MASTER

User based fault detection on building level
a feasibility study

Tuip, B.G.C.C.

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2010

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User based fault detection on building level

A feasibility study

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October 2010
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Eindhoven University of Technology

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Preface

This report is the result of a graduation project in the Building Services Master program of Eindhoven University of Technology. The project is performed as a cooperation between the university and Strukton Worksphere. The research is about the development of a new method for fault detection in buildings.

For the last year I have been working on this project with great pleasure. A very educational experience was the writing of a paper for the ICEBO conference. Thanks to the critical guidance of the supervisors, the submission of the paper resulted in a nomination for the best student paper of the conference.

First I would like to thank professor Jan Hensen for his help in making strategic decisions and his guidance at the progress meetings. Although it took some time in the beginning to narrow down the subject, I am very glad we came to this focus which kept the project interesting all the time.

Also a special thanks goes to both other supervisors, dr. ir. Rinus Van Houten and dr. dipl.-ing. Marija Trcka. The meetings with Marija where always very useful and pleasant. Her critical and perfectionist guidance was very instructive. Then Rinus, who guided me in the past six years trough different projects during my study in Eindhoven. Although he was not completely convinced of the idea of the prototype procedure the first time I told him, his enthusiasm for the project kept surprising me the rest of the project and resulted in the writing of the conference paper.

The cooperation with Strukton Worksphere gave the opportunity to apply and test all theory in practice. This practical application resulted in a high variation in type of work and made the project extra challenging. For this I would like to thank Strukton Worksphere, and especially ir. Eric Mimmel. Without their investments in the measurement system, support with the installation in the testcase building and the helpfulness of all colleagues, finishing the project with the same results would have cost me another year.

Barry Tuip

October 2010
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 (ANN) model is used to predict building energy consumption based on realtime weather conditions and occupancy. Fault detection is performed by comparing the predicted consumptions with measured values. Occupancy is measured by the difference in CO₂ concentration between inlet and exhaust air in the central ventilation system.

The prototype procedure is tested in an office building in Maarssen. Measurements of outdoor conditions and CO₂ concentration were used to predict heating, cooling and total electricity consumption by three ANN models. Due to a fire incident, measurement data was limited and the application of the prototype procedure had to be tested with the 7 weeks of data collected so far.

The prototype procedure is tested for three cases: an early starting working day, fire detection, and a changed situation in the air handling system. Total electricity consumption and gas consumption predictions both showed to be capable of detecting the case situations. Cooling power could not be predicted in a sufficient way for fault detection due to the unsuitable cooling system of the testcase building.
1 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 [Bailey 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].

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 user behavior from the faulty system behavior.

In this chapter, an introduction to the subject is given by a summary of literature. The first section contains an overview of common building problems found in literature. Next to the building problems, typical situations of unexpected use of a building are described. The second part introduces existing methods and tools for fault detection and diagnostics (FDD). In the third section an introduction is given to Artificial Neural Network (ANN) models. Section four gives an overview of the content of the rest of the report.

1.1 Building problems

Problems in building can have different causes and occur in different levels and parts of the technical system. In a research performed by the Portland Energy Conservation and the Battelle Northwest Division [Portland 2003], a matrix was developed to evaluate problems with systems and equipment based on the likelihood that the problems would benefit from automated commissioning. Over 139 problems associated with 19 common building systems components are judged by experts on different criteria. The most significant problems are:

- faulty economizer operation;
- uncalibrated or malfunctioning sensors in Economizer Air systems;
- uncalibrated or malfunctioning valves or dampers and actuators in Economizer air systems;
- faulty or improper ventilation control strategies;
- uncalibrated or malfunctioning sensors or actuators;
- malfunctioning economizers and dampers;
- improper setpoint settings.

The faults in the Portland research where categorized in 19 system components with as most common ones: the building automation system, air handler, large and small packaged units, economizer and exhaust fan system.

The ANNEX 25 report of the IEA Energy Conservation shows a different categorization [IEA 1996]. In Annex 25, a distinction is made into four main systems: heating systems, chillers and heat pumps, VAV air handling units and thermal storage systems. Per system, different components with typical problems are described and ranked.

A Dutch research [Elkhuizen 2008] to building performance and common problems shows an uncategorized list with 25 common problems as wrong setpoints in control system, disfunctioning valves, errors in sensors and blocked air inlets by building users.
Different researches show long lists of typical building problems, all presented in different ways. For this project, the most common building problems are summarized and divided into 3 categories:
- faults in the system setup (made during design, system installation or use of the system);
- faults in the hardware components such as chillers, heatpumps, valves, etc (during use of system);
- faults in the control system (made during design, system installation or use of system).

These problems are all described as real faults. A second type of faults is introduced: situations which can be detected as a fault but are caused by unexpected user behavior. These unexpected use situations are divided into two categories:
- changes in internal gains;
- in-/outdoor heat exchange.

<table>
<thead>
<tr>
<th>Faults in system setup</th>
<th>Unexpected use:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Wrong system design</td>
<td>- Change in internal gains</td>
</tr>
<tr>
<td>- Incorrect tuning</td>
<td>- Occupancy</td>
</tr>
<tr>
<td>- Change of building use without changing the system</td>
<td>- Lighting</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Faults in hardware components of system</th>
<th>Unexpected use:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Heating system</td>
<td>- Change in working hours</td>
</tr>
<tr>
<td>- Chillers and heat pumps</td>
<td>- Electrical devices</td>
</tr>
<tr>
<td>- Air handling unit</td>
<td>- In-/outdoor heat exchange</td>
</tr>
<tr>
<td>- Local heating/cooling equipment</td>
<td>- Windows closed/open</td>
</tr>
<tr>
<td>- Storage systems</td>
<td>- Doors closed/open</td>
</tr>
<tr>
<td>- Distribution system (water and air)</td>
<td>- Solar shading devices</td>
</tr>
<tr>
<td>- ...</td>
<td>- Solar shading devices</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Faults in control system</th>
<th>Unexpected use:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Control software</td>
<td>- Change in internal gains</td>
</tr>
<tr>
<td>- Configuration</td>
<td>- Lighting</td>
</tr>
<tr>
<td>- Control setpoints</td>
<td>- In-/outdoor heat exchange</td>
</tr>
<tr>
<td>- Measure equipment</td>
<td>- Windows closed/open</td>
</tr>
<tr>
<td>- ...</td>
<td>- Doors closed/open</td>
</tr>
</tbody>
</table>

For this project, an important addition to the technical problems found in literature is the unexpected use category. During system design, assumption are made regarding internal electrical gains, occupancy numbers and working hours. Since changes in this exert influence on the performance of the building and technical system, taking unexpected use situation into account is one of the objectives in the development of the prototype procedure.

### 1.2 FD&D methods and tools

This section starts with an introduction in commissioning and an overview of fault detection methods and the different levels in which fault detection can be applied. An overview of existing tools is given in section 1.2.3 and in section 1.2.4 blank areas in research of fault detection are described. One of the fault detection methods, artificial neural networks, is described in more detail in section 0.
1.2.1 Commissioning

Commissioning is one of the new approaches to manage the complexity of today’s building and HVAC systems. Commissioning is an approach in which building performance is monitored from the design phase of the building process through the total lifetime of the building. Constantly comparing building performance with design prediction can result in significant energy savings, gives a long life to building systems and maintains or even improves indoor comfort [Portland 2003, Haves et al 2001].

In the annex 40 project [Visier 2004] a broad view is presented which aims to bridge the gaps between 4 different visions: the expectations of the building owner, the project of the designer, the assembled system of the contractor, and the running system of the operator. In this view the commissioning process starts in the predesign phase and continuous through the occupancy and operation phase.

Table 2. Four different types of commissioning [Visier 2004]

<table>
<thead>
<tr>
<th>Initial Commissioning</th>
<th>Ongoing Commissioning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Commissioning</td>
<td>Re-Commissioning</td>
</tr>
<tr>
<td>Missing Initial Commissioning (or missing documentation on Initial Commissioning)</td>
<td>Retro-Commissioning</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production</th>
<th>Operation &amp; Maintenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-Design</td>
<td>Design</td>
</tr>
<tr>
<td>Program</td>
<td>Planning</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Four different types of commissioning are described in table 2. Initial commissioning in the production phase, and three types of commissioning are distinguished during building operation:

- Retro-Commissioning is the first time commissioning is implemented in an existing building in which a documented commissioning process was not previously implemented.
- Re-Commissioning is a commissioning process implemented after initial commissioning or Retro-Commissioning when the owner hopes to verify, improve and document the performance of building systems.
- On-Going Commissioning is a commissioning process conducted continually for the purposes of maintaining, improving and optimizing the performance of building systems after Initial-Commissioning or Retro-Commissioning.

In this project the focus will be on the on-going type of commissioning during operation phase of a building.
1.2.2 Fault detection and diagnostics

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; Isermann 2006].

Figure 1 shows an scheme with a categorization of the variety of FDD methods. Quantitative model-based methods include those based on detailed physical models as well as those based on simplified models of the physical processes. These models can be steady-state, linear dynamic, or nonlinear dynamic. Qualitative model-based approaches include rule-based systems and models based on qualitative physics. For rule-based systems, we further distinguish between those based on expert rules (i.e., expert systems) for which there may, in some cases, be no underlying first principles from physics, rules derived from first principles, and simple limit checks (which serve as the basis for alarms). [Katipaluma and Brambley 2005]

In contrast to the first two groups where a priori knowledge of the process is assumed, the third group is based solely on process history, i.e., a large amount of historical data is assumed to be available. These models include black-box (input-output) methods for which the models are derived purely from the data and gray-box models that use first principles or engineering knowledge to specify the mathematical form of terms in the model but for which parameters (such as coefficients in the model) are determined from process data. Black-box methods include statistically derived models (e.g., regression), artificial neural networks (ANNs), and other pattern-recognition techniques. [Katipaluma and Brambley 2005]

Fault detection and diagnosis can be performed on different levels. From comparison of energy consumption on building level [Katipamula 2003, Haves 2003], to the analysis of temperatures in system components as radiators and air handling units [Qin 2005, Katipamula et al 2003]. Bing Yu developed a Level-oriented approach for FDD in climate installations [Bing 2003]. A top down approach from building level to component level is developed for FDD through the entire system (Figure 2).
1.2.3 Existing Tools

Tools for fault detection based on the described FDD methods are applicable on various levels. The Dutch research institute of TNO developed a method based on energy consumption comparison of households on municipal level. A software tool is developed which compares gas consumption of households in order to locate the highest consumption with the highest saving potential [Soethout et al 1997]. On component level, APAR is an example of a rule based fault detection tool for air handling units (AHU’s). Expert rules derived from mass and energy balances are used to check measured performance of AHU’s [Bushby et al 2001].

The Pacific Northwest National Laboratory created a module based multi-level FDD system. The system analyses whether the air handler is supplying adequate outdoor air and if possible, if free cooling with outdoor air is used. The whole building module analyses actual energy consumption by comparing it to measurements. History based predictions are used combined with weather conditions. [Katipamula et al 2003]

The Energy Systems Laboratory developed the automated building commissioning analysis tool (ABCAT) tool [Claridge 2009]. Calibrated simulations are combined with diagnostics techniques to analyze building energy consumption. Current energy consumption and cumulative consumption of a longer period are analyzed.

On the different levels for fault detection, different types of data are needed. If the commissioning process is included in a new building design, sensors for fault detection can be taken into account in the construction process of the building. In existing buildings it can be difficult and expensive to equip a building with all sensors, cables and software needed.
In the development of the prototype procedure of this project, the method should be applicable in both: existing buildings and in new buildings.

1.2.4 Blank areas in research
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.

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.

1.3 Introduction to artificial neural networks (ANN)
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 3).

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.

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 for good training data. An ANN model can only be used within the range of learned input/output. Thus for new situations, 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].
1.4 Prototype procedure

To meet project objectives, a prototype procedure is developed. 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 4).

![Figure 4. Fault detection principle](image)

To predict building performance, an ANN model will be used. The ANN approach in this project is based on the assumption that with a well functioning technical installation and constant comfort requirements, heating, cooling and electrical power 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: people come to work, adapt clothing to expected indoor and outdoor climate conditions and the average metabolism remains the same due to the same kind of work. Thus, the building performance will only change in time due to changes in outdoor conditions, the number of users, and faults in the system.

By measuring real time occupancy and outdoor conditions and using them for on-line energy predictions (Figure 6), a disparity in predicted and measured power consumption can only be caused by faults in the building system.

![Figure 5. ANN model in-/output for prototype procedure](image)

![Figure 5. Impression of fault detection principle: comparison of model predictions and measurements](image)

Figure 5 shows an impression of the fault detection principle of the prototype procedure. To measure the number of users, a new method to use CO₂ measurements on a building level is tested.
1.5 Contents
The next chapter of this report describes the method of this research. The developed theory (prototype procedure) to meet the objective of this research is described and more information about the test case building in which measurements are performed is given. Two important modeling parts of the prototype procedure are described separately in the method chapter.

The third chapter describes the results of this research. Again, the results of the ANN models are described in separate sections of this chapter.

In chapter four the application of the prototype procedure is tested with three practical cases.
2 Method
The prototype procedure described in section 1.4 is tested in practice. The office building used for the experiment, as well as the measurement setup are described in section 2.1. As already mentioned in the description of the prototype procedure, CO₂ measurements are used on building level as an indication of the occupancy. Section 2.2.1 contains the method of predicting occupancy by CO₂ measurements with the use of an ANN model. The use of ANN modeling in the prototype procedure is described in Section 2.2.2.

2.1 Measurements
To develop, test and optimize the prototype procedure, Strukton Worksphere facilitated their main office buildings as a Testcase building. The building has 92 office desks but is usually occupied by approximately 50 people. The building is located at the Planetenbaan in Maarssen in 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;
- Air handling unit of 10,000 m³/hour
- heat recovery (no recirculation of air);
- local cooling by 45 fancoil units;
- central heating by air and radiators;
- entrance security system.

The floors on the different levels are quite similar. Figure 8 shows the floor plan of the second floor. In the middle the central core with stairs, elevator and toilets (yellow), along the facade the offices (blue) and in between the corridor (green). The red space in the middle is the central coffee and repro office.
The following data is collected by different measurements systems:

**Outdoor measurements:**
- temperature;
- relative humidity;
- air velocity 1;
- air velocity 2;
- wind direction;
- solar irradiation.

**Air duct measurements:**
- CO2 concentration at central inlet;
- CO2 concentration at central exhaust;
- CO2 concentration at exhaust floor 1;
- CO2 concentration at exhaust floor 2;
- air velocity in central inlet duct;
- air velocity in central exhaust duct;
- air temperature in exhaust duct.

**Energy consumption:**
- total electricity consumption;
- electricity consumption for cooling on subgroup;
- gas consumption.

**Entrance security system:**
- exact times of people entering or leaving the building through all exits.

**Logs:**
- Visitors entering the building;
- opening times of all windows in the building.

More information about the measurement system can be found in attachment 1.
The measurements started in April and should have lasted until the end of July to gather enough data for the ANN training. Unfortunately in the early morning of June 16, a protest group firebombed the Strukton office as a protest against a maintenance project Strukton is involved in. The building was mainly damaged on the ground floor, but also on other floors the smoke gave a lot of nuisance.

After the fire a lot of things changed. The main entrance could not be used anymore so the entrance security system didn’t work, windows and doors where constantly opened and the first few weeks after the fire, employees were asked to work from home or other offices.

To gather training data for the ANN network, the fire incident created two sets of data: before the fire and after the fire. In this project the data before the fire is used for neural network training as described in the next paragraphs. A small part of data collected after the fire is used as an incident to test the fault detection applicability of the prototype procedure in Chapter 4.
2.2 ANN modeling

In this section the use of the ANN models in this project is described. The ANN modeling is divided into two parts: ANN1, in which the application of CO₂ measurements as indicator for occupancy is tested, and ANN2, containing the ANN models of the prototype procedure.

2.2.1 ANN1: CO₂ based occupancy predictions

As described in the previous section, 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. To make this distinction we assumed that by knowing the number of people in the building, electricity, cooling and heating power consumption can be predicted more accurately. Instead of making assumptions for the occupancy and working hours, real time data can be used to monitor building functioning.

People counting systems are not available in every building, in large buildings with a lot of entrances a central measurement method might be preferred. Since CO₂ sensors are becoming cheaper every day, the use of CO₂ sensors to develop a widely usable method to measure the number of people in a building is tested. Research about the relation between occupancy and indoor CO₂ 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 CO₂ 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 CO₂ concentration in supply and exhaust air is tested as an indication for the number of people within the building.

To test the capability of an ANN model to predict the occupancy based on two CO₂ measurements on building level, a separate ANN model is used. The procedure of testing and optimizing this model is described in this paragraph.

**Background**

There is little evidence of the similar approach (to use CO₂ 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 ΔCO₂. The experiment was performed during one day and present people where counted on a minute base. Figure 9 and Figure 10 show the similarity between the ΔCO₂ measurements and the occupancy. More information about the one day test in a single office space is included in attachment 2.
An important issue for the application of $\text{CO}_2$ measurements is the accuracy of $\text{CO}_2$ 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 $\text{CO}_2$ sensors has shown wide variation of accuracies, seven out of eighteen $\text{CO}_2$ 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 less 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]. The method and results of the calibration process are described in attachment 3. When using the $\text{CO}_2$ difference as an input for the ANN model, values are scaled so the absolute values of the difference of the sensors are not important, only the changes are.

**The model**

The principle of the ANN model is shown in Figure 11. The delta $\text{CO}_2$ is used as the input of the model to predict the occupancy.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{CO}_2$ (exhaust-inlet)</td>
<td>ANN model</td>
</tr>
<tr>
<td></td>
<td>Number of people</td>
</tr>
</tbody>
</table>

Figure 11. Principle of ANN model for occupancy predictions

In the Testcase building, six weeks of information about the number of people is gathered by the entrance security system and the reception log for visitors. In contrast to the eight weeks of data available for the testing of the prototype procedure, two weeks of data is missing due to an error in the entrance security system.

There are several parameters that influence the $\text{CO}_2$ measurements and therefore are taken into account in this analysis:

<table>
<thead>
<tr>
<th>Variable</th>
<th>measured by</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Air leaks like through open windows</td>
<td>log at every window</td>
</tr>
<tr>
<td>2. Constant ventilation rates</td>
<td>Air velocity in ducts</td>
</tr>
<tr>
<td>3. Infiltration</td>
<td>outdoor air velocity</td>
</tr>
</tbody>
</table>

To test the influence of these variables on the ANN predictions, the measurements described in Table 3 are tested as an extra input for the ANN model. If the model performance improves, the variables seem to be important to measure, otherwise they can be neglected.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \text{CO}_2$ (exhaust-inlet)</td>
<td>ANN model</td>
</tr>
<tr>
<td>Boundary condition 1,2,3</td>
<td>Number of people</td>
</tr>
</tbody>
</table>

Figure 12. Principle of ANN model for occupancy predictions with multiple inputs
To find the best performance of ANN for occupancy predictions, not only the inputs of the model are changed, also different setups and settings are tested to end up with the best performing model. The results of this optimization process is presented in paragraph 3.1.1. An overview of the parameters used in the optimization process is described in the text below.

**ANN layout**
The number of hidden layers and the number of neurons per layer can be varied to optimize the network for a specific situation. When the ANN model exists of only a few neurons, it might not be able to learn a complex systems behavior. If the model is too complex, the amount of training data might not be sufficient for optimal learning.

**Training function**
Matlab supports a large number of functions which all use different types of training of the ANN [MathWorks 2010 (1)]. The Levenberg-Marquardt backpropagation training function is the most recommend one to start with. Different training functions are tested and results are compared to find the best performing one.

**Transfer function**
The behavior of the ANN depends on the weights of the connections of the neurons and the input-output function (transfer function) specified for the layers of neurons [MathWorks 2010 (2)].

The functioning of the input-output calculation of an elementary neuron with \( R \) inputs is shown in figure 13. Each input is weighted with an appropriate \( w \). The sum of the weighted inputs and the bias forms the input to the transfer function \( f \). Neurons can use any differentiable transfer function \( f \) to generate their output.

Multilayer networks often use the log-sigmoid transfer function.

The Log-Sigmoid transfer function generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig which uses outputs between -1 and 1. For the purpose of the occupancy predictions, scaling the data between -1 and 1 gave the best model results. Therefore the tan-Sigmoid transfer functions is used in all layers.
Delay on exhaust air CO\textsubscript{2} concentration
Transporting the CO\textsubscript{2} produced by the occupants to the central exhaust duct will take some time. Air refreshment rates and ventilation efficiency in the rooms are both of influence on this delay. The delay is therefore building specific. To take this delay into account in the ANN model, the delta CO\textsubscript{2} is calculated with a variable delay. A delay of 30 minutes would for example result in a delta CO\textsubscript{2} being calculated with the CO\textsubscript{2} inlet concentrations at 09:00 and the exhaust concentration at 09:30 hour thus would be an indication of the occupancy at 09:00 hour.

Input variables
The basic input variable is the delta CO\textsubscript{2}. In order to improve the prediction performance, measurements of boundary conditions were added in order to gain higher prediction accuracy. The different variables are:
- \(\Delta\text{CO}_2\) (main exhaust)
- \(\Delta\text{CO}_2\) (floor 1)
- \(\Delta\text{CO}_2\) (floor 2)
- Duct air velocity
- Outdoor air velocity
- Wind direction
- Outdoor temperature
- Open windows
- Working day

Measure interval
CO\textsubscript{2} concentrations are measured per five seconds and the entrance security system registers peoples presents per second. The measurement data of the ANN model is interpolated to a specific interval. A very small interval can cause an oversensitive model with high fluctuations due to the fluctuations in CO\textsubscript{2} concentrations. To determine the minimum interval to obtain highest prediction accuracy, different intervals are tested.

Minimum training data needed
How much training data does the ANN need in order to predict in an accurate way? The number of training days is varied to find the minimum amount of data needed and still obtain high accuracy in model predictions.

Influence of test period on simulation performance
The optimization process is performed with one specific week of testing data. To test the performance of the ANN in different weeks, the optimized model performance is tested for other weeks.

Model performance
The applicability of the ANN models is dependent on the accuracy of the predictions. To assess the ANN performance the coefficient of determination is used.

\[
R^2 = 1 - \frac{\sum(Y_i - Y_i')^2}{\sum(Y_i - \bar{Y})^2}
\]
With:

\[ R^2 = \text{coefficient of determination} \]
\[ Y_i = \text{measured value} \]
\[ Y'_i = \text{predicted value} \]
\[ \bar{Y} = \text{average of measured values} \]

Essentially, \( R^2 \) tells us how much better \( Y_i \) can be predicted by using the model and computing \( Y'_i \) than by just using the mean \( \bar{Y} \) as a predictor. The maximum \( R^2 \) value is one. One would mean a perfect match, zero would mean the models predicts as good as using the average to predict systems behavior and the model is therefore useless. [Mendenhall and Sincich 2003]

Next to the coefficient of determination, the average absolute error is used, expressed in the unit of the ANN predictions, in this case: number of persons.

\[
E_{abs} = \frac{\sum \sqrt{(Y_i - Y'_i)^2}}{\sum i}
\]

\( E_{abs} \) = average absolute error
\( Y_i \) = measured value
\( Y'_i \) = predicted value
\( i \) = measurement

### 2.2.2 ANN2: Energy predictions

For the ANN model predictions of the prototype procedure, the \( \Delta CO_2 \) over supply- and exhaust air will be the indicator for the occupancy. The other inputs of the ANN models are related to the outdoor conditions: temperature, relative humidity, total solar irradiation and air velocity.

Within the prototype procedure, energy consumption is divided into three parts: cooling-, heating- and other electrical power consumption. Fault detection will be based on comparing the predicted values of the ANN model with the measured power consumptions.

Using one neural network to predict all three energy consumptions does not give the best performance. The three energy consumptions are all dependent on different variables. Gas consumption for example is very time related. At a specific time in the morning, the system starts pre-heating the building to meet the comfort requirements during working hours. Time is thus an important input to predict gas consumption.

To predict building energy consumption based on occupancy and outdoor conditions, time may not be used as an input of this ANN model. Adding time as an input might learn the ANN the relation
of electricity consumption over time, not taking into account unexpected building user behavior. Therefore, three ANN models are used to predict the three different power consumptions.

Because the user is of influence on all three power consumptions, this input parameter will be used in all the models. As a result of the optimization process of paragraph 4.1.2, the delay of 36 minutes in the delta CO₂ measurements will be used in all three energy models.

The method of testing the ANN performance is similar to the method of the optimization of the previous ANN for occupancy predictions. The following settings are tested in a same way as described in the paragraph 2.2.1:
- ANN layout
- Training function
- Input variables
- Measure interval
- Minimum training data needed
- Influence of test period on simulation performance

For energy predictions, all variables are tested for the three different models.

Model performance is again tested by the R² value and the average error. The average error is expressed in the unit of the ANN output:
- ANN for total electricity consumption: [kW]
- ANN for electrical cooling consumption: [kW]
- ANN for gas consumption: [m³/hour]


3 Results
The main result of this project exist of the optimized ANN models and the prototype procedure, both described separately in this chapter. The ANN modeling section shows the different steps of the optimization process, each step resulting in an optimized variable. Section 3.2 describes the optimized prototype procedure meeting designed to meet project objectives.

3.1 ANN modeling
Again, the ANN modeling is divided into two sections. First the results of the optimization of the ANN for occupancy predictions is described. Section 3.1.2 contains the optimization process of the three models of the prototype procedure.

3.1.1 ANN 1: Occupancy predictions
The different settings described in section 2.2.1 are compared based on the performance of the ANN model. Because during the ANN training process a local minimum can be seen as the optimum, all performance values mentioned are the best performances of three runs with equal settings. The measurement data is divided into a training and a test part. The test part is not used for ANN training and exists of a normal week with five working days. All ANN modeling in this project is performed with the neural network toolbox of Matlab 7.10.0.

ANN layout and training functions
To find the best performing ANN layout, the starting values for the other variables of the optimization process are assumed to be as follows:
- Delay: 0
- Input: ΔCO2
- Timestep: 1 minute
- Training period: 33 days
- Test period: 17-24 May

The by Matlab recommended training function to start with is the Levenberg-Marquardt function (trainlm). This function is often the fastest backpropagation algorithm of the Matlab toolbox but uses more memory then most other functions.

First the layout of the ANN model is tested by varying the number of hidden layers and neurons per layer. The ANN performance is compared by $R^2$ value and average error. Table 4. shows the performance of the tested network layouts.
The ANN layouts with only one hidden layer seems not able to learn the system behavior. Figure 17 shows an example of the predicted values of a one layer ANN, compared to the best performing network (Figure 18), a one hidden layer networks seems not able to learn the lower level CO₂ – occupancy relation.

Table 4. Performance of ANN models for occupancy predictions with different layout

<table>
<thead>
<tr>
<th>Hidden layers</th>
<th>Neurons</th>
<th>$R^2$</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>-1.141</td>
<td>26,476</td>
</tr>
<tr>
<td>1</td>
<td>8</td>
<td>-1.141</td>
<td>26,476</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>-1.141</td>
<td>26,476</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>-1.141</td>
<td>25,029</td>
</tr>
<tr>
<td>2</td>
<td>4 4</td>
<td>0.901</td>
<td>3,195</td>
</tr>
<tr>
<td>2</td>
<td>6 6</td>
<td>0.901</td>
<td>3,328</td>
</tr>
<tr>
<td>2</td>
<td>8 8</td>
<td>0.901</td>
<td>3,154</td>
</tr>
<tr>
<td>2</td>
<td>12 12</td>
<td>0.900</td>
<td>3,175</td>
</tr>
<tr>
<td>3</td>
<td>4 4 4</td>
<td>0.900</td>
<td>15,401</td>
</tr>
<tr>
<td>3</td>
<td>8 20 8</td>
<td>0.900</td>
<td>3,181</td>
</tr>
</tbody>
</table>

The best performing layout (two hidden layers, 8 neurons per layer) is used to test the performance with the use of different training functions.

Table 5. Performance of ANN models with different training functions

<table>
<thead>
<tr>
<th>Training function</th>
<th>$R^2$</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainrp</td>
<td>0.901</td>
<td>3,118</td>
</tr>
<tr>
<td>trainbfg</td>
<td>0.901</td>
<td>3,111</td>
</tr>
<tr>
<td>traincgb</td>
<td>0.900</td>
<td>3,111</td>
</tr>
<tr>
<td><strong>traincfg</strong></td>
<td><strong>0.901</strong></td>
<td><strong>3,095</strong></td>
</tr>
<tr>
<td>traingd</td>
<td>0.899</td>
<td>3,373</td>
</tr>
<tr>
<td>trainscg</td>
<td>0.901</td>
<td>3,144</td>
</tr>
<tr>
<td>trainlm</td>
<td>0.901</td>
<td>3,133</td>
</tr>
<tr>
<td>traingda</td>
<td>0.893</td>
<td>3,463</td>
</tr>
<tr>
<td>trains</td>
<td>-0.306</td>
<td>11,968</td>
</tr>
</tbody>
</table>
The differences in the calculated $R^2$ value are small for most functions, in the average error the variation is higher. The Fletcher-Powell conjugate gradient backpropagation training function (traincfg) gives the best scores in both performance indicators, therefore, this training function will be used for further testing of the other settings.

**Delay on exhaust CO$_2$ concentration**
The delay on the exhaust air to calculate the delta CO$_2$ is varied between 0 and 90 minutes. ANN performance is visualized in figures 19 and 20.

![Figure 19. R$^2$ value for different delays.](image1)

![Figure 20. Average error for different delays.](image2)

The highest $R^2$ value (0.9533) is found at a delay of 36 minutes. Because of small fluctuations in the calculated average error, a line is fitted through the data points. Also the minimum average error occurs at a delay of 36 minutes.

The testcase building's technical system is designed on an air change rate of two. So with a perfect functioning ventilation system a delay of 30 minutes would be expected. In practice the efficiency of ventilation in a room can be lower than one. Also other variables are influences on the building specific delay: the use of open windows, the layout of inlet and outlet grids and the location of the people in relation to the exhaust duct. Therefore 36 minutes seems to be a logic result in the testcase building.

**Input variables**
The basic input variable is the delta CO$_2$. In order to improve the prediction performance, measurements of boundary conditions such as outdoor temperature and the number of open windows were added in order to gain higher accuracy of the prediction. The different variants tested are with the accompanying performances are given in table 6.
Table 6. Overview of input variations with ANN performances for occupancy predictions (not all performances could be calculated due to missing data of some sensors)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔCO₂ (main exhaust)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>ΔCO₂ (floor 1)</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔCO₂ (floor 2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Inlet air velocity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exhaust air velocity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open windows</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor temperature</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor air velocity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working day</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R² Value</td>
<td>0,954</td>
<td>0,767</td>
<td>?</td>
<td>?</td>
<td>0,918</td>
<td>0,956</td>
<td>0,946</td>
<td>?</td>
<td>0,954</td>
<td>0,952</td>
<td>?</td>
</tr>
<tr>
<td>Average error</td>
<td>2,22</td>
<td>3,806</td>
<td>?</td>
<td>?</td>
<td>3,01</td>
<td>2,14</td>
<td>2,41</td>
<td>?</td>
<td>2,25</td>
<td>2,32</td>
<td>?</td>
</tr>
</tbody>
</table>

Not all data was collected with the same measurement system. The air velocities in ducts and the wind direction are measurement by a Eltek wireless measurement system. During the preparation of the data for the ANN training, missing data points were found on random times during the measure period. The calculation of the performance values is therefore not possible for the models including these measurements. However, the graphs of the results of models 3, 4, 8 and 9 show no significant improvement compared to the basic model 1.

Because outdoor conditions change daily and it’s hard to imagine there’s a relation between occupancy and outdoor temperature, more simulations are performed to check the influence of the outdoor conditions on the model performance.

Different test periods are used to check whether the performance remains the same in different weeks. As a result, two graphs are shown in Figure 21 and Figure 22. The model with outdoor temperature as an input performs slightly better by comparing the R² value. However, this is caused due to less fluctuations in occupancy predictions during night times. During working hours, the difference error even becomes larger with the outdoor temperature as input. In another week with higher fluctuations in outdoor temperature, the ANN performance becomes much worse compared to the model with only delta CO₂ as input (R² value of 0,85 compared to 0,94 for the 1 input network).

Therefore, only the delta CO₂ will be used as an input in the rest of this report.
**Timestep**

The measure interval of the CO₂ concentration is 5 seconds. In the previous ANN calculations, all data is synchronized and interpolated on a 1 minute basis. To predict the occupancy with a higher resolution, a smaller timestep can be used. However, CO₂ concentrations can highly fluctuate so predicting occupancy with a very small interval can create a model which is too sensitive. Different timesteps are used to calculate the best ANN performance. Results are shown in Table 7.

Both performance indicators, the $R^2$ and the average error seem not to differ much with different timesteps. Choosing the best timestep is therefore dependent on the purpose of the use of the model. For the objective of the prototype procedure, measuring the occupancy on a minute base would be sufficient. A higher measurement interval would increase the sensibility which would cause the model to respond the short fluctuations in the CO₂ measurements. To optimize the next parameter, a one minute interval will be used as timestep.

**ANN training period**

The prediction performance of the ANN is highly dependent on the quality and quantity of training data. The training data must cover the whole range of situations in which the ANN will be used. The graphs below are a good illustration of this.

![Visualization of training data and ANN predictions for occupancy](image)

---

**Table 7. ANN 1 performance with different timesteps**

<table>
<thead>
<tr>
<th>Timestep [minutes]</th>
<th>$R^2$</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/6</td>
<td>0.954</td>
<td>2.25</td>
</tr>
<tr>
<td>1/3</td>
<td>0.953</td>
<td>2.25</td>
</tr>
<tr>
<td>1/2</td>
<td>0.954</td>
<td>2.25</td>
</tr>
<tr>
<td>1</td>
<td>0.954</td>
<td>2.22</td>
</tr>
<tr>
<td>2</td>
<td>0.954</td>
<td>2.23</td>
</tr>
<tr>
<td>5</td>
<td>0.953</td>
<td>2.26</td>
</tr>
<tr>
<td>10</td>
<td>0.955</td>
<td>2.22</td>
</tr>
<tr>
<td>15</td>
<td>0.949</td>
<td>2.31</td>
</tr>
<tr>
<td>20</td>
<td>0.953</td>
<td>2.24</td>
</tr>
<tr>
<td>30</td>
<td>0.953</td>
<td>2.22</td>
</tr>
<tr>
<td>40</td>
<td>0.953</td>
<td>2.31</td>
</tr>
<tr>
<td>50</td>
<td>0.954</td>
<td>2.13</td>
</tr>
<tr>
<td>60</td>
<td>0.954</td>
<td>2.24</td>
</tr>
</tbody>
</table>
The black line is the ANN prediction, the colored dots represent the training data. Within the range of training data, the ANN model calculates the occupancy as expected (in the middle of the measured values). If the ANN model is tested with a decreasing delta CO₂ in the range of negative values where no training data is given, the ANN predicts an increasing number of occupants.

To test the minimum time of training data, the same test period of the previous calculations is used. The standard test period exist of 33 days of data, in figures 24 and 25 the ANN performance is visualized for the different training periods.

An increase of the training days increases ANN performance. However, after two weeks of training data the R² value and average error both reach a constant maximum and only show a small increase in performance when the length of the training period is extended.

**Testperiod**

All ANN predictions are tested in the same week (17 May – 24 May). Measurements have been performed from 24th of April to the 15th of June with some missing data in between (from 27th of May to 11th of June).

In Table 8 the results of testing the ANN performance with different test periods:

<table>
<thead>
<tr>
<th>Period</th>
<th>Working days</th>
<th>R²</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26 April - 3 May</td>
<td>4</td>
<td>0.940</td>
<td>2.15</td>
</tr>
<tr>
<td>3 May - 10 May</td>
<td>5</td>
<td>0.947</td>
<td>2.49</td>
</tr>
<tr>
<td>10 May - 17 May</td>
<td>3</td>
<td>0.965</td>
<td>1.41</td>
</tr>
<tr>
<td>17 May - 24 May</td>
<td>5</td>
<td>0.954</td>
<td>2.18</td>
</tr>
</tbody>
</table>

Differences mainly seem to occur due to number of working days and the input CO₂ concentration at night. It happens more than once that when ventilation shuts down, CO₂ concentration in exhaust air did not decrease to outdoor level. Since the delta CO₂ is the only input of the ANN, it's impossible for the model to give perfect predictions in this situations.
Visualization results

To present the ANN results, measurements and the accuracy range of the predictions are plotted over time.

![ANN predictions vs. measurements](image)

**Figure 26. Visualization of ANN predictions for occupancy predictions with accuracy range and measurements**

The black line represents the measurements. The red range represents the ANN predictions with a 95% accuracy range, based on the standard deviation of the error of the test period results. The error in ANN predictions is dependent on the input delta CO\textsubscript{2}. Errors are highest at the concentrations occurring in morning and noon when most people enter or leave the building. Figure 27 shows the standard deviation per input value.

The test data of one week is used to calculate the standard deviation per input value. Assuming a normal distribution of the errors of the ANN predictions per input value, the given percentage of certainty wanted by the user of the model results in the number of standard deviation to be used in the calculation of the red range. A higher certainty results in a wider (red) range in the model predictions of Figure 26.

![Standard deviation of error per delta CO\textsubscript{2}](image)

**Figure 27. Standard deviation of error per delta CO\textsubscript{2}**
### 3.1.2 ANN2: energy predictions

As mentioned in the method, three different ANN models are used to predict the energy consumption. This chapter is therefore divided into three subchapters, all describing the optimization process for the different models.

In the same way as ANN1, the three ANN models for energy predictions are optimized stepwise. One setting is changed at a time to end up with the combination of best performing models.

To start the optimization process, the following settings are used for all three models:

- **Training function**: trainlm (best performing in ANN1)
- **Transfer function**: tansig
- **Timestep**: 5 minutes
- **Train data**: 24 April – 15 June (not including the test data)
- **Test data**: 31 May – 7 June

Because the energy consumption can highly fluctuate over short time spans, a longer timestep than with ANN1 will be used. To start, all three models will use a 5 minute timestep for the calculations. Later on during the optimization of the timesteps, the optimum timestep for each network will be determined.

Also the test period to start the optimization process with changed. For testing a week with both, heating and cooling is necessary. The final step of the optimization process will be to check the influence of the test week.

The occupancy will be of influence on all three models. Results of the previous chapter showed that an ANN model is able to predict occupancy based on the delta CO$_2$ over inlet and exhaust air. In the three models of this chapter, again the delta CO$_2$ will be used as an input to give an indication of the occupancy.

**Total electricity consumption**

The model to predict the total electrical power consumption will have several inputs. Delta CO$_2$ will be used as an indicator of the occupancy. Further the measured outdoor conditions will be used as an input too. To start the optimization process, the next inputs are used:

- $\Delta$CO$_2$;
- outdoor temperature;
- outdoor relative humidity;
- solar irradiation;
- air velocity;
- time schedules technical installation.

The technical installation is programmed to pre-heat the building in the morning. In the evening a security check is manually performed between 21:30 and 22:00. As a part of this check, all lighting and standby electricity consumption is turned off. The preheat time in the morning and the manual shutdown in the evening are time related. As described in chapter 3.2.2, time may not be an input of the ANN for electricity consumption. Therefore a time schedule is used, which only distinguishes an on/off situation as input of the ANN. Startup time is 04:00, for the shutdown time the average closing time of 21:43 is calculated based on data of the entrance security system.
The graph below shows the power consumption of the test period. Maximum consumption differs daily, even as the variation during the day. The objective of the ANN for total electricity consumption is to predict the energy consumption shown in figure 28 based on input variables and settings as described.

Figure 28. Total electricity consumption during test week

ANN layout
For the layout of the ANN model different number of hidden layers with different numbers per layer are tested. Per layout the ANN performance is shown in the table below.

<table>
<thead>
<tr>
<th>Hidden layers</th>
<th>Neurons</th>
<th>$R^2$</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>0.066</td>
<td>7.37</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>0.064</td>
<td>7.41</td>
</tr>
<tr>
<td>2</td>
<td>4 4</td>
<td>0.967</td>
<td>1.04</td>
</tr>
<tr>
<td>2</td>
<td>6 6</td>
<td>0.963</td>
<td>1.17</td>
</tr>
<tr>
<td>2</td>
<td>8 8</td>
<td>0.950</td>
<td>1.36</td>
</tr>
<tr>
<td>2</td>
<td>10 10</td>
<td>0.948</td>
<td>1.34</td>
</tr>
<tr>
<td>2</td>
<td>12 12</td>
<td>0.953</td>
<td>1.22</td>
</tr>
<tr>
<td>3</td>
<td>4 4 4</td>
<td>0.959</td>
<td>1.24</td>
</tr>
<tr>
<td>3</td>
<td>4 8 4</td>
<td>0.954</td>
<td>1.24</td>
</tr>
<tr>
<td>3</td>
<td>8 8 8</td>
<td>0.957</td>
<td>1.51</td>
</tr>
</tbody>
</table>

Compared to the influence of the ANN layout on ANN1, results are quite similar. One layer networks do not have enough capacity to learn the systems behavior while the networks with multiple hidden layers perform much better and results are quite similar. The differences in average error is larger than comparing the $R^2$. The 2 hidden layer network with 4 neurons in both layers seems to perform best in both performance indicators, therefore this value will be used in the further optimization process.

Training functions
The best performing layout is used to test the different training functions. Again differences between results are small, but trainlm is performing best for both performance indicators (Table 10).
Table 10. ANN performance total electricity consumption with different training functions

<table>
<thead>
<tr>
<th>Training function</th>
<th>R²</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainrp</td>
<td>0.959</td>
<td>1.21</td>
</tr>
<tr>
<td>trainbfg</td>
<td>0.953</td>
<td>1.30</td>
</tr>
<tr>
<td>traincgb</td>
<td>0.956</td>
<td>1.26</td>
</tr>
<tr>
<td>traincfg</td>
<td>0.958</td>
<td>1.26</td>
</tr>
<tr>
<td>traincgf</td>
<td>0.546</td>
<td>5.00</td>
</tr>
<tr>
<td>trainscg</td>
<td>0.955</td>
<td>1.31</td>
</tr>
<tr>
<td>trainlm</td>
<td>0.963</td>
<td>1.13</td>
</tr>
<tr>
<td>traingda</td>
<td>0.945</td>
<td>1.62</td>
</tr>
<tr>
<td>trains</td>
<td>-0.141</td>
<td>9.23</td>
</tr>
</tbody>
</table>

Input variables
The performance of ANN models with different input variables is compared. In addition to outdoor conditions and CO₂ measurements, more time related variables are introduced. To distinguish weekends and working days and to be able to predict longer preheating times on Mondays, the day of the week is introduced as an input of the ANN. Seven inputs are used which represent the different days by zeros and ones.

Table 11. Performance of ANN models for total electricity consumption with different input variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔCO₂ (main exhaust)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Outdoor temperature</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar Irradiation</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative Humidity</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor air velocity</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System on/off</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day of the week</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R² Value</td>
<td>0.871</td>
<td>0.361</td>
<td>0.863</td>
<td>0.869</td>
<td>0.868</td>
<td>0.879</td>
<td>0.960</td>
<td>0.963</td>
<td>0.953</td>
<td>0.947</td>
<td>0.954</td>
<td>0.956</td>
</tr>
<tr>
<td>Average error</td>
<td>2.46</td>
<td>9.19</td>
<td>2.50</td>
<td>2.38</td>
<td>2.31</td>
<td>2.18</td>
<td>1.22</td>
<td>1.14</td>
<td>1.35</td>
<td>1.33</td>
<td>1.29</td>
<td>1.26</td>
</tr>
</tbody>
</table>

The ANN performance is highest using all inputs. Adding system on/off schedule makes a major improvement in the ANN performance. Adding the day week a week makes the network aware of weekend situations and longer preheating on Mondays. Therefore ANN 8 with all input variables will be used in the next steps of the optimization.

Figure 29. Best performing ANN model with all inputs
Timestep
The timestep is varied to test its influence on ANN performance. Increasing the timestep results in more averaged values with less fluctuations. Predicting these values with the use of the ANN model might therefore be easier. A disadvantage of longer timesteps would be the decreased sensitivity for changes which would lower the functionality for fault detection. The graphs below show the ANN performance for an increasing timestep.

![Figure 30. R² value, total electricity consumption for different timesteps](image)

![Figure 31. Average error, total electricity consumption for different timesteps](image)

Figures 30 and 31 show the performance of the ANN for total energy consumption with the use of different timesteps. With low timesteps performance is highest, increasing the timestep results in lower ANN performance. Best results for both performance indicators are obtained at a 12 minute timestep.

ANN training period
The training period needs to cover all situations in which the ANN will be used. To cover a four season building behavior, measurements of all extreme situations are needed. The measurements used for ANN testing in this section cover an average spring situation, same as the training data.

![Figure 32. R² values total electricity consumption for different training days](image)

![Figure 33. Average errors total electricity consumption predictions for different training days](image)
Both performance indicators increase most during the first week of learning data. After one month, ANN performance seems to achieve a constant maximum.

**ANN test period**

Table 12. ANN performance total electricity consumption for different test periods

<table>
<thead>
<tr>
<th>Period</th>
<th>Working days</th>
<th>$R^2$</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26 April - 3 May</td>
<td>4</td>
<td>0.941</td>
<td>1.39</td>
</tr>
<tr>
<td>3 May - 10 May</td>
<td>5</td>
<td>0.959</td>
<td>1.13</td>
</tr>
<tr>
<td>10 May - 17 May</td>
<td>3</td>
<td>0.905</td>
<td>1.51</td>
</tr>
<tr>
<td>17 May - 24 May</td>
<td>5</td>
<td>0.961</td>
<td>1.05</td>
</tr>
<tr>
<td>24 May - 31 May</td>
<td>4</td>
<td>0.964</td>
<td>0.98</td>
</tr>
<tr>
<td>31 May - 7 June</td>
<td>5</td>
<td>0.970</td>
<td>1.09</td>
</tr>
<tr>
<td>7 June - 14 June</td>
<td>5</td>
<td>0.872</td>
<td>2.07</td>
</tr>
</tbody>
</table>

Performance of ANN predictions is quite constant during the different test weeks. Midweek days which are no working days seem to be difficult for the ANN to predict and are therefore of negative influence on the ANN performance. More non working days should be learned to increase ANN performance in these periods. Because the weather in the last week of measuring differed compared to the previous periods, energy consumption predictions were less accurate.

**Cooling electrical power consumption**

For the cooling power predictions, different inputs are used to start the optimization procedure:
- Delta CO2
- Outdoor Temperature
- Solar Irradiation

For cooling, the building seems not to be as suitable as assumed in the beginning of the project. As described in the measurement section of the method, cooling is generated by 45 split units. The split units are divided over two electricity groups (in contrast to provided drawings of the electrical installation), and more then half of the units did not function any more. What’s left are five measured units which generate cooling for 5 small offices. The units are controlled by the occupants of the five rooms. This makes the energy consumption dependent on the presence of the users and their personal comfort preferences. Therefore the cooling power loads behave quite random (Figure 34) and seems to be highly difficult to predict by the ANN model. Nevertheless, in this section an attempt is made.

![Figure 34. Electrical power consumption for cooling during test week](image-url)
ANN layout
For the layout of the ANN model different number of hidden layers with different neurons per layer are tested. Per layout the ANN performance is shown in the table 13.

Table 13. ANN performance cooling power consumption with different neuron layouts

<table>
<thead>
<tr>
<th>Hidden layers</th>
<th>Neurons</th>
<th>$R^2$</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>-62.327</td>
<td>0.87</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
<td>-62.327</td>
<td>0.87</td>
</tr>
<tr>
<td>2</td>
<td>4 4</td>
<td>0.063</td>
<td>0.03</td>
</tr>
<tr>
<td>2</td>
<td>6 6</td>
<td>0.044</td>
<td>0.03</td>
</tr>
<tr>
<td>2</td>
<td>8 8</td>
<td>0.036</td>
<td>0.03</td>
</tr>
<tr>
<td>2</td>
<td>10 10</td>
<td>0.049</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>12 12</td>
<td>0.021</td>
<td>0.03</td>
</tr>
<tr>
<td>3</td>
<td>4 4 4</td>
<td>0.018</td>
<td>0.02</td>
</tr>
<tr>
<td>3</td>
<td>4 8 8</td>
<td>0.045</td>
<td>0.02</td>
</tr>
<tr>
<td>3</td>
<td>8 8 8</td>
<td>-0.015</td>
<td>0.04</td>
</tr>
</tbody>
</table>

The first results of the different ANN models show that the cooling behavior is difficult to predict, all $R^2$ scores are very low. Since the use of two hidden layers has shown to give best results in previous models, a network of two hidden layers, both containing four neurons is chosen to continue the optimization process.

training functions
ANN performance is tested for different training functions. Again differences between results are small and performance is bad. However, a small increase is visible compared to the previous results.

Table 14. ANN performance cooling power consumption with different training functions

<table>
<thead>
<tr>
<th>Training function</th>
<th>$R^2$</th>
<th>average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainrp</td>
<td>0.024</td>
<td>0.03</td>
</tr>
<tr>
<td>trainbfg</td>
<td>0.058</td>
<td>0.02</td>
</tr>
<tr>
<td>traincgb</td>
<td>0.033</td>
<td>0.03</td>
</tr>
<tr>
<td>traincfg</td>
<td>0.058</td>
<td>0.03</td>
</tr>
<tr>
<td>traingd</td>
<td>-0.017</td>
<td>0.04</td>
</tr>
<tr>
<td>trainscg</td>
<td>0.070</td>
<td>0.03</td>
</tr>
<tr>
<td>trainlm</td>
<td>0.063</td>
<td>0.02</td>
</tr>
<tr>
<td>trainlda</td>
<td>0.073</td>
<td>0.02</td>
</tr>
<tr>
<td>trains</td>
<td>-223.749</td>
<td>1.63</td>
</tr>
</tbody>
</table>

The trainlda (Gradient descent with adaptive learning rate backpropagation) functions performs best in $R^2$ value and average error. This training function will be used in the next optimization steps.
Input variables
To predict the cooling power consumption, different combinations of inputs are tested to optimize the ANN performance.

Table 15. Performance of ANN models for cooling power consumption with different input variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta CO₂ (main exhaust)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor temperature</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar Irradiation</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative Humidity</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outdoor air velocity</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day a week</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>System on/off</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R² Value</td>
<td>0.004</td>
<td>0.011</td>
<td>0.024</td>
<td>0.073</td>
<td>0.013</td>
<td>0.003</td>
<td>0.029</td>
<td>0.052</td>
<td>0.018</td>
<td>0.044</td>
<td>0.060</td>
<td>0.044</td>
</tr>
<tr>
<td>Average error</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
</tr>
</tbody>
</table>

The $R^2$ value of input combination four gives the highest $R^2$ value so for the timestep optimization these inputs will be used.

Timestep
Varying the timestep for the cooling power consumption did not change the prediction performance because cooling occurred quite randomly in the testcase building and is therefore very difficult to predict. Two graphs of different timesteps are used to visualize the situation:

Figure 35. ANN predictions cooling power consumption with 10 minute timestep

Figure 36. ANN predictions cooling power consumptions with 26 minute timestep
Because of the big difference between measurements and predictions, no optimum timestep can be determined. Therefore, the timestep for cooling will be chosen equal to the timestep for heating (gas consumption).

**ANN training period**

The training period seems to be of low influence on the ANN results. This again has to do with the low ANN performance.

**ANN test period**

<table>
<thead>
<tr>
<th>Period</th>
<th>Working days</th>
<th>$R^2$</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26 April - 3 May</td>
<td>4</td>
<td>0.261</td>
<td>0.09</td>
</tr>
<tr>
<td>3 May - 10 May</td>
<td>5</td>
<td>0.019</td>
<td>0.03</td>
</tr>
<tr>
<td>10 May - 17 May</td>
<td>3</td>
<td>-0.478</td>
<td>0.03</td>
</tr>
<tr>
<td>17 May - 24 May</td>
<td>5</td>
<td>0.144</td>
<td>0.06</td>
</tr>
<tr>
<td>24 May - 31 May</td>
<td>4</td>
<td>-2.807</td>
<td>0.05</td>
</tr>
<tr>
<td>31 May - 7 June</td>
<td>5</td>
<td>0.132</td>
<td>0.08</td>
</tr>
<tr>
<td>7 June - 14 June</td>
<td>5</td>
<td>0.035</td>
<td>0.09</td>
</tr>
</tbody>
</table>

The cooling performance of different periods is highly related to the outdoor conditions and the corresponding energy consumption. Again, due to the difficulty of predicting the cooling power, results vary highly when the test period is changed. In some weeks, using average consumption would provide better predictions than those given by the ANN model.
Gas consumption
To start the optimization process, the model for gas consumption predictions uses the following inputs:
- Delta CO2
- Outdoor Temperature
- Solar irradiation
- Time

The time variable is needed (as described in the methodology section) to be able to predict preheating in the morning.

Gas consumption of the test period is shown in Figure 39. Peaks are visible in mornings for preheating the building, the rest of the daily consumption varies per day. Outdoor temperature increases during the test week so gas consumption decreases.

![Figure 39. Gas consumption during test week](image)

ANN layout
For the layout of the ANN model different number of hidden layers with different numbers per layer are tested. Per layout the ANN performance is shown in the table below.

<table>
<thead>
<tr>
<th>Table 17. ANN performance gas consumption model with different neuron layouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hidden layers</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>3</td>
</tr>
</tbody>
</table>

Again, a one layer network seems not able to learn the systems behavior while a network with multiple hidden layers perform much better. The 2 hidden layer network with 10 neurons in both layers performs best in $R^2$ and second best with a very small difference in average error. Therefore this network will be used in further optimization.
training functions
Table 18 shows the results of the use of different training functions with the previous determined network layout. The trainlm training function performs highest in both performance indicators.

<table>
<thead>
<tr>
<th>Training function</th>
<th>$R^2$</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainrp</td>
<td>0.150</td>
<td>1.05</td>
</tr>
<tr>
<td>trainbfg</td>
<td>0.258</td>
<td>1.01</td>
</tr>
<tr>
<td>traincfg</td>
<td>0.190</td>
<td>0.99</td>
</tr>
<tr>
<td>traincfgf</td>
<td>0.119</td>
<td>1.03</td>
</tr>
<tr>
<td>traingd</td>
<td>0.120</td>
<td>1.08</td>
</tr>
<tr>
<td>trainscg</td>
<td>0.182</td>
<td>0.94</td>
</tr>
<tr>
<td>trainlm</td>
<td>0.287</td>
<td>0.93</td>
</tr>
<tr>
<td>trainstda</td>
<td>0.133</td>
<td>1.16</td>
</tr>
<tr>
<td>trains</td>
<td>-0.119</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Input variables
Table 19 shows that the time related inputs are important to improve ANN performance. Adding time as an input almost doubles the $R^2$ value and the combination of inputs with system startup time and day of the week results in the best performing network. Occupancy, outdoor temperature and solar irradiations are the other inputs of the best performing network.

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta CO2 (main exhaust)</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Outdoor temperature</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Solar Irradiation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Relative Humidity</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Outdoor air velocity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Time</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Day a week</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>System on/off</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>$R^2$ Value</td>
<td>0.143</td>
<td>0.247</td>
<td>0.115</td>
<td>0.120</td>
<td>0.234</td>
<td>0.146</td>
<td>0.216</td>
<td>0.228</td>
<td>0.241</td>
<td>0.286</td>
<td>0.339</td>
<td>0.031</td>
</tr>
<tr>
<td>Average error</td>
<td>1.06</td>
<td>1.92</td>
<td>1.05</td>
<td>1.03</td>
<td>0.97</td>
<td>1.01</td>
<td>0.99</td>
<td>1.02</td>
<td>0.97</td>
<td>0.96</td>
<td>0.90</td>
<td>1.51</td>
</tr>
</tbody>
</table>

Timestep
The timestep is varied to test its influence on ANN performance. Increasing the timestep results in more averaged values with less fluctuations. Predicting these values with the use of the ANN model might therefore be easier. A disadvantage of longer timesteps would be the decreased sensitivity for changes which would lower the functionality for fault detection. The graphs below show the ANN performance for an increasing timestep.
Figure 40. $R^2$ values gas consumption predictions for different timesteps

Figure 41. Average error gas consumption predictions for different timesteps

Best results for both performance indicators are obtained with a timestep larger than 30 minutes. 32 Minutes is the first peek of the high performance and will therefore be used as timestep for both ANN models: for heating and cooling.

ANN training period
Again the minimum training period is tested. After a month of training data ANN performance is highest.

Figure 42. $R^2$ values gas consumption predictions for different training days

Figure 43. Average errors gas consumption predictions for different training days
ANN test period

The optimized model is tested over different weeks.

<table>
<thead>
<tr>
<th>Period</th>
<th>Working days</th>
<th>$R^2$</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>26 April - 3 May</td>
<td>4</td>
<td>-0,217</td>
<td>0,68</td>
</tr>
<tr>
<td>3 May - 10 May</td>
<td>5</td>
<td>0,81</td>
<td>0,98</td>
</tr>
<tr>
<td>10 May - 17 May</td>
<td>3</td>
<td>0,659</td>
<td>1,32</td>
</tr>
<tr>
<td>17 May - 24 May</td>
<td>5</td>
<td>0,677</td>
<td>0,75</td>
</tr>
<tr>
<td>24 May - 31 May</td>
<td>4</td>
<td>0,672</td>
<td>0,67</td>
</tr>
<tr>
<td>31 May - 7 June</td>
<td>5</td>
<td>0,430</td>
<td>0,70</td>
</tr>
<tr>
<td>7 June - 14 June</td>
<td>5</td>
<td>0,091</td>
<td>0,32</td>
</tr>
</tbody>
</table>

Performance is highest in weeks with a higher gas consumption because of the more constant pattern of these consumptions. When gas consumption is low, a few peaks occur to meet comfort requirements seem to be difficult to predict.
3.2 Prototype procedure

As described in the introduction, 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. The principle developed to meet project objectives, the prototype procedure, is introduced in section 1.4 and the basic principle is shown again in figure 44.

For fault detection, energy consumption is divided into three parts: heating, cooling and other electricity consumption. Comparing measurements of these three building performance indicators with simulation predictions forms the basis for fault detection in the prototype procedure.

ANN models are used to predict building performance based on outdoor conditions, occupancy and time related inputs. Containing the optimized ANN models from the previous section, the final setup of the prototype procedure is described in this section.

The prototype procedure will consist of two modes:
- Learning mode
- Simulation mode

When applying the prototype procedure in practice, a "new situation check" needs to be performed on the input data. If all input variables lie within the range of already learned data, fault detection mode can be used. For new situations the ANN will switch to training mode to extend the range applicability.

When applying the prototype procedure in a building for the first time, a large set of training data is needed to cover a wide range of situations and increase the methods applicability. For new built buildings and most existing buildings, measurements are needed to collect sufficient training data. The two different modes based on measurements are visualized in the figures 46 and 47. The dotted lines represent measurements, the colored, lines represent the predictions by the ANN models.

For existing buildings with all required data available in the BEMS, this data can be used for ANN training. Not only energy measurements, but also CO₂ measurements in exhaust air, or real occupancy numbers need to be known. Faulty situations from the past should be filtered from the learning data.
Based on the findings of the optimization process in the previous section, the functionality of the simulation mode is demonstrated in figures 48, 49 and 50. The colored line are the ranges calculated by the ANN models, the black lines are the real consumptions.

The bands give the range of inaccuracy of the ANN predictions. Highest accuracy is realized in the total electricity consumption predictions. Gas consumption is less accurate, and cooling power consumption proved to be extremely hard to predict in the testcase building. Therefore, the width of the bands also differs in all three figures.

For fault detection the narrower the band, the more faults can be detected. However, not enough width could make the system too sensitive.

When the amount of available data for testing is higher, the standard deviation of the error can be calculated more precisely and the functionality for fault detection would increase. This should be taken into account when using the prototype procedure in practice.
4 Application

The optimized ANN models are learned with data of before the fire incident. Creating real faults to test the application of the prototype procedure was not possible anymore because the ventilation situation in the building was changed due to the fire. To test the application of the prototype procedure in practice, three cases are created with the use data before, during and after the fire. All three cases are tested with the ANN models of total energy consumption and gas consumption. Cooling power is not included since the accuracy obtained in the optimization step is not high enough for fault detection in the testcase building. In section 4.1, an early working day is simulated. Section 4.2 shown the functioning of the prototype procedure during a fire, and section 4.3 tests the use of the prototype procedure when the ventilation situation changed.

4.1 Case 1: Early working day

The fist case is created with the use of data before the fire incident. The delta CO$_2$ as input is shifted over time to check the influence on model predictions. Moving the delta CO$_2$ two and four hours forward imitates a situation in which people start working earlier. As a result of this, total electricity consumption predicted by the ANN model increases earlier in the morning, and decreases earlier in the afternoon. The fluctuation in the afternoon can most likely be explained by the new situation the model is dealing with. So in practice the the simulation/training filter described in section 4.2 should be used.

In gas consumption predictions, the effect of the early occupancy is visible in a reduced preheating gas consumption. The pink line shows the case of a 4 hour shift of occupancy, in which the model seems to be aware of heat generated by the occupants. Since preheating starts at 4, a 2 hour shift is of less influence on model predictions.

![Figure 51. Total electricity consumption Case 1](image)

![Figure 52. Gas consumption Case 1](image)
4.2 Case 2: The fire incident

The second case is used to analyze a spin-off functionality of the prototype procedure: fire detection. The smoke generated with the fire produced high amounts of CO$_2$, even in central inlet and exhaust ducts trough which was no mechanical airflow. Although both sensors, inlet and exhaust, measured a high increase in CO$_2$, the short delay between both measurements caused the high delta CO$_2$, shown in figure 53.

The ANN, not trained for this situation, responds with a large increase in predicted gas and energy consumption (figures 54 and 55). The two peaks are caused by a different response time of the measurements of inlet and exhaust CO$_2$ concentrations.

The prototype procedure designed in this project would definitely respond to fire. Fire detection would even be possible with a very quick response. In fact, CO$_2$ measurements during the fire showed a high increase of CO$_2$, eight minutes before the fire safety system sent out an alarm signal.

However, for fire detection the method should be optimized. A high measure interval is needed and multiple sensors should be compared to avoid fire alarms caused by people blowing into a sensor.
4.3 Case 3: After the fire incident

Especially the first weeks after the fire, the ventilation in the building changed significantly. Air velocities in ducts decreased from 5.5 m/s to 4.5 m/s. For the prototype procedure, the situation after the fire can be seen as a real fault, not caused by unexpected building use.

Applying the learned ANN’s from the optimization process shows indeed a difference in predicted and real power consumption.

For total electricity consumption, the new situation decreased the measured delta CO₂. Less CO₂ means less people so the ANN predicts a lower electricity consumption. As shown in figure 57, real energy consumption lies just outside the uncertainty range during longest parts of the day.

Gas consumption looks overrated in figure 58. Pre-heating starts too early and the amount of gas used is much too high. This is also likely to be caused by the changed situation. However, gas consumption prediction of the ANN where less accurate during optimization then the prediction for total energy consumption. To gain the best results, more training data should be used.
5 Discussion

In this chapter the results described in chapter 3 are discussed. Section 5.1 contains the discussion of the modeling part results, section 5.2 is about the results of the prototype procedure and its application in the testcases described in chapter 4.

5.1 ANN modeling

The ANN modeling part is again described in two sections. Section 5.1.1 contains the discussion of the results of the ANN model for occupancy predictions, section 5.1.2 is about the ANN models for energy predictions in the prototype procedure.

5.1.1 ANN1: Occupancy predictions

For the prototype procedure of this project, CO2 measurements have shown to be useful in calculating building occupancy with an ANN model. Whether the same principle can be used in other situations depends on the building, the objective, and the required accuracy.

After the optimization procedure, the average error of the best performing network is 2.2 persons. Although peak error can reach values of 20 persons, this only occurs over very short periods of time due to fast changing occupancy numbers or changing air flow rates when the air handling unit shuts down or starts.

With hindsight, the testcase building in Maarssen was not the perfect situation to get the best results from the CO2 – occupancy relationship analysis. Air exhaust was located directly under the supply air grid, windows could be opened, and people could enter or leave the building in groups, with only one of them checking in or out.

Nevertheless, prediction accuracy was higher than expected at the beginning of this project. For energy predictions in the prototype procedure, the obtained accuracy in occupancy predictions seemed to be sufficient.

Different day patterns are well predicted by the ANN model, lunch breaks are visible, and starting and ending times are well predicted. In energy modeling, timesteps are larger, which makes high errors in occupancy predictions over short periods of time less important.

During this project the question about how to apply this method in different projects raised quite often. Using only two sensors in a building to measure the total occupancy could be useful in a large variety of applications. However, the need for collecting learning data would be the biggest barrier. For future research, making this method generally applicable without the need of training data would be a major improvement.

One way to do so would be by introducing two more parameters to the model settings: the total air volume flow and the air tightness of the building. Another option is the use of other modeling techniques which might suite this standalone application better then the use of an ANN model.
Another finding worth extra research is the effect of air flow on CO₂ sensors. The CO₂ measurements in ducts showed a pattern of decreasing concentration when the air handling unit turned off, and an increase when the system started again. One explanation might be that because of difference in density of air and CO₂, CO₂ particles sink and get concentrated in a lower level of the ducts, while sensors are placed in the middle.

A variation of scale would also be interesting for extra research. With at maximum 59 people in the building during the measurements, the office can be considered as a mid range office building. Applying the same method to larger building would cause a change in delta CO₂ per person.

During the development of the prototype procedure, different influences on the measurements are considered to be constant and learnable by the ANN models. Examples are the leakage of indoor air via decentral exhaust points, the ventilation efficiency of the rooms, night mode of the ventilation system, the influence of plants on CO₂ measurements, and openable windows.

Maybe the most important boundary condition for the use of the prototype procedure is a constant ventilation rate during operating hours. A change in the amount of ventilation air will cause differences in CO₂ measurements for the occupancy predictions. In case of buildings with CO₂ controlled ventilation systems, the power consumption of the fan could replace the CO₂ measurements as input of the ANN as the indicator of the occupancy. Another option to make the method more uniformly applicable is to use the air velocity in the exhaust duct as an extra input of the model. In this way variation in air leakage would be taken into account and in case of demand controlled ventilation, changes in ventilation rates are also measured.

In the testcase building, measuring the exhaust air velocity was not possible in a correct way. Taking into account the guidelines for correct measurements [Testo 2001], locating the sensor in the prescribed places in the duct system was not possible.

5.1.2 ANN2: energy predictions

The optimization of the ANN models for energy predictions gave different results for all three models. Total electricity consumption has shown to be predictable in an accurate way. The R² value of 0.97 showed a high correlation between model predictions and real electricity consumption.

In cooling power consumption predictions, obtained results were less accurate. The testcase cooling system of the building was not working the way it should be and the power consumption of only a few split unit showed to be hard to predict. The user controlled on/off switching of the units created an unpredictable behavior. To predict cooling loads with an ANN, controlling the cooling should be done automatically or in case of individual control, on a larger scale.

The gas consumption was well predictable, but accuracy of results differed per week and per day. Since outdoor conditions varied a lot in the spring period in which measurements data is collected, using more training data would probably increase prediction accuracy. Another difficulty in predicting gas consumption by an ANN model is the on/off switching of the heating system. Since indoor temperature is not an input of the ANN, predicting gas consumption controlled by this indoor temperature is difficult. In periods of low consumption, predicting gas consumption with a small timestep is therefore difficult.
5.2 Prototype Procedure

As became clear in the optimization process, having a well functioning building with a good indoor comfort and a well performing technical system is the basic requirement when applying the prototype procedure. During the collection of data for ANN training, it is important to continuously check building performance. In case when faults occur during the collection of training data, ANN predictions will become less accurate and limit the functionality for fault detection. Good cooperation with the facility manager of the building is therefore really important.

In the testcase building, the cooling system was not working properly and this part of the prototype procedure could therefore not be optimized in a proper way for fault detection. For predictions of total electricity consumption, correlation of simulation results and measurements was much higher. Gas consumption predictions showed good correlation too, but due to the strong relation to outdoor conditions and the high variety in outdoor conditions during the measure period, more training data would increase ANN performance.

By the optimization of ANN1, the delta CO₂ has shown to be a good indicator of the occupancy. This makes the prototype procedure applicable in almost every building with a mechanical ventilation system.

Due to the fire incident in the testcase building, the measurement period was limited and creating real faults in the system to test the application of the prototype procedure was not possible anymore. Therefore, three cases were developed to test the prototype procedure within the limitations of the testcase situation.

In the first case with employees starting their working day two and four hours earlier, the ANN predicted an earlier increase of total electricity in mornings, and a decrease in preheating gas consumption due to heat generation by people. Both predictions are as expected but due to the fire, the situation could not be tested in practice and was therefore tested by changing the delta CO₂ concentrations of the ANN model manually. Whether real power and gas consumption would differ equally should therefore be tested in future work.

The fire incident itself was also detected by the prototype procedure predictions. However, for fire detection purposes the prototype procedure should be optimized for fast detection with high certainties.

The measurements of the situation after the fire lie outside the range of ANN predictions which would indicate a faulty situation. The ventilation situation changed that much that the system is not behaving the way it should according to the ANN model. Since in this situation the building suffered a heavy change, smaller faulty changes need to be tested in future work in order to test the applicability of the prototype procedure in more detail.

During the optimization of this project, some questions arise which might be worth future research:

- Is the optimal optimization setup also optimal for other situations?
  The whole optimization process is new based on one testcase situation in spring. Would the same procedure in another season, building, or climate result in the same optimal settings?

- How can small, constant errors be detected by the prototype procedure?
  Adding a cumulative error for fault detection could improve the capability of detection of small, constant errors which might now be undetectable due to the uncertainty bandwidth of the ANN predictions.
Instead of using ANN models to calculate the current power consumption, predicting power consumption in the near future can prevent faulty situations.

Instead of collecting measuring data in new buildings to train the ANN models, first principle models used in the design process of the building can be used to generate training data. Model predictions can be optimized later by adding real measurement data.
6 Conclusion

6.1 ANN modeling
- An ANN model can be trained to calculate the occupancy of a building based on measurements of the central inlet and exhaust CO₂ concentrations.
- The usability of this method depends on the building, the objective, and most important the required accuracy.
- The use of CO₂ as an occupancy indicator introduces a delay, caused by the time between the production of CO₂ and the measurements of the CO₂ concentration in the central exhaust duct. The delay is mainly dependent on the air change rate and ventilation efficiency of the building and therefore has to be determined per building.
- Despite some disadvantages of the testcase building like openable windows and a bad location of the exhaust air grid, a coefficient of determination (R²) of 0.96 was obtained and the average error of the predictions in the testcase building was 2.2 persons.
- A disadvantage of the use of an ANN model to calculate occupancy is the need of real numbers of occupant data. In the prototype procedure of this project, the delta CO₂ is used as indicator of the occupancy and therefore real numbers of people are not needed.

- Using outdoor conditions and the delta CO₂ as an input, the total electricity is predicted with a R² value of 0.97.
- Gas consumption predictions where less accurate with a maximum R² value of 0.80. Due to the high relation with outdoor conditions and the high fluctuations of outdoor conditions in the measure period, results could be improved when more data is used to train the ANN.
- The cooling system of the testcase building showed not to be suitable for testing the prototype procedure. Part of the system was broken and because of the user controlled functioning of the few cooling units left, cooling behavior was very unpredictable and predictions of cooling loads were not accurate enough for fault detection.
- Since gas and cooling consumptions can highly fluctuate, timesteps in the range of 30 minutes are needed to optimize the performance of neural network predictions and to increase the applicability for fault detection.

6.2 Prototype Procedure
- The developed prototype procedure has shown potential for fault detection, taking into account the occupants.
- The self learning principle of the neural networks, combined with the use of delta CO₂ as an indicator for the occupancy makes the prototype procedure flexible and widely usable.
- Although real faults could not be applied in the technical system, three alternative cases were used. All cases showed potential for the use of the prototype procedure in different situations: early starting working day, fire detection, distinguishing a changed situation.
- Due to limitations of the Testcase building, further research is needed to fully test the prototype procedure and determine the capability for fault detection on a higher level of detail.
The high fluctuations in power consumption results in the need of a larger timestep to optimize ANN prediction performance. A larger timestep introduces a delay in the real time fault detection.
References


Bing, Y. 2003. Level-Oriented Diagnosis for Indoor climate Installations, PHD dissertation, Department of Mechanical Engineering, Shanghai Jiaotong University, China.


a) Measurement system

For this project Strukton Worksphere invested in a wireless measurement system. The installation and optimization of this system is performed as part of this graduation project. Most time for this is spent on the testing of the Wisensys wireless communication system, the calibration of the CO₂ sensors, the installation of the webserver and the coupling of the measurement database with Matlab.

The wireless communication system is called Wisensys and is made by Wireless value. All kind of sensor with a analogue output can be connected to a wireless transmitter. The central basestation communicates via GPRS with a server. On the server, the website www.gebouwinbeeld.nl makes measurement data available for the users.

![Figure 60 Overview of wireless measurement system](image-url)
Different suppliers are used for the sensors of the measurement setup. Table 21 shows an overview of the components of the measurement system.

<table>
<thead>
<tr>
<th>Description</th>
<th>Technical description</th>
<th>Amount</th>
<th>Price</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO2 sensor for air duct</td>
<td>Catec EE85 series</td>
<td>4</td>
<td>+/-€300</td>
<td>€1200,--</td>
</tr>
<tr>
<td>Transmitters</td>
<td>WS-DLXv</td>
<td>4</td>
<td>€235,-</td>
<td>€940,--</td>
</tr>
<tr>
<td>3-phase Energy Sensor</td>
<td>WS-DLXp</td>
<td>Already bought</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transmitters</td>
<td>WS-DLXv</td>
<td>Already bought</td>
<td></td>
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</tr>
<tr>
<td>Gas sensor pulse connection</td>
<td>WS-DLRc</td>
<td>1</td>
<td>€150,-</td>
<td>€150,--</td>
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<tr>
<td>Transmitters</td>
<td>WS-DLXv</td>
<td>1</td>
<td>€235,-</td>
<td>€235,-</td>
</tr>
<tr>
<td>Solar irradiation</td>
<td></td>
<td>1</td>
<td>+-€300</td>
<td>€300,-</td>
</tr>
<tr>
<td>Air Velocity sensor</td>
<td>ABB Busch-Jaeger 6190-0031</td>
<td>1</td>
<td>€407,-</td>
<td>€407,-</td>
</tr>
<tr>
<td>Transmitters</td>
<td>WS-DLXv</td>
<td>2</td>
<td>€235,-</td>
<td>€470,-</td>
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<td>Temperature</td>
<td>WS-DLTI</td>
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<td>Humidity</td>
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<tr>
<td>Base station</td>
<td>WS-BU-gprs</td>
<td>1</td>
<td>€850,-</td>
<td>€875,-</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>€4577,-</td>
</tr>
</tbody>
</table>

The database of the measurement system is connected with Matlab for exchange of data. In this way, measurements can be used imported to Matlab as input data for a model, and results of Matlab can be exported to the webinterface.

Figure 61. Connection of Matlab with measuredatabase
At [www.gebouwinbeeld.nl](http://www.gebouwinbeeld.nl) all data is visualized. For a demonstration:

**Loginname:** demo  
**Password:** +demol

Realtime data is available from all connected sensors of the testcase building.

Matlab data currently has to be exported manually. The automation of the export to the website for real time ANN predictions is planned by Worksphere employees to finish soon.
b) One day measurements

Occupancy measurement at the Strukton Worksphere office Eindhoven
Friday, februari 5

CO₂ measurements were performed at 17 location in a six person office room to test the correlation between CO₂ concentrations and occupancy.
Image impression of measurement setup
At three spots, sensors were placed on different heights: 0.5m, 1.5m and 2.5m.
Results

The graph above shows the original measurements, without correction for the accuracy offset.

An correction is performed, base on the night measurements. From the period between 00:00 and 06:00 an average is calculated. The difference between this average and the measured value is shown in the graph above. For now, this might be the best approach to analyze the correlation of people entering the room, and the measured values on the different points in the office space.
The Occupancy has been counted on a minute level. The floorplan from page 66 shows all 6 seats. Seats are clustered to divide CO2 production into three spots: Spot 1 (seat 1 and 2), spot 2 (seats 3 and 4) and spot 3 (seats 5 and 6).
Corrected with average, measurements spot 1

Corrected with average, measurements spot 2

Corrected with average, measurements spot 3

Occupancy
c) Relative calibration of CO2 sensors

Because different measurements have shown constant differences in measured values of the CO2 sensors, a calibration measurement has been performed. For this, all CO2 sensors were connected to a 12 Volt power supply and placed in a close box. To mix the air in the box, a small fan was placed inside the box as well.
Results
As expected, the measurements showed a quite constant difference per sensor.
Root mean square error per sensor

Best scoring sensors
Correcting formula determination

Corrected Value

Measurements after correction
Difference with reference sensor

Measurement setup for duct-sensor calibration.