CO2$

Figure 6. Counted occupancy

As a next step in testing the applicability of CO_2 measurements as an indicator for the occupancy in the prototype procedure, a simple ANN model is used. Model occupancy predictions are compared with occupancy numbers of the entrance security system (ESS) of building, first results are presented in the result chapter of this paper.

An important issue for the application of CO_2 measurements is the accuracy of CO_2 sensors. To predict the exact number of persons, dependent on the ventilation rates and occupancy, an increase of 1 or 2 ppm on building level could be an indication of one person entering the building.

Research on the accuracy of different CO_2 sensors has shown wide variation of accuracies, seven out of eighteen CO_2 sensors will not meet the estimated required accuracy of 20% of the measured value [Fisk et al 2007]. However, for this research the accuracy of the absolute value is not important since the difference of two sensors is used. A relative calibration method is used to gain higher accuracies when comparing different values measured [Stum 2006].

For the ANN model predictions of the prototype procedure, the ΔCO_2 over supply- and exhaust air will be the indicator for the occupancy. The other inputs of the ANN model are related to the outdoor conditions: temperature, relative humidity, total solar irradiation and air velocity.

Testcase
The prototype procedure is tested in a small office building in Maarssen, the Netherlands.
The characteristics of the building are:
- 3 floors;
- 620 m² per floor;
- 77 fixed employees;
- 92 office desks;
- built in 1983;
- windows can be opened;
- solar shading devices;
- working hours between: 7:00 and 18:00;
- working days: Monday – Friday.

The characteristics of the Technical system are:
- mechanical ventilation system;
- heat recovery (no recirculation of air);
- local cooling by fancoil units;
- central heating by air and radiators;
- entrance security system.

All measurements needed for the ANN model are performed in this building. For occupancy, CO_2 sensors are placed in the central supply and exhaust ducts, as in the exhaust ducts on the different floors. The exact occupancy is also registered by the ESS and a reception log. As a boundary condition for the prototype procedure, the ventilation rate should be

constant. To check this, air velocity in ducts is measured. Also logs are used to register open windows.

Figure 7.   Testcase building in Maarssen

RESULTS

The research is still ongoing: measurement data of a 8 week period has been collected and currently the first ANN models are tested.

For now, the first results obtained from the testcase measurements and the ANN model for occupancy predictions are promising. Figure 8 shows one week of measurements of the ΔCO_2 over supply and exhaust air. This week, the 30th of April was a national holiday, so no increase of ΔCO_2 is visible. From Monday 26th till Thursday the 29th, different day patterns are visible: morning peeks (except on the 27th), decreasing concentrations at lunch times and a difference in maximum values on different days.
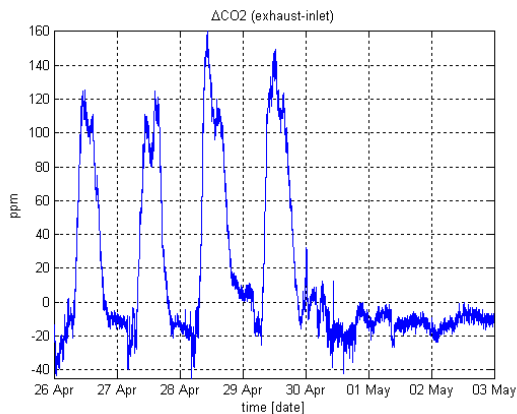

Figure 8. ΔCO_2 supply-exhaust air of one week period

For power measurements, the relation with outdoor conditions is also visible (Figure 9). On a relatively hot, sunny day as the 29th of April, gas consumption is minimal while cooling power peeks. On Friday the 30th of April, the absents of occupants and thus internal gains causes a higher gas consumption while cooling power is zero.
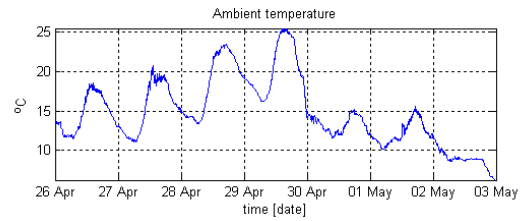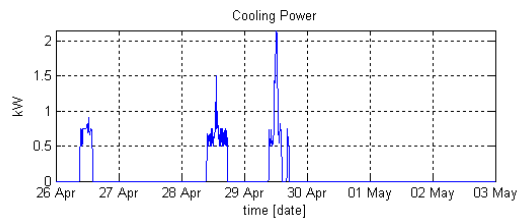

(a)
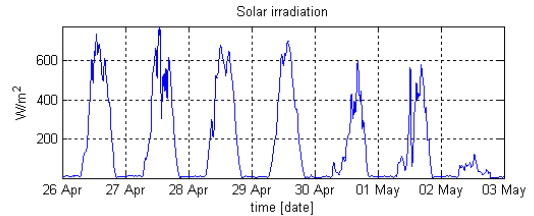
(b)
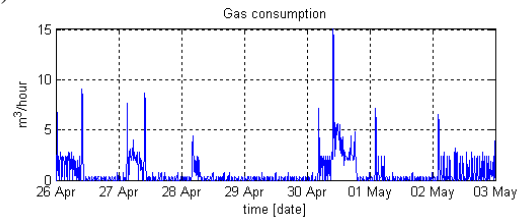
(c)

(d)

Figure 9.   Relation ambient temperature (a), solar irradiation (b), and gas consumption(c), and cooling power (d).

The first step in the modeling part of this project is to test the applicability of CO_2 as an indicator for the occupancy. For this, a simple ANN model is used to predict occupancy based on the CO_2 difference over supply and exhaust air.

With this model, the best results obtained so far are produced with a feedforward network with backpropagation training and two hidden layers. Four weeks of training data with a 1 minute measure interval is used for learning. The result of the occupancy predictions for the testperiod of one week is shown in figure 10. As input for the ANN, the ΔCO_2 from figure 8 is used. The R² value of the simulation results is 0,95 and the average error in predicting the number of people is 1,96.

Absolute errors of the ANN predictions vary. At night situations the error is almost zero, while at daytime and especially during fast changing occupancy numbers, the difference between real occupancy and predicted values can be over 20. The standard deviation of the error is 4,38 and overall the ANN model gives an indication of the occupancy

which seems to be accurate enough for the use in the prototype procedure.
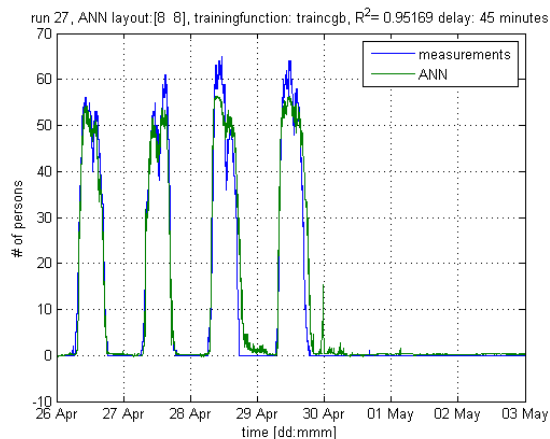
Figuur 10.   First results of ANN occupancy prediction.

Future Work

The next step in this research is to optimize the ANN model for occupancy predictions and to develop the ANN model for the prototype procedure. After training this model, sensitivity of the inputs, the accuracy of the predictions and the fault detection ability of this model will be tested as a final result of this project. Model predictions will be visualized in an on-line web-based user interface.

DISCUSSION

During the development of the prototype procedure, different influences on the measurements are considered to be constant and learnable by the ANN model. Examples are the leakage of indoor air via decentral exhaust point, the ventilation efficiency of the rooms, night mode of the ventilation system, the influence of plants on CO_2 measurements, and openable windows.

A boundary condition for the use of the prototype procedure as described in this paper is a constant ventilation rate during operating hours. A change in the amount of ventilation air will cause differences in CO_2 measurements for the occupancy predictions. In case of buildings with CO_2 controlled ventilation systems, the power consumption of the fan will replace the CO_2 measurements as input of the ANN as the indicator of the occupancy.

To check the applicability of CO_2 as an occupancy indicator, data of the entrance security system is used as reference for the real occupancy. Unfortunately, employees don't always used their entrance card to enter or leave the building. Based on the ESS data, small negative occupancy occurred at the end of the day. These values are changed to zero before ANN training but they still create an uncertainty in the ANN model for occupancy predictions.

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