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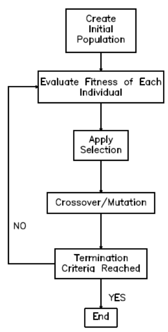

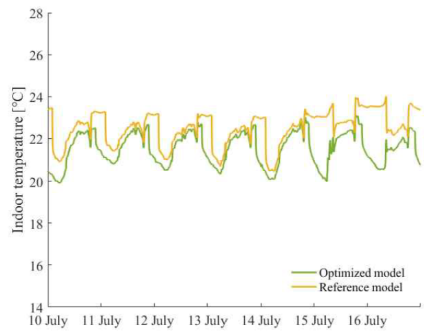

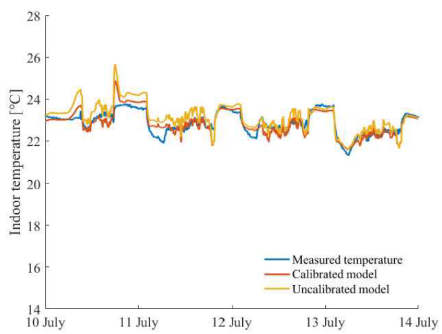

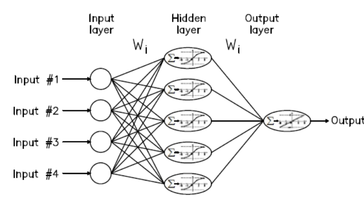

Optimization of Night Cooling in Commercial Buildings

Using Genetic Algorithms and Neural Networks

Master's thesis in Structural Engineering and Building Technology

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Division of Building Technology
Building Physics
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ABSTRACT

Periodically since the two oil crisis in the 1970s, there has been a focus in Sweden on reducing the energy use in buildings. This focus has evolved into the building regulations used today. With the stricter energy requirements and the interest from society in environmental issues there is a need to use more optimized control systems for cooling and ventilation. Night cooling is an example of this. The purpose of night cooling is to decrease the cooling need in buildings by ventilating at night with cold outdoor air.

The thesis uses case studies to examine if it is possible to optimize night cooling set points and time schedules regarding energy consumption and indoor climate for two retail stores in Göteborg. The optimizations were done with genetic algorithms, neural networks and building energy models, based on logged control data for the two stores.

The study suggest that the energy consumption could be reduced with 15% for both facilities with the optimized control settings compared to the original. The project also shows that even unoptimized night cooling has benefits to energy consumption. The sensitivity analysis shows that a reduction around 10% for similar buildings are plausible with the optimized settings from the case studies.

The projects concludes that the use of logged control data in combination with genetic algorithms and neural networks is an efficient way for both calibration and optimization of building energy models. The industry moves towards an increase of available logged control data. As such, it is important to be able to properly utilize the data for improving the accuracy of building energy simulations. The method used in this project is an example of this.

Keywords: Night cooling, free cooling, genetic algorithms, neural networks, building energy modelling, HVAC control systems, energy consumption, commercial buildings

Optimering av nattkyla i kommersiella fastigheter
med genetiska algoritmer och neurala nätverk
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SAMMANFATTNING

Periodvis sedan de två oljekriserna på 1970-talet har det varit fokus på att minska energiförbrukningen i Sveriges byggnader. Dagens hårdare energikrav och samhällets intresse i miljöfrågor leder till att det finns ett behov för mer optimerade och anpassade styrsystem inom kyla och ventilation. Nattkyla är ett exempel på detta. Syftet med nattkyla är att lagra kyla i byggnadsstommen under nattetid genom att ventilera med kall uteluft. Denna lagrade kyla ska under dagtid agera som buffert mot de interna värmelasterna och därmed bidra till en lägre energianvändning.

Projektet undersöker med fallstudier om det är möjligt att optimera nattkylans inställningar i avseende på energi och inneklimat, för två butiker i Göteborg. Optimeringen utfördes med hjälp av genetiska algoritmer, neurala nätverk samt energimodeller, baserad på loggad kontrolldata för två butiker.

Studien visar att energianvändningen kan reduceras med 15% för båda affärerna med de optimerade inställningarna. Projektet visar också att de ursprungliga inställningarna gav mindre energianvändning än ingen nattkyla. Känslighetsanalysen indikerar att en energieffektivisering med 10% är möjlig för liknande lokaler med samma inställningar som för fallstudierna.

Projektet kommer fram till att användandet av loggad data tillsammans med genetiska algoritmer och neurala nätverk är ett effektivt verktyg för kalibrering och optimering av byggnadsenergimodeller. Den ökade datamängden som finns tillgänglig i branschen gör metoden mer relevant.

Nyckelord: Nattkyla, frikyla,genetiska algoritmer, neurala nätverk, energiberäkning, installationsstyrning, energikonsumtion, kommersiella fastigheter

CONTENTS

PREFACE

This thesis is a part of the master's program Structural Engineering and Building Technology and was conducted at the division of Building Technology at Chalmers University of Technology together with Vasakronan. The aim for the study was to develop night ventilation strategies for Vasakronan using logged control system data.

We would like to thank our supervisors at Chalmers and Vasakronan, Professor Angela Sasic Kalagasidis and Eric Eliasson for their help during the project. Furthermore we would like to thank "Fikagruppen" for their never ending entertainment and support. We also feel a special gratitude to our friends Lemmy Rowenstream and Jörgen Grek.

Göteborg, June 2017
Emmy Dahlström and Linus Rönn

Acronyms

AHU Air Handling Unit.

CHTC Convective Heat Transfer Coefficient.

GA Genetic Algorithm.

NN Neural Network.

SCADA Supervisory Control and Data Acquisition.

SFP Specific Fan Power.

VAV Variable Air Volume.

Glossary

Hysteresis Hysteresis is the dependence of the state of a system on its history. In a control system a hysteresis ensures a different stop condition if the start condition is met and thus prevents frequent switching of state.

Nomenclature

Subscripts

a	Air
el	Electricity
int	Internal gains
mass	Thermal mass
trans	Transmission
vent	Ventilation
w	Windows

Greek letters

α	Efficiency [-]
ρ	Density [kg/m^3]

Roman lower case letters

q	Power [W]
c	Specific heat capacity [J/kg°C]
g	Shading coefficient [-]

Roman capital letters

$\dot{V}$	Flow [m^3/s]
C	Thermal mass [$J/$°C]
I	Solar radiation [W/m^2]
K	Thermal conductance [$W/$°C]
R	Air leakage [m^3]
T	Temperature [°C]
V	Volume [m^3]

1 Introduction

1.1 Background

Periodically since the two oil crisis in the 1970s, there has been a focus in Sweden on reducing the energy use in buildings. This focus has evolved into the building regulations used today. With the stricter energy requirements and the interest from society in environmental issues there is a need to use more optimized control systems for cooling and ventilation. One example of this is the use of night cooling.

Vasakronan is a real estate company and they have a long-standing ambitious goal of improving energy efficiency in their building stock. Their properties should consume 50% less energy compared to the industry average, thereby reducing operation cost and promoting the company's environmental image. Night cooling has been suggested by energy consultants in the past to reduce energy and power usage for offices and commercial buildings. It uses cold nighttime air to cool the thermal mass of the building and thereby creating a cooling buffer that then reduces and shifts the cooling demand during the next day. However, there are still uncertainties regarding how it should be implemented and used. This uncertainty is due to the complexities of night cooling as it involves several different parameters such as internal gains, losses, outdoor temperature, indoor temperature and thermal inertia. The uncertainty exits as night cooling could result in bad thermal climate and increased energy use.

The knowledge concerning the implementation of night cooling is limited since it involves many parameters and parties in the life cycle of the building. Therefore, the set points values for night cooling are often reused for several different buildings regardless of the characteristics of the building. These control set points are hard to understand and the function they control, hence they are sometimes changed on a trial and error basis.

1.2 Purpose and aim

The aim of this thesis is to:

- Optimize ventilation strategies for night cooling to reduce cooling demand for a selected commercial building in Göteborg owned by Vasakronan. These strategies should not interfere with the function of the building or causes adverse effects.

- Evaluate the use of genetic algorithms and neural networks with post-processed data to improve building energy simulations.

1.3 Limitations

Limitations of the study are:

- This thesis is based on two retail stores but in the same building in Göteborg, therefore the result might not be applicable to other buildings or similar buildings in other climates.
- The data used and tested towards are limited to the year 2016, as data was not available for all parameters in previous years.
- Any effect of humidity will not be included in the simulation.

2 Method

The project includes the use of several different methods: a literature study, data collection from the field, developing a building energy simulation model, calibration and validation of the model, optimize the night cooling and perform a sensitivity analysis. In Figure 2.1 a flow chart over the process used in the project is shown with the respective building energy model used at each step.

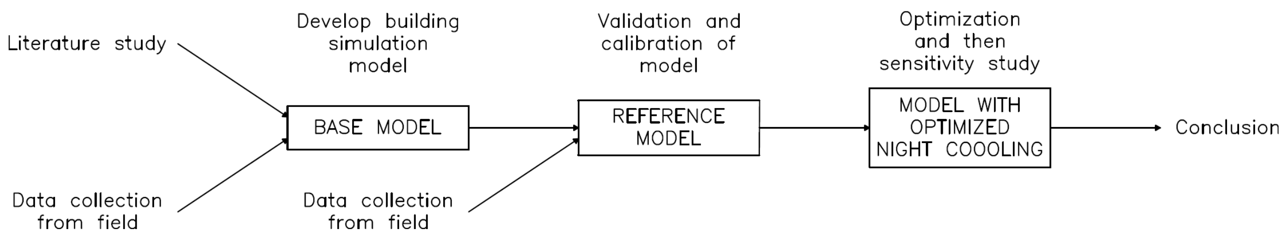


Figure 2.1: Flowchart over methods used and models that are produced in the project.

The project started with a literature study on the functions and limitations of night cooling, as described in Chapter 3. The literature study allowed us to select suitable reference facilities from Vasakronans building stock to use as case studies. The choice of case studies were also influenced by the building data that were available and how representative the facilities would be of Vasakronans owned properties.

The use of case studies provided real building cases that were already defined and had logged building data that allowed verification of the model result against the measured data from the building in use. The choice fell on two facilities that are located in the same building, with similar business activities. Both of them are retail stores but with different thermal mass capacities, window area and heat gain from lightning.

The buildings in question have data logging system of control data such as; temperatures, CO^2-levels, air-flows and valve openings which saves measurements every third minute. This SCADA-system of logged control signals worked as a base for a building energy simulation model developed in Simulink, which is a toolbox for MATLAB. Simulink allows for graphical programming and simulation of differential equations, such as the heat balance equation. This is further described in Chapter 4.

The first model, the base model, uses logged ventilation data from the SCADA-database, calculated values of thermal masses and values from other projects done regarding our stores for internal heat loads. This model is then calibrated towards the logged values of the indoor temperature of the facility using genetic algorithms and a neural network. The genetic algorithms are used in this project to calibrate different building constants, such as heat transfer coefficients between the air and the thermal mass, the thermal mass of the air and the building, internal heat loads and how they are divided between the thermal masses. The aim of the calibration is to achieve as little difference as possible between the measured indoor temperature and the simulated temperature. The model was calibrated towards the entire cooling season, the first of May to the last of September. With this long calibration most weather conditions are tested. The calibration of the building constants with the measured airflows and supply air temperatures for the ventilation in the simulated building model. The reference model was created with these calibrated constants applied to the model and using a simulated ventilation system instead of logged ventilation data.

From the reference model night ventilation was optimized by varying the control parameters using the same optimization scheme as when calibrating the model. The night ventilation was then optimized regarding energy usage and indoor temperature. The case studies were used as reference points for a sensitivity analysis in which the ventilation strategies were tested with different building parameters before condensing the results into general strategies.

3 Theoretical background

The purpose of night cooling is to decrease the energy demand of a facility, by ventilation during night with cold nighttime air. This ventilation decreases the temperature of the thermal mass of the facility during night when there are no occupants in the building. The chilled thermal mass will cool the air during daytime and reduce the cooling needed, resulting in a reduced energy demand.

Night cooling is often referred to as free cooling, since there is no energy being used to cool the supply air. However, night cooling uses the ventilation system and its energy use must be considered. Therefore night cooling is dependent on several factors to be beneficial. To achieve efficient night cooling the following criteria should be meet:

- The building should have sufficient thermal mass, so the energy storage is large enough to have an impact on the cooling need during daytime.
- Accessible thermal mass, the accessibility is important to allow interaction between the air and the thermal mass. The thermal mass is often covered to satisfy other qualities of the building, such as acoustical properties, fire regulations or aesthetics.
- The outdoor temperature is below the building indoor air temperature, since the cooling potential is strictly dependent on the temperature difference.

Night cooling can be made dependent on several factors, these exists both to ensure energy efficiency and a good thermal climate.

- Date limitation, sets a limitation on what time of the year night cooling can be active. Normally set from first of May to last of September, which is the cooling season in Göteborg.
- Ventilation schedule, exists so the night cooling is active during night and not during the scheduled occupancy hours. Different times are set dependent on weekdays and weekends, since there are a difference in occupancy hours. Properly adjusting this control signal the indoor air can adjust the temperature to the thermal mass in the morning, thereby preventing over cooling and bad thermal climate.
- Outdoor temperature limitation, the limitation creates a range for which outdoor temperatures the night cooling is allowed to be active. A minimum temperature is set so the night cooling can only be active if the temperature is above the limit value, this to ensure that the building and installations are not damaged by too cool air. The maximum limit is set to ensure effectiveness of night cooling so that the night cooling does not ventilate with warm air.
- Indoor temperature limitation, if the temperature is above a certain value the night cooling can start, thereby ensuring that there is a cooling need and ensuring the effectiveness of the night cooling. The stop temperature is set to prevent over cooling the facility and endangering the indoor climate.

- Temperature limit on the supply air, a limit can be set on the temperature in the room for safety reasons. This makes it possible to go even lower in outdoor temperatures without endangering the installations with too cold air. When the outdoor temperature is lower than the limit on supply air the heat recovery unit will be active so the demand on supply air is still fulfilled.
- Temperature difference demand, the difference between the room temperature and the outdoor temperature must be high enough so there is a benefit for night cooling. Since the cooling effect is proportional to the difference in temperature and to ensure that is it worth it to start the fans.

3.1 Literature study

In a study done by Artmann (2009), he concludes that the Scandinavian countries have a beneficial climate for night cooling, with cold summer nights and warm summer days. However, the urban heat island effect should be considered and uncertainties of temperature increase the climate change will bring about. Therefore, the basic conditions for night cooling is achieved.

Le Dreau, Heiselberg, and Jensen (2013) highlight the importance of the correct surface Convective Heat Transfer Coefficient (CHTC), since it is the main heat transfer mechanism for night cooling due to the relatively small effect of radiative heat transfer on air. Moreover Le Dreau et al., states that the choice of CHTC can influence the energy transfer by a factor of 5 and is dependent on surface and if an upward, downward or vertical heat flux the transfer coefficient changes. The convective heat transfer coefficient proposed in Table 3.1 below is based on the standard EN ISO 6946. However the CTHC is highly dependent on the air velocities and ventilation strategy, if it is displacement strategy or if it mixing strategy is used.

Table 3.1: Convective heat transfer coefficient for different heat fluxes, according to EN ISO 6946.

Area	**Downwards**	**Sideways**	**Upwards**
α_c	$0.7W/m^2$	$2.5W/m^2$	$5.0\ W/m^2$

An important aspect of night cooling is the energy consumption of fans during the active hours. A study by Lain and Hensen (2006) states that the benefits of night cooling can be balanced out by the fan energy needed, as the fans consumes power in a quadratic relationship to the ventilation flow. Furthermore, they highlight the need for extra communication between the involved parties in the buildings life cycle to ensure an energy efficient building with more complex technical systems.

In a master thesis by Larsson (2015) using post processed data for optimization of night cooling for an office in Göteborg suggested a method of simplistic modelling of the building and larger focus on calibration of the internal gains and losses. This concept proved to be successful and can be applied for this project. In the thesis the urban island effect and the beneficial Scandinavian climate that Artmann highlighted can be seen.

3.2 Model optimization

The following sections covers a brief theory behind the optimization used in the project. In Chapter 6 and Chapter 7 the implementation and the results of the genetic algorithm and neural network are presented.

3.2.1 Genetic algorithm

Genetic Algorithms (GAs) operates in a way that can be described similar to evolution, which is the reason for its name (Aria, 2015). The algorithms are random and stochastic search algorithms. A genetic algorithm uses a population pool of variable-sets, the population pool makes it possible to search for the global minimum instead of a local as multiple potential solution are kept in the population pool. Each variable set are tested by the objective function and gets an associated fitness value. The objective function is the function for which the global minimum is searched and the fitness value is a measure of the variable-sets suitability as a solution.

Initially the algorithm creates a number of variable-sets; see Figure 3.1 for flow chart over the algorithm and an example of it for the first GA of the optimization. The initial variable-sets can be generated according to rules. For this project, they were generated randomly spread within the variable-sets with the only limitations being the upper and lower boundary of the variables. These variable-sets are evaluated and paired with their associate fitness value before the reproduction operator uses the values to select the most suitable variable-sets to be the parents of the new generation of variable-sets. The crossover operator defines new variable sets; the number of crossover is determined by the crossover rate. The crossover operator chooses two parent sets and combines some of their characteristics to create the new child variable-set. This child will then be entered into the population pool for the next generation. After the crossover operation is complete the mutation operator randomly changes some variable-set, the amount of mutation is dependent on the specified mutation rate as it determines the probability of mutation happening for each variable-set. Both the non-mutated and mutated variable sets are then returned to the population. Mutation is used to prevent variable-sets from becoming too similar and thereby allowing an escape from a local minimum.

The selection, crossover and mutation operators are called the genetic operators and will create a new population that is based on the old generation. Their fitness values are determined and variable-sets with worse fitness values are eliminated with each generation to so that the genetic algorithm eventually converges to a solution. Thus, one generation cycle consists of the genetic operators and a determination of their fitness values. The genetic algorithm will continue until the termination criteria are met, often the amount of generations or a lack of change in the fitness values.

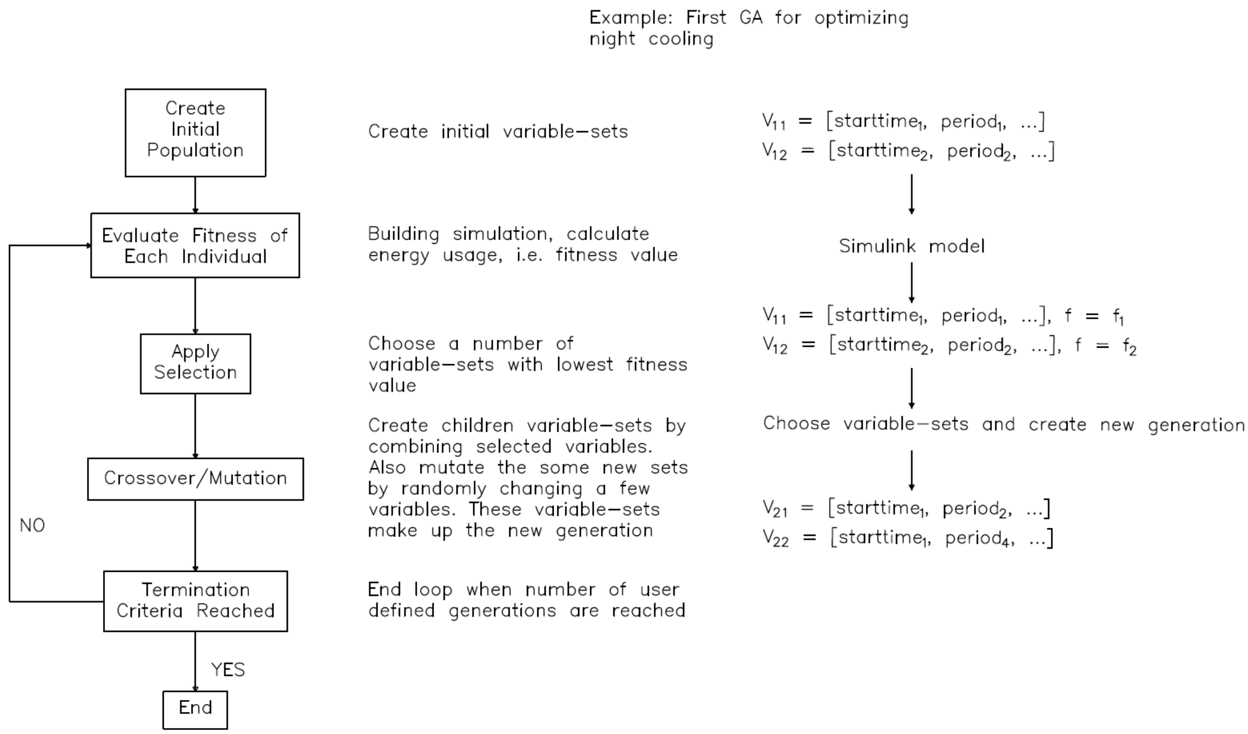


Figure 3.1: Flow chart for genetic algorithm with one example how it is used for opimizing night cooling.

3.2.2 Neural networks

Neural networks can be used to approximate the results of functions that are relatively unknown and they can depend on large numbers of input (Aria, 2015). Neural networks needs to be trained to do a specific job. The training is done by providing the network with examples of input variables and its respective outputs. It will then learn the relation between the input and the output and can then be used to approximate outputs with new input.

A Neural Network must consist of at least an input layer and an output layer but most neural networks also include at least one hidden layer as seen in Figure 3.2. The purpose of the hidden layer is to allow for more complexity and better approximate nonlinear behavior as different inputs can effect each other before they effect the output. Each layer consists of neurons, the output and the input layer has the same number of neurons as the amount of inputs and outputs. The hidden layer however has a user described number of neurons; the amount of neurons needed is often dependent on the number of control variables i.e. the inputs. Between each layer of neurons, there is a weighting of the input. Each neuron in the hidden and output layer is a transfer function as seen in Figure 3.2 that consist of a summation of the weighted input and an activation function that uses the summed input. To fit the activation function and the weights the neural network needs training, as the weights and activation functions are initially randomly generated.

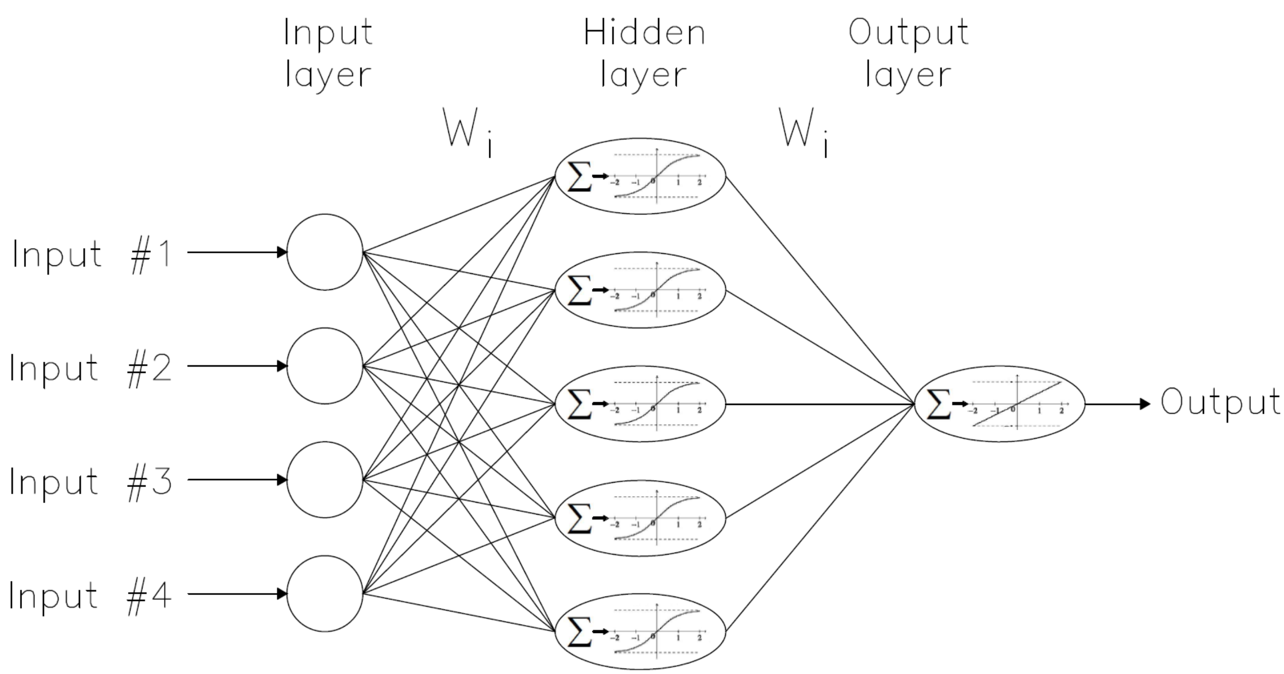


Figure 3.2: Generic scheme over a neural network including transfer functions in neurons.

4 Simulink model

The following chapter covers the development of a lumped building energy model in Simulink. See Appendix D for the Simulink model.

4.1 Simulation of base models

The models uses the same base architecture. The different thermal masses are divide into separate lumps that only interacts with each other through a single connection. This system allows for easy construction of the different models and could differentiate the thermal mass into multiple parts. Both models have one air part and at least one part for the thermal mass of the structure and the heat gains and losses influences these parts with different factors dependent on radiative or convective heat transfer. The model simulate the operative temperature in the room and has been simplified by adding the radiative heat transfer coefficient directly to the convective. In Figure 4.1 the heat gains, losses and thermal masses are presented.

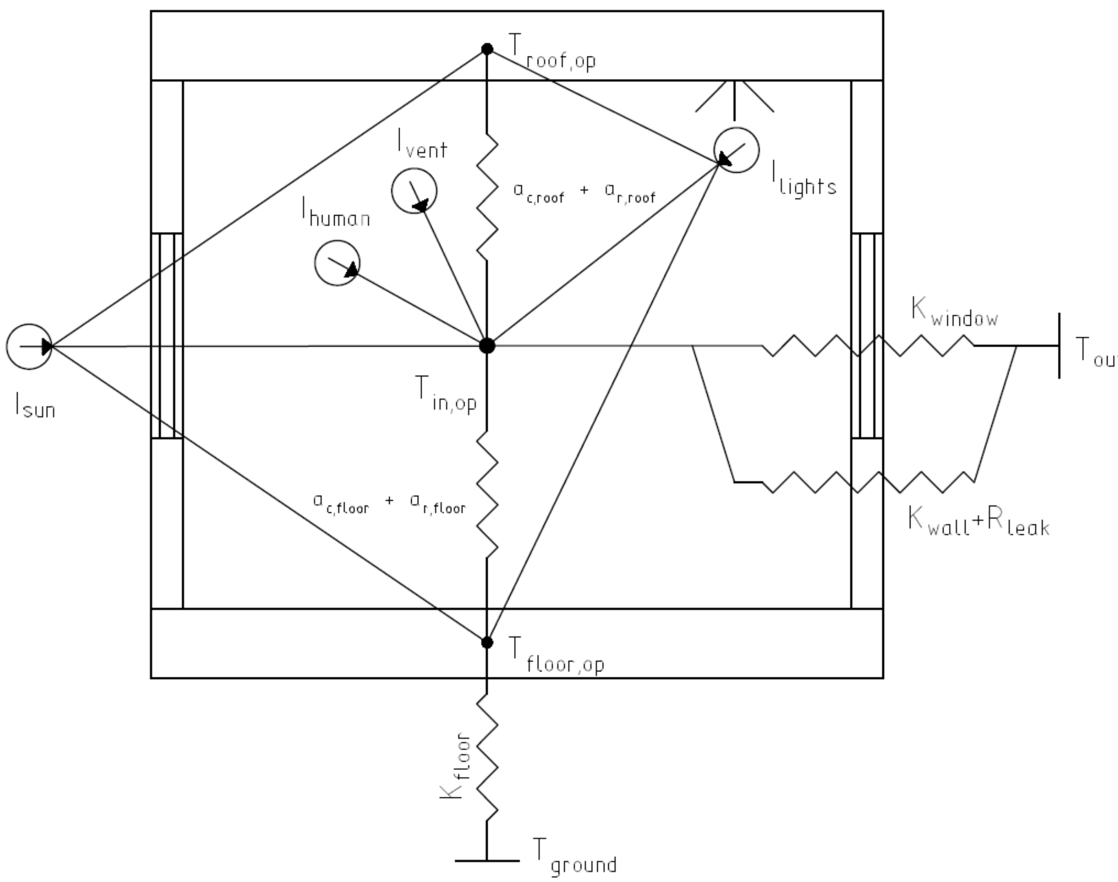


Figure 4.1: Simulation circuit that displays the distribution of heat gains and losses, for a store with access to the thermal mass of the floor and the roof.

4.1.1 Heat gains and losses

The different heat gains are added with different factors straight to the thermal mass of the structure or the air dependent on whether the heat transfer mechanism is convective or radiative. The heat gains and losses and how they affect the model:

- The power usage for the lighting has been measured by Vasakronan and then implemented in the Simulink model as a recurring sequence for each week based on the electricity consumption.
- Heat load from people is assumed to be 7.5 W/m^2 and applied during opening hours for the stores based on previous energy simulations of the building.
- Solar radiation is taken from an input file that is general for all of Göteborg and is not measured at the building site. As the building is built in the urban environment, they are close to other buildings, which cast shadows over the buildings affecting the solar heat gain.
- Transmission losses to the outdoor environment takes mainly place through glass façades. This heat flow is assumed only to affect the air of the model because of the façade's low thermal mass and thereby low energy storage capabilities.
- The ventilation system is directly affecting the temperature of the air.
- Air leakage: In a similar manner to the ventilation, air leakage is also assumed to only interact with the heat equation of the air. The air leakages are assumed to only consist of leakages though the entrances.

The air leakages through the entrance are correlated to the number of people passing through the entrance. Air leakages are approximated using the method for sliding doors described in a study by Karlsson (2013) and the number of entrances is assumed to follow the number of people.

The heat loads are distributed to the different thermal masses according to the Table 4.1 below. This division is dependent on the heat transfer mechanisms of the heat load, if it is radiative or convective heat transfer. Radiative heat transfer influences the thermal mass of the structure to a greater extent than the convective heat transfer. Convective heat transfer on the other hand mainly affects the air.

Table 4.1: Heat load distribution between radiative and convective heat transfer

Load	Distribution
Solar heat load	
Floor slab	75%
Roof slab	5%
Air	20%
Lighting heat load	
Floor slab	55%
Roof slab	5%
Air	40%
Human heat load	
Air	100%

4.2 Simulation method

The equations used in the Simulink model are based on are presented in the following section. All equation in this section is derived from Hagentoft (2001).

4.2.1 Thermal mass

The thermal inertia of the facility is represented by the thermal heat capacity. The thermal mass of the building is calculated as the sum of the effective volume of each layer, if the layer is in direct contact with the indoor air.

$$C_{structure} = \sum_j d_j \, \rho_j \, A_j \, c_{p,j} \tag{4.1}$$

Where:

$C_{structure}$	is the combined thermal mass of the structure. [J / °C]
d_j	is the penetration depth of the layer. [m]
ρ_j	is the density of layer. [kg/m^3]
A_j	is the area of the layer. [m^2]
$c_{p,j}$	is the specific heat capacity. [J / kg°C]

The thermal mass of the air is calculated with the following equation.

$$C_{air} = \rho_a V_a c_{pa} \tag{4.2}$$

Where:

C_{air}	is the thermal mass of the air. [J / °C]
ρ_a	is the density of air. [kg/m^3]
V_a	is the volume of the air. [m^3]
c_{pa}	is the specific heat capacity for air. [J / kg°C]

4.2.2 Heat balance equation

The simulation of the thermal masses including the indoor air temperature is based on the differential heat balance equation, the derivative of the temperature is described by the following equation:

$$C \frac{dT_{mass}(t)}{dt} = q_{trans}(t) + q_{ground}(t) + q_{vent}(t) + q_{sun}(t) + q_{int}(t) + q_{leak}(t) + q_{thermal}(t) \tag{4.3}$$

Where:

T_{mass}	is the temperature of the thermal mass. [°C]
q_{trans}	is the heat transmitted though the building envelope. [W]
q_{ground}	is the heat transmitted though the floor. [W]
q_{vent}	is the heat lost or gained by the ventilation. [W]
q_{sun}	is the heat gained solar radiation. [W]
q_{int}	is the summation of internal gains. [W]
q_{leak}	is the heat transmitted though air leakage. [W]
$q_{thermal}$	is the heat transmitted from the buildings thermal mass to the indoor airs thermal mass. [W]

The differential equation is integrated numerically using a explicit time scheme:

$$\int_{t}^{t+\Delta t} \frac{dT_{mass}(t)}{dt} dt = (T_{out}(t) - T_{in}(t)) \tag{4.4}$$

Each new time step is calculated from values in the current time step.

$$T_{mass}(t + \Delta t) = T_{mass}(t) + \frac{q_{trans}(t) + q_{ground}(t) + q_{vent}(t) + q_{sun}(t) + q_{int}(t) + q_{leak}(t) + q_{thermal}(t)}{C} \tag{4.5}$$

4.2.3 Heat transmission

The heat transmission through the building envelope is described with the following equation. K_{trans} is a sum of the envelope's conductance including windows, walls and roof including thermal bridges.

$$q_{trans} = K_{trans} \, (T_{out}(t) - T_{in}(t)) \tag{4.6}$$

Where:

q_{trans}	is the heat transmitted though the building envelope. [W]
T_{out}	is the outdoor temperature. [$°C$]
T_{in}	is the indoor temperature. [$°C$]
K_{trans}	is the conductance for the building envelope. [W / $°C$]

The heat transmission through the floor is approximated with a constant temperature directly underneath the ground isolation. According to the following equation.

$$q_{ground} = K_{floor} \, (T_{ground} - T_{in}) \tag{4.7}$$

Where:

q_{ground}	is the heat transmitted though the floor. [W]
T_{ground}	is the ground temperature. [$°C$]
K_{floor}	is the conductance for the floor. [W / $°C$]

4.2.4 Ventilation

The energy effects from the ventilation is described by the equation below.

$$q_{vent} = c_{pa} \, \rho_a \, \dot{V} \, (T_{supply} - T_{in}) \tag{4.8}$$

Where:

q_{vent}	is the heat lost or gained by the ventilation. [W]
T_{supply}	is the supply air temperature. [$°C$]
$\dot{V}$	is the ventilation flow. [m^3/s]

4.2.5 Ventilation heat- and cooling recovery

The heat and cooling recovery unit in the model is simulated with the equation below. The recovery unit has a varying effectiveness that is dependant on the outdoor temperature.

$$T_{reco} = T_{out} + \alpha_{eff} \, (T_{exhaust} - T_{out}) \tag{4.9}$$

Where:

T_{reco}	is the supply air temperature after the heat recovery. [$°C$]
$T_{exhaust}$	is the exhaust air temperature. [$°C$]
α_{eff}	is the effectiveness of the heat and cold recovery. [-]

4.2.6 Solar heat gains

The solar heat gain trough windows is calculated with the equation below. The solar radiation values is measured for a vertical surface.

$$q_{sun} = g_w \, g_c \, A_w \, I_{sun} \tag{4.10}$$

Where:

q_{sun}	is the heat gained solar radiation. [W]
g_w	is the g-value for the windows. (0-1)
g_c	is the g-value for the external shading. (0-1)
A_w	is the area of glass excluding frames. [m^2]
I_{sun}	is the global irradiation on the surface. $[W/m^2]$

4.2.7 Internal heat gains

The internal heat gain of the building takes into account the heat transfer from humans and the electricity generated by equipment. Note that these are time dependant and varies with activity.

$$q_{int} = q_{people} + q_{el} \tag{4.11}$$

Where:

q_{int}	is the summation of internal gains. [W]
q_{people}	is the heat generated by people in the building. [W]
q_{el}	is the heat generated by electricity usage in the building. [W]

4.2.8 Air leakage

The air leakages are included in the model using the following equation.

$$q_{leak} = R_a \, c_{pa} \, \rho_a \, (T_{out} - T_{in}) \tag{4.12}$$

Where:

q_{leak}	is the heat transmitted though air leakage. [W]
R_a	is the leakage flow though the building envelope. $[m^3/s]$

4.2.9 Interaction between the masses

The interaction between the different lumps are described in in the model with the following equation.

$$q_{thermal} = K_a \left(T_{thermal} - T_a\right) \tag{4.13}$$

Where:

$q_{thermal}$	is the heat transmitted from the buildings thermal mass to the indoor airs thermal mass. [W]
K_a	is the conductance between the indoor air and the buildings thermal masses. [W/°C]
$T_{thermal}$	is the temperature of the buildings thermal mass. [°C]

5 Case studies

5.1 Description of Perukmakaren

Perukmakaren is a six-story building excluding a basement floor. It is located in central Göteborg originally built in 1966 but underwent a large renovation in 2014. During this renovation, equipment was added that allows logging of control system data. The basement and the main floor are used for retail purposes (floor 1-2) while floor 3, 4 and 5 comprise of hotel facilities and a parking garage. The two top floors (floor 6-7) contains a garage and technical rooms. The floor area is divided so that 62% is used for parking garage, 28% for retail and storage and 10% of the area is used for hotel purposes.

The building is serviced by four Air Handling Unit (AHU) operating with a Variable Air Volume (VAV). The primary heat and cooling source is district heating and district cooling. The supply air, radiators and air curtains distribute the heating while the supply air solely distributes the cooling.

The facilities of interest for further investigation in regards of night cooling are the retail facilities, which have a cooling need during daytime and are not occupied during night. Compared to the hotel part of the building, which has more flexible occupancy hours. The retail area contains 14 different shops with varying size and thermal mass. The facility most suitable for night cooling is a clothing store with two third of its area on the basement floor, with exposed concrete floor and half of the concrete ceiling covered by acoustic ceiling rafts giving it a large thermal mass. This will be referred to as store A. Store A is almost completely surrounded by other shops or storage areas with similar indoor climate; the only contact with the outdoor environment is at the entrance. The store is ventilated by a single AHU and it is the main user of the AHU, however the facility is divided into three climate zones with varying set point temperatures.

The other facility of interest located in Perukmakaren, store B, has low thermal mass availability, since the roof is completely covered by acoustic plates. The facility is more exposed to the outdoor climate and has windows towards the south, with higher solar heat load. The concrete slab is covered by screed and has tiles as a finish; these will negativly influence the penetration depth of the thermal mass since they have lower thermal conductivity than concrete. The store is ventilated by a single AHU and half of the flow is used for the ventilating the store. In Appendix A, there are floor plans for both stores.

5.2 Control and ventilation system at Perukmakaren

The data logging-system in Perukmakaren is mainly used for monitoring current energy need and thermal comfort for the different tenants. The system logs values every third minute except the outdoor temperature, which is logged every 15 minute. The main control system of the Perukmakaren can monitor these values and dependent on inputs such as indoor temperature, time or outdoor temperature and controls the supply air. The ventilation flow is dependent on the indoor comfort and varies to achieve the set-point temperature. It can also be dependent on time or enthalpy. The control system is divided into three different parts, an overall data collecting system called Supervisory Control and Data Acquisition (SCADA), the control system for the AHU and internal control system for VAV-dampers and other equipment.

The AHUs in the building is constructed in the same way, with no heating coil, see Figure 5.1 for a basic sketch. The temperature sensors before and after the cooling coil, in the AHU worked as a base for calculating the measured cooling energy. The supply airflow is in controlled by the VAV-dampers that regulate the airflow to achieve a set-point air temperature for that zone. The AHU is damper regulated and adjusts the flows so one damper is 90% open.

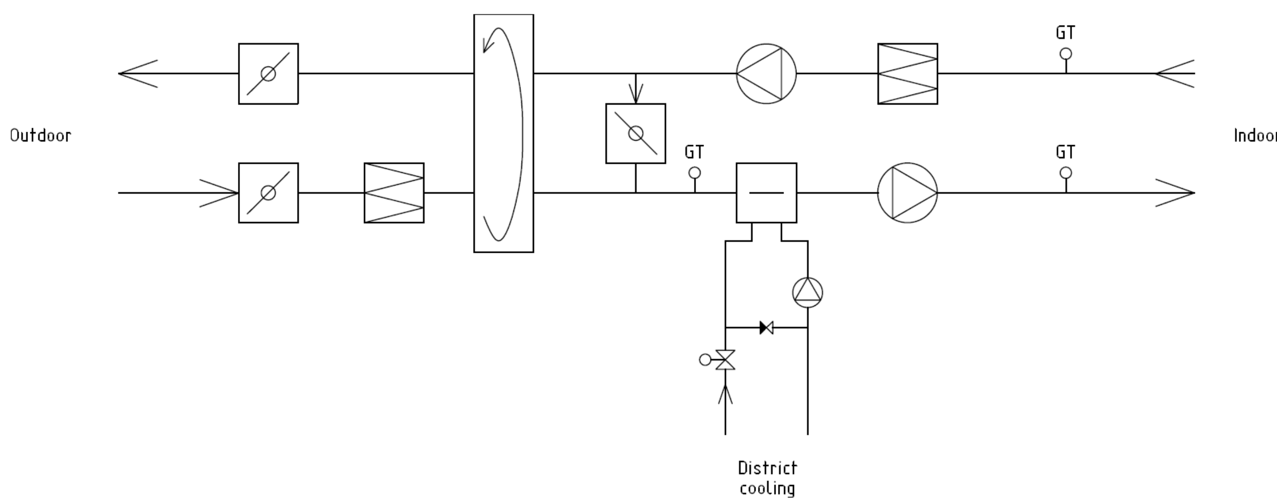


Figure 5.1: Basic sketch of Air Handling Unit for Store A and B

5.2.1 Fan energy

In section 3.1 of this project it has been concluded the electricity used for operating the fans is important for the overall effectiveness of night cooling. To examine the energy use, the logged data over Specific Fan Power (SFP) for the AHUs and the total supply airflow is plotted against each other. This relationship was then approximated by using a second-degree polynomial curve and the least square method was used to evaluate how well the data fitted the curve. Since the AHUs serve several shops, the relationship between the AHU supply airflow and the supply air to the store in question is examined. This relationship is calculated by a second degree polynomial, the results from this is shown Section 5.3.3 and Section 5.4.3

for respective store.

5.2.2 Weather data

Outdoor temperature is taken at the building site; there are a large number of externally placed temperature sensors. The solar radiation is taken from SMHI climate data file from Göteborg for 2016.

5.3 Store A- with high available thermal mass

5.3.1 Control system for store A

In the following tables the original control set points for store A, that are of concern for summer conditions, are covered for both daytime and nighttime ventilation. In Table 5.1 the daytime set points are presented and in Table 5.2 the set points for night cooling. The notes regarding source of information is either from "Data" which means that the information is obtained by analysis of data sets, "Interface" means that the information is taken from the respective control system interface.

Table 5.1: Daytime set point for the ventilation for store A

Function	Set points	Notes
Ventilation schedule	Weekdays 07:30-19:30 Weekends 09:00-18:30	Collected from data
Opening hours	Weekdays 10:00-19:00 Saturdays 10:00-18:00 Sundays 11:00-17:00	
Maximum airflow	3.1 m^3/s	Collected from data
Minimum airflow	0.82 m^3/s	Collected from data
Supply air set point	13°C-17°C	Dependent on outdoor temperature
Heat and cooling recovery minimum requirement	$\Delta T_{Tout-Texhaust}$ >2.2°C	Collected from interface
Room temperature set point when occupied	20.5 °C	Collected from interface
Room temperature set point when empty	19 °C	Collected from interface

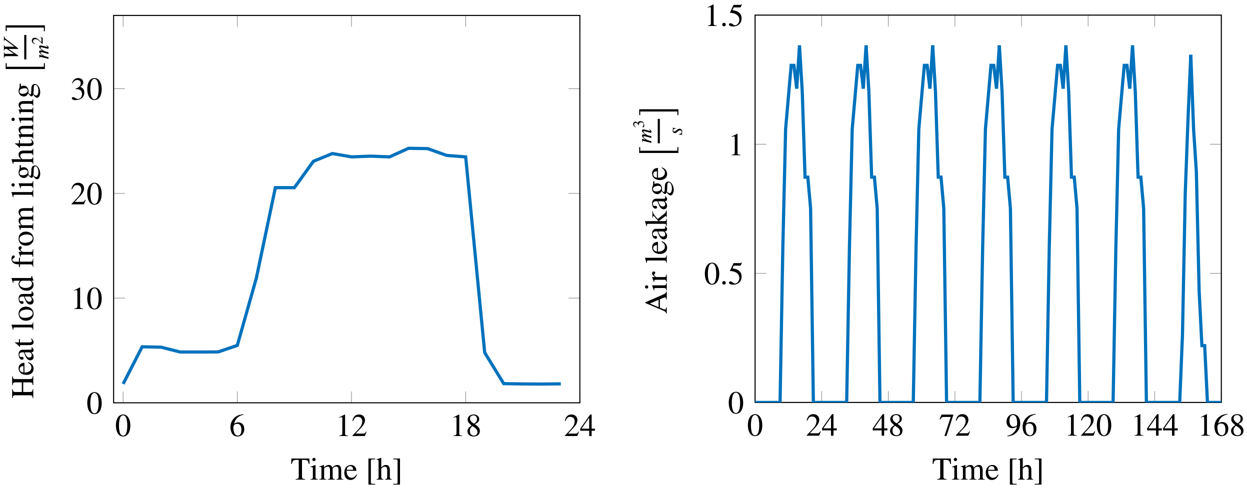
Table 5.2: Original night cooling set points for store A

Function	Set points	Notes
Date limitation	Starts May the 15th Stops September the 15th	Collected from interface
Ventilation schedule	Weekdays 02:00-08:00 Weekends off	Collected from interface
Ventilation flow	1.86 m^3/s	Collected from data
Indoor temperature limitation	Start condition T_{in} > 22°C Hysteresis T_{in} = 2°C	Collected from interface
Outdoor temperature limitation	Start condition T_{out} > 16°C Hysteresis T_{out} = 10°C	Collected from interface
Temperature difference demand	Start if $\Delta T_{Tin-Tout}$ >3.5°C Stop if $\Delta T_{Tin-Tout}$ =1.0°C	Collected from interface
Supply air set point	Min 10.0°C	Collected from interface
Room temperature set point	18°C	Collected from interface

5.3.2 Base model for store A

The base model includes three lumped models, the first representing the air, the second the ceiling and the third represents the floor. This division between the floor and the roof is due to the difference in thermal mass and temperature of the slabs. The floor slab has the capability to act as a semi-infinite thermal mass. This semi-infinite mass has been simplified to a constant temperature directly underneath the insulation of the slab according to Hagentoft (2001) and results in a temperature of 17 degrees. The suspended rafters with acoustic plates are assumed to make half of the thermal mass of the ceiling slab available. The store has three climate zones that are simplified into one and assumed to be completely mixed.

The sequence for the applied heat load for lightning over a day for store A are shown in Figure 5.2. With a maximum value of 24.5 W/m^2 during opening hours and an average of 3.5 W/m^2 when the store is closed. During weekends the applied heat load from lightning are applied with the same profile but shortened to fit the open hours of the store. The air leakages are shown in Figure 5.2.



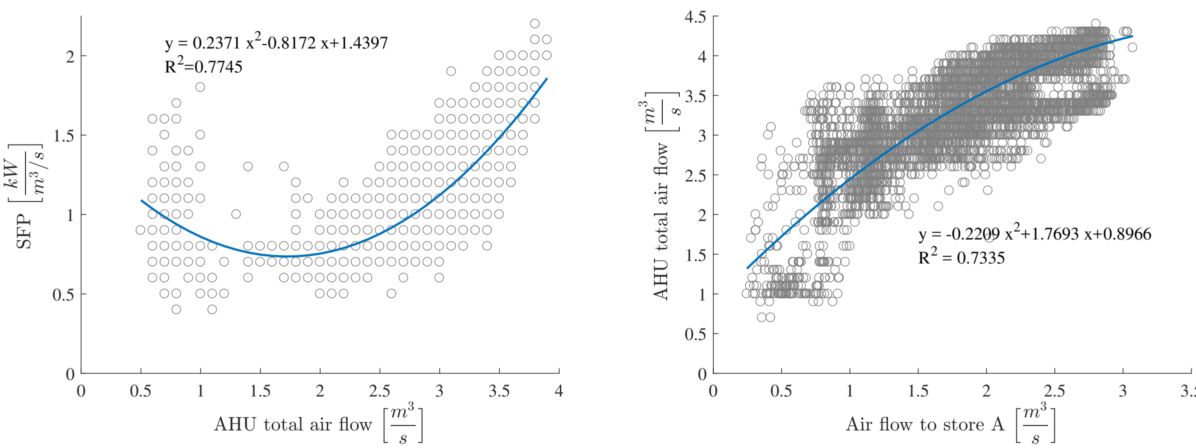
(a) The heat load from lightning in W/m^2 during a weekday for store A.

(b) Air leakages in m^3/s during a week for store A.

Figure 5.2: Graphs showing the heat gains from lightning and losses by air leakages for store A

5.3.3 Ventilation input for store A

In Figure 5.3 the relation between the specific fan power and total airflow from the AHU is plotted and the equation is used to calculate the energy usage for the fan. The airflow to store A is plotted and correlated to total flow from the AHU.



(a) SFP vs. AHU total airflow.

(b) AHU total airflow vs. airflow to store A.

Figure 5.3: Graphs showing the SFP and airflow for AHU for store A, and the correlation between the total airflow through the AHU and the total airflow for the store

5.4 Store B- with low thermal mass

5.4.1 Control system for store B

In the following tables the original control set points for store B, that are of concern for summer conditions, are covered. In Table 5.3 the daytime set points are presented and in Table 5.4 the set points for night cooling.

Table 5.3: Daytime set point for the ventilation for store B

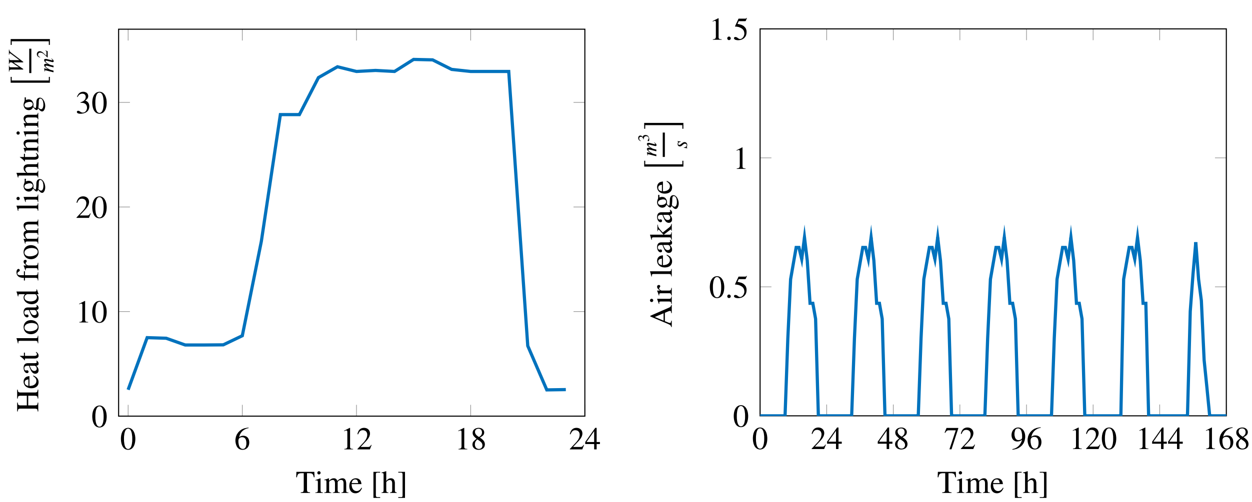
Function	Set points	Notes
Ventilation schedule	Weekdays 08:00-20:00 Saturdays 09:00-18:30 Sundays 10:00-17:30	Collected from interface
Opening hours	Weekdays 10:00-20:00 Saturdays 10:00-18:00 Sundays 12:00-17:00	
Maximum airflow	2.2 m^3/s	Collected from data
Minimum airflow	0.15 m^3/s	Collected from data
Supply air set point	13°C-17°C	Dependent on outdoor temperature
Heat recovery minimum requirement	$\Delta T_{Tout-Texhaust}$ >2.2°C	Collected from interface
Room temperature set point when occupied	21 °C	Collected from interface
Room temperature set point when empty	24 °C	Collected from interface

Table 5.4: Original night cooling set points for store B

Function	Set points	Notes
Date limitation	Starts May the 15th Stops September the 15th	Collected from interface
Ventilation schedule	Weekdays 02:00-08:00 Weekends 02:00-08:00	Collected from interface
Ventilation flow	1.2 m^3/s	Collected from data
Indoor temperature limitation	Start condition T_{in} > 22°C Hysteresis T_{in} = 3°C	Collected from interface
Outdoor temperature limitation	Start condition T_{out} > 18°C Hysteresis T_{out} = 10°C	Collected from interface
Temperature difference demand	Start if $\Delta T_{Tin-Tout}$ >3.5°C Hystersis $\Delta T_{Tin-Tout}$ =1.0°C	Collected from interface
Supply air set point	Min 10.0°C	Collected from interface
Room temperature set point	18°C	Collected from interface

5.4.2 Base model for store B

The base model includes two lumped models, one representing the air and the other the thermal mass of the structure. In store B there is only one air zone and the air is assumed to be completely mixed. The sequence for the applied heat load for lightning for store B are shown in Figure 5.4. With a maximum value of 32.5 W/m^2 during opening hours and an average of 4.5 W/m^2 when the store is closed. During weekends, the applied maximum hours are shortened to the fit the open hours of store B.



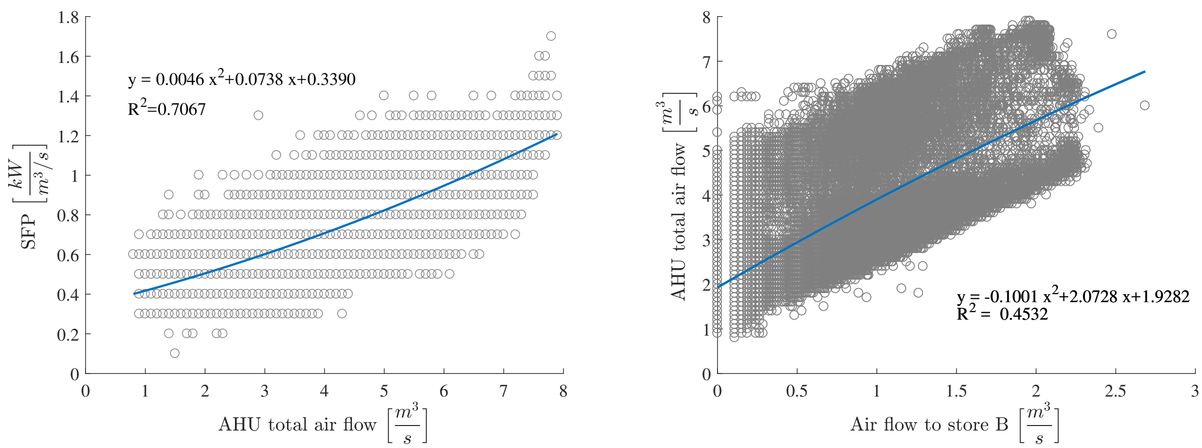
(a) The heat load from lightning in W/m^2 during a weekday for store B.

(b) Air leakages in m^3/s during a week for store B.

Figure 5.4: Graphs showing the heat gains from lightning and losses by air leakages for store B.

5.4.3 Ventilation input for store B

In Figure 5.5 the specific fan power and total airflow is plotted and the correlation between the airflow to store B and the total airflow through AHU.



(a) SFP vs. AHU total airflow.

(b) AHU total airflow vs. airflow to store B.

Figure 5.5: Graphs showing the SFP and airflow for AHU for store B, and the correlation between the total airflow through the AHU and the total airflow for the store

5.5 Sources of errors

5.5.1 Heat gains and losses

The heat gains and losses were inserted in the model on a weekly basis, which does not take into account the seasonal variations. For example there are more customers during cloudy days than sunny, thereby affecting the heat gain from humans, number of door openings and the air leakage.

Store B tends to have their entrance fully open during the opening hours if the weather allows it, this was not included in the model as the weekly schedule is based on door openings.

5.5.2 Fan energy and SFP

SFP values are only logged from September and therefore the values are taken from this period and not the simulated period. This resulting in fewer values of peak flows as the peak flows are not reached during the colder part of the year. During the winters the ventilation strategy is to minimize the airflows, reducing the air volume needed to be heated and thereby decreasing the energy consumption. The strategy during summer is the opposite; maximize the supply airflows to reduce the need for dehumidification of the air. Cooling in the summer uses latent energy if the supply air is chilled below its dew point temperature, as the relative humidity cannot exceed 100%. Thus increasing the amount of supply air allows a higher set point temperature while achieving a comfortable indoor climate and less energy consumption.

In theory the SFP-curve should be a polynomial close to x^2. The AHUs in Perukmakaren regulates to keep at least one damper 90% open. This can result in high air pressure losses at low airflows resulting in data points that do not match the theory. This regulation explains the high values of SFP during low flows.

The SFP curve for store B's AHU is close to linear; this affects the results as is not as energy demanding to operate the fans at a higher flow rate compared to a quadratic curve. Therefore, the results could be misguiding. The mean square method shows a low correlation between the flow from the AHU and the flow to store B; this is due to the AHU serves other facilities, which uses high airflows when store B requires a low supply of air. However, the curve fitting is deemed to be sufficient since the flows varies a lot to the store.

5.5.3 Ventilation system

In the simulation, the energy savings from the the recirculation air is assumed to taken into account by the heat recovery unit as there is no data on the volume of recirculation air. The model does not include a simulation of air pressure in the duct, nor did Vasakronan have direct access to dampers as they have internal control system. This resulted in a simplification in the building model; the ventilation flow is based on the temperature difference between the room and the set-point temperature multiplied by a factor to achieve the simulated ventilation flow.

6 Calibration of models

The objective for the calibration is to get the smallest difference in degree hours between the measured room temperature and the simulated room temperatures. This was accomplished using genetic algorithms, see Section 6.1 for the method. Before running the genetic algorithm, some alterations were made to the data sets from the base model. The time schedule for the internal gains was changed and moved ahead one hour earlier as the room temperature was too low during these hours. The heat gains from humans and the leakages were halved during Sundays since the simulated indoor temperature always was too high during that day.

During the project several different models were used in Table 6.1, the naming and the difference between them are presented.

Table 6.1: Name and difference between the used building energy models.

Name	Comments
Base model	Calculated building constants with measured supply airflows and temperatures.
Calibrated model	Calibrated building constants with measured supply airflows and temperatures.
Reference model	Calibrated building constants with simulated ventilation system using original night cooling set points.
Optimized model	Calibrated building constants with simulated ventilation system using optimized night cooling set points.

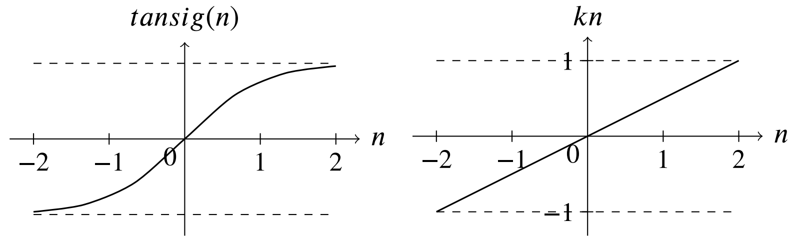
6.1 Calibration method

The optimization for this project needs to be rather robust as the problems that are optimized can have a number of local minimum. This makes a deterministic approach for the general optimization a bad choice, as it will not be able to handle multiple minimum. Instead, a genetic algorithm is used, as it is better suited to find a global minimum.

In the calibration for this project, the objective function for the first genetic algorithm is running the building simulation in Simulink. The fitness value is then defined as the numerical integration between the measured indoor temperature and the simulated indoor temperature, thereby calculating the error in degree hours.

All the variable-sets that are tested by the first GA with their respective fitness value are used as inputs and targets to train a neural network. This trained neural network can then approximate the fitness value based on new input. The second genetic algorithm uses the neural network as its operative function to get the most optimized variable set that will make the building simulation best represent reality. See Figure 6.2 for flow chart of the calibration method.

The neural networks in this project uses common parameters and many default values in MATLAB. It is a feed forward network using back propagation training methods with a tan-sigmoid activation function in the hidden layer and linear activation function in the output layer as shown in Figure 6.1.



(a) Tan sigmoid (b) Linear function

Figure 6.1: Transfer functions for each node, Tan sigmoid function for the nodes in the hidden layer and linear function for the output layer.

Running the simulation model takes fairly long time, thereby limiting the amount of input data available to train the neural network (MATLAB, 2017). Small changes to the simulation model can lead to large changes in the fitness value, consequently the examples for the neural networks can be rather scattered. Therefore, the default algorithm, Levenberg-Marquardt, for training the neural network is replaced with a Bayesian Regularization. Bayesian Regularization is more suited for small and scattered problems. Another alternative would be Scaled Conjugate Gradient, that uses a gradient approach instead of using Jacobian calculations as the other two training algorithms.

The data from the building simulations are split into 70% being used for training, 15% used for validation of generalization and to stop over fitting of the network and the remaining 15% will test the training to validate it.

Neural networks are used as they are able to approximate the fitness value for a variable-set much faster than the Simulink model and thus allows the use of a much broader genetic function with larger populations and more generations. The time to simulate the building energy model during the first genetic algorithm is 1500 times slower than to use the neural network.

Step 3 in the calibration is a local search algorithm, it is included to ensure that the local minimum was found. A local search can be used, as the genetic algorithm hopefully finds a result close to the global minimum. For this purpose, a deterministic gradient-based method is used, as it will quickly converge to a minimum.

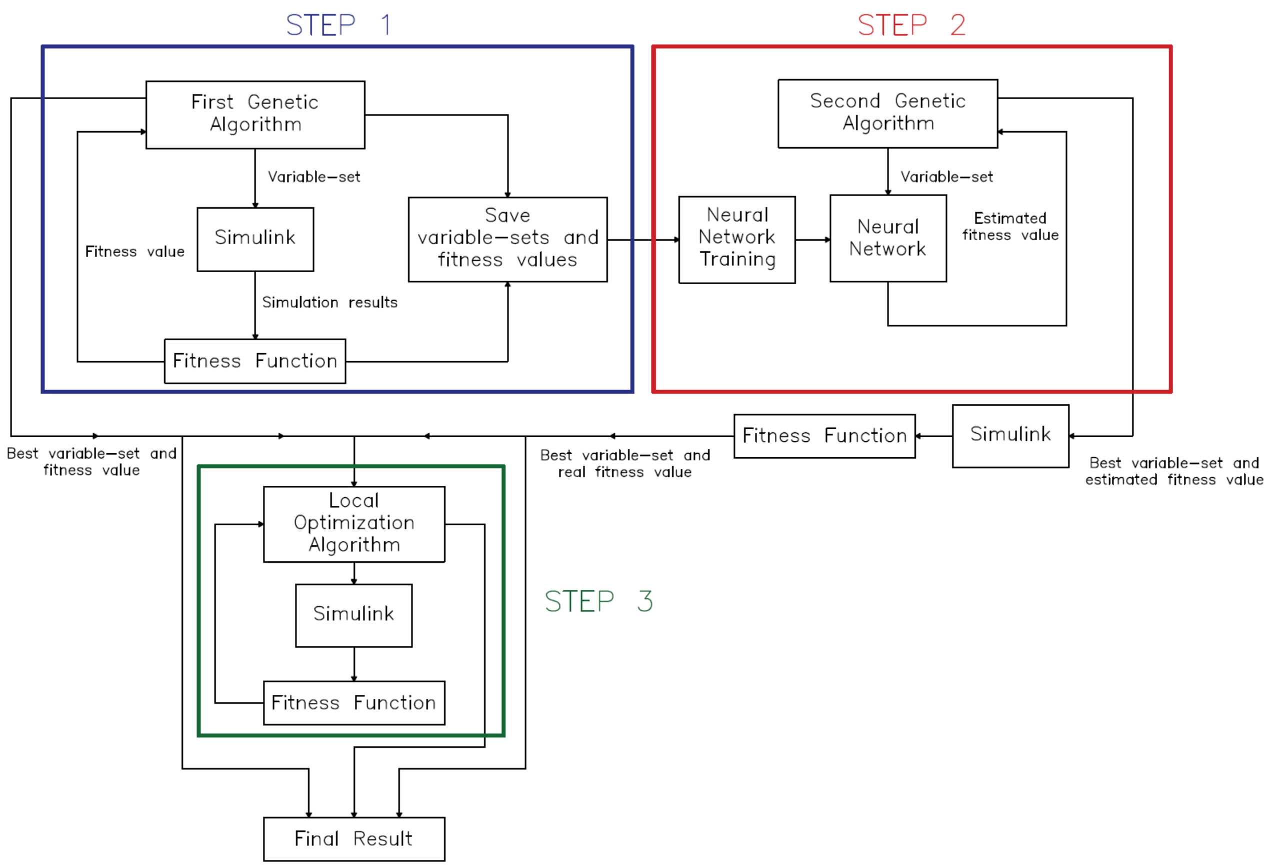


Figure 6.2: Calibration flow chart, Step 1: Uses a genetic algorithm with the Simulink model. Step 2 uses the trained NN. The third step is a local search algorithm.

6.2 Calibration parameters and boundaries

In the calibration the following parameters were allowed to change, within the boundaries presented in Table 6.2 for store A and Table 6.3 for store B. The boundaries are factors that are multiplied with the corresponding variable. For example, the calculated value for the thermal mass of the floor is multiplied with the factor for thermal mass floor.

- Solar thermal load: The thermal load from the sun is based on weather data but the GA is used to estimate how much shading that takes place and how the thermal load from the sun is divided among the different thermal masses. See Appendix A for location of the building and neighbouring buildings that can cast shadows over the stores.

- Lighting thermal load: The thermal load from the indoor lights is based on how much electricity the lights use, the GA is used to determine how the load is divided among the lumps in the model.

- Thermal transfer coefficient between thermal masses and the air: The transfer coefficient between the thermal masses is originally calculated with convection and radiation but to get a better functioning model the transfer coefficient is fitted with the help of the GA.

- Thermal mass: The amount of thermal mass in the separate thermal masses are initially calculated but are then fitted in the reference model with the help of GA.

- Coefficient for air leakage: The leakage for the building is hard to estimate, so the starting value is calculated with the help of empirical models and then adjusted to better represent reality.

The boundaries were set by empiric experience and an educated estimation on what was reasonable.

Table 6.2: Boundary conditions for variable sets during calibration for store A

Parameter	**Lower limit**	**Upper limit**
Lighting thermal load on air	25%	75%
Lighting thermal load on roof	2.5%	7.5%
Lighting thermal load on floor	22.5%	67.5%
Solar thermal load on air	20%	60%
Solar thermal load on roof	2.5%	7.5%
Solar thermal load on floor	27.5%	82.5%
Transfer coefficient, roof/air	70%	130%
Transfer coefficient floor/air	70%	130%
Thermal mass of air	70%	130%
Thermal mass of roof	70%	130%
Thermal mass of floor	70%	130%
Coefficient for air leakage	50%	150%

Table 6.3: Boundary conditions for variable sets during calibration for store B

Parameter	**Lower limit**	**Upper limit**
Lighting thermal load on air	13.3%	40%
Lighting thermal load on floor	20%	60%
Solar thermal load on air	12.5%	37.5%
Solar thermal load on floor	27.5	52.5%
Transfer coefficient floor/air	70%	130%
Thermal mass of air	70%	130%
Thermal mass of floor	70%	130%
Coefficient for air leakage	50%	100%

The local search algorithm starts from the result of the second GA, for this algorithm the boundary conditions are changed and based on the results from the GA. The lower and upper limits are described as 50% and 150% of the GA respectively. This allowed the algorithm to operate outside the normal boundary conditions; this was done to see if significant improvement could be found outside boundaries.

6.3 Store A- with high available thermal mass

6.3.1 Calibration parameters for store A

In table 6.4 the results from the optimization algorithms are presented. The algorithm does not take the source of heat or losses into account. It just fits the temperature to the measured data.

Table 6.4: Calibration variables

Parameter	First GA	Second GA	Local search
Lighting thermal load on air	31.9%	25.7%	29.4%
Lighting thermal load on roof	3.3%	5.9%	8.8%
Lighting thermal load on floor	61%	66.7%	65.1%
Solar thermal load on air	26.9%	20.2%	10.1%
Solar thermal load on roof	2.5%	2.6%	1.3%
Solar thermal load on floor	38.5%	27.5%	13.8%
Transfer coefficient, roof/air	90.2%	70.2%	35.1%
Transfer coefficient, floor/air	108%	110%	120%
Thermal mass of air	126%	129%	194%
Thermal mass of roof	129%	129%	194%
Thermal mass of floor	126 %	129%	194%
Coefficient of air leakage	70.9%	59.2%	70.3%
Difference in degree hours (Fitness value)	1810°Ch	1740°Ch	1580°Ch
Average temperature difference	0.50°C	0.48°C	0.44°C

The thermal load from the lighting is based on the energy usage from the lighting and results from the calibration shows that the load distribution is similar for all the different optimization steps. The sum of the lighting gain is between 95% and 103% of the original load for all the results which shows that original lighting load works well for the model.

Solar thermal load varies in total between 68% to 25% and is thereby significantly lower than the original value. The base model however did not include any external shading factor, as it was unknown, so a smaller sum was expected. The table shows that the fitting values are close to the boundaries for both the GAs and for the local optimization.

The results shows higher thermal masses than the calculated masses. That could be explained for the floor and ceiling by penetration depth for the thermal mass and the coverage of the ceiling with acoustical plates. The initial assumption that if the ceiling is covered with plates, there are no access to the thermal mass. However since that plates are suspended some heat exchange will occur even if the ceiling is covered.

The heat transfer coefficient for the floor is larger than calculated, and the coefficient is lower than calculated for the roof. These results are hard to comment on as the calculation is based on a set of values from an ISO standard and many assumptions regarding the stores and the interior ceilings. The literature study on heat transfer coefficients also concluded that convective heat transfer is hard to estimate and is highly dependant on ventilation type and building materials.

The project continues with the results from the second GA. The reference model is created by combining the calibrated building model and the simulated ventilation system. The values from the second GA were selected because the thermal masses from the local search are deemed too large. This would affect the results as the temperature would be less sensitive to changes and the energy usage would increase. In Figure 6.3 the room temperature for a week is shown, the measured temperature, the temperature from the calibrated model and the reference model are presented. In Appendix E and Figure E.1 the temperature for the entire season is shown.

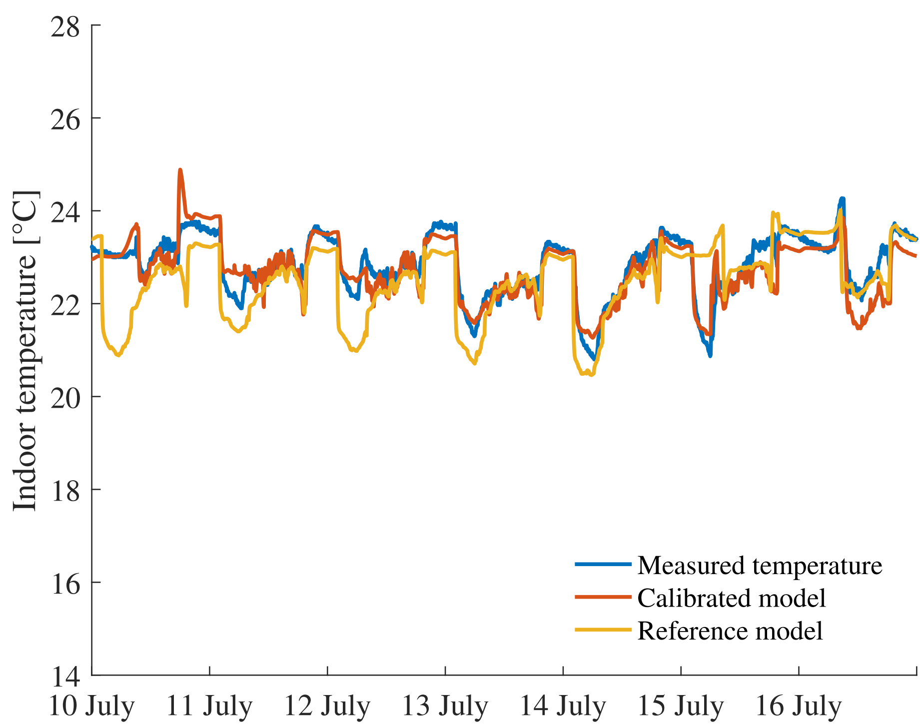


Figure 6.3: Store A - Indoor temperature for a week in July, where the blue line is the measured temperature, the red line the temperature from the calibrated model and the yellow the reference model.

The graphs shows a good correspondence of the indoor temperature for both the calibrated model and the model used for reference. The reference models show a lower temperature during the first night. This is a result of the simulated ventilation system in the reference model that has activated night cooling during the night before, while the measured and calibrated model don't. This is further explained in the discussion.

6.3.2 Calibration results for store A

Table 6.5 shows the results of the calibration i.e. the mean temperature and difference in degree hours.

Table 6.5: Calibration results for store A

Variable	Measured	Base model	Calibrated model	Reference model
Mean temperature Difference	22.71°C -	22.94 °C 1.03%	22.79°C 0.34%	22.34°C -1.65%
Degree hour difference Average temperature difference	- -	2207°Ch 0.6°C	1740°Ch 0.47°C	2140°Ch 0.58°C

Table 6.6 shows the difference in energy usage, ventilation flow and maximum cooling power for the measured data and the reference model.

Table 6.6: Energy difference between the measured data and the reference model for store A

Variable	Measured	Reference model
Cooling Energy Difference	18.82 kWh/m^2 -	19.22 kWh/m^2 2.1%
Fan Energy Difference	11.30 kWh/m^2 -	9.51 kWh/m^2 -15.8%
Total Energy Difference	30.12 kWh/m^2 -	28.74 kWh/m^2 -4.6 %
Average Ventilation Flow Difference	1.27 m^3/s -	1.19 m^3/s -5.9 %
Max Cooling Power Difference	65.14 W/m^2 -	47.43 W/m^2 -27.2%

The results show a better fit to the measured temperature after the calibration. The cooling energy for the reference model is with in acceptable limits. However, the fan energy is almost 16% lower than the measured but this is further explained in the discussion of this chapter. The total ventilation flow corresponds adequately to the measured data and shows that the model works well and is calibrated.

6.4 Store B- with low thermal mass

6.4.1 Calibration parameters for store B

In table 6.7 the results from the first, second genetic algorithm and the local search are presented for store B.

Table 6.7: Calibration variables for store B

Parameter	First GA	Second GA	Local search
Lighting thermal load on air	17.8%	13.4%	19.6%
Lighting thermal load on floor	37.7%	39.6%	56.2%
Solar thermal load on air	33.9%	39.5%	31.2%
Solar thermal load on floor	16.0%	13.2%	12.5%
Transfer coefficient, floor/air	111.7%	114.4%	111.2%
Thermal mass of air	129.9%	129.9%	194.5%
Thermal mass of floor	123.8%	129.7%	194.8%
Coefficient of air leakage	81.6%	83.6%	89.5%
Difference in degree hours(Fitness value)	3080°Ch	3050°Ch	2900°Ch
Average temperature difference	0.84°C	0.83°C	0.79°C

The lightning thermal load is in total around 55% of the value in the base model for the first algorithms and for the floor it's not close to the boundary. But, for the lightning load applied to the air tend to push the lower limit for the second genetic algorithm. The solar heat gains are around 60% of the total, as these does not push the upper limits the total value of heat gains are deemed be appropriate.

The results shows a higher thermal mass than the calculated mass. That could be explained for the floor by penetration depth, and the assumption of density and heat capacity of the flooring.

The heat transfer coefficient for the floor is larger than calculated but without pushing the boundary showing that it close to the calculated value.

The result from the second GA are used for the same reason as store A, they show the least error while having a reasonable thermal mass.

The project continues with the results from the second GA and from now called the reference model. In Figure 6.4 the room temperature for a week is shown, the measured temperature, the temperature from the calibrated model and the reference model is presented. In Appendix F and Figure F.1 the temperature for the entire season is shown.

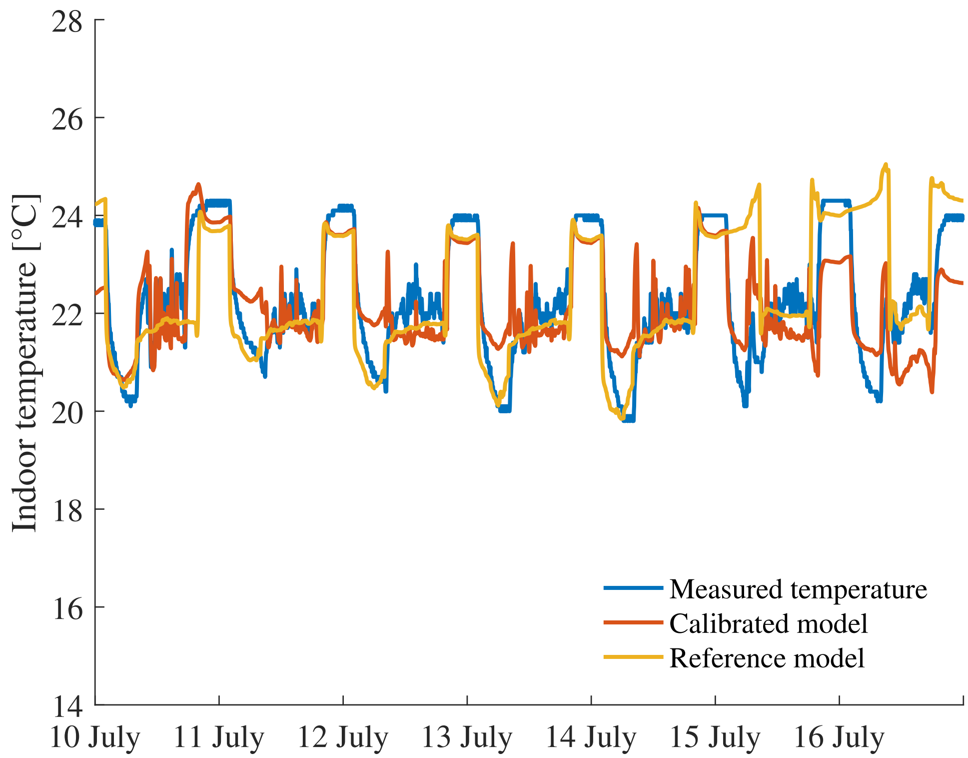


Figure 6.4: Store B - Indoor temperature for a week in July, where the blue line represent the measured temperature, the red line is the temperature from the calibrated model and the yellow line shows the reference model.

The simulated temperature follows the trends of the measured temperature. However the temperature for the reference model fluctuates less than both the calibrated and the measured data. This is due to the highly varying air flows for store B.

At the 15 and 16 of July the reference model did use night cooling contrary to the measured ventilation flow.

6.4.2 Calibration results for store B

Table 6.8 below displays the difference in temperature between the measured data and the models.

Table 6.8: Calibration results for store B

Variable	**Measured**	**Base model**	**Calibrated model**	**Reference model**
Mean temperature Percentile error	22.50°C -	22.02°C -2.11%	22.35°C -0.67%	22.13°C -1.634%
Degree hour difference Average temperature difference	- -	3429°Ch 0.93°C	3052°Ch 0.83°C	3221°Ch 0.88°C

Table 6.9 show the energy difference between the measured data and the reference model.

Table 6.9: Energy difference between the measured data and the reference model for store B

Variable	**Measured**	**Reference model**
Cooling Energy Difference	34.10 kWh/m^2 -	32.48 kWh/m^2 -4.76 %
Fan Energy Difference	11.88 kWh/m^2 -	8.88 kWh/m^2 -25.3 %
Total Energy Difference	45.99 kWh/m^2 -	41.35 kWh/m^2 -10.1%
Average Ventilation flow Difference	1.05 m^3/s -	0.99 m^3/s -6.0%
Max Cooling Power Difference	115.15 W/m^2 -	79.77 W/m^2 -31.2%

The results shows a better fit to the measured temperature after the calibration. The cooling energy is with acceptable limits; nevertheless, the fan energy is almost 25% lower than the measured. However, the total ventilation flow corresponds adequately to the measured data. As both the cooling energy and total flow for the reference model is below the measured model it could be an indication that the thermal mass is slightly too small but it is acceptable for the project.

6.5 Reflections

The results in Chapter 6 show how the simulation can be improved by adding a number of fitting factors to the model inputs. However, this is done with a numerical method and the result are not always based in reality as the function cannot make a difference in terms of the thermal loads source or if the thermal mass is reasonable. Therefore, the result is a model that works very well for our purpose but the fitting values can not be used in another project as they are not true but they can give some indication for reality.

As shown in Table 6.4 and Table 6.7 above the thermal mass will increase if the boundaries are relaxed. This is because a higher thermal mass is easier to fit, as it will not react as quickly. If the boundaries are more relaxed, the calibration will be able to use larger fitting values to get a more precise fitting but it would be further from reality and would not be reliable. In addition, if higher thermal masses and thermal loads are allowed it will result in a model that requires more energy to heat and cool and would give an increased energy usage. This would make the model invalid for our purpose and so the thermal mass must be kept fairly close to the calculated value. An additional source of error is that timing and distribution of the original loads are incorrect; this is not something that can be solved by the calibration.

This calibration of the model was done for a five-month period. As the calibration period is fairly long, it ensured that the simulated building is able to respond in a similar manner to the actual building and that the optimization algorithm did not over fit the model for a short period of time. The over fitting would make the model inaccurate outside the short calibration period and could result in a large discrepancy in energy use between the model and the building.

For the calibration of the building model the simulated control system for airflow is not used, but the measured ventilation flow and temperature are used. This allow the building model to be better fitted to represent reality. However, after the calibration is done the modelled control system is tested to see how well it corresponds to the measured indoor temperature. Using the simulated control system results in greater difference in degree hours than using the actual flow and temperature data. This is to be expected, as the simulated control system will never be able to completely simulate reality with local differences in temperature and inaccuracies in the measurements.The night cooling airflow is constant in the simulation compared to the reality where the flow is regulated at room level with the VAV-dampers.

The final results show that there is a difference in energy usage between the calculated energy usage from the measurements and the energy usage from the simulation. This is most likely due to the difference in ventilation flow, because in reality the flow can change rather quickly due to the VAV-dampers. These quick changes to the supply air result in a larger amount of maximum flow in reality than in the simulation. The lower energy use in the model is a consequence of this.

The model uses the actual set-point value for the AHU as the supply air-temperature, however in reality the air temperature has a certain inertia and will not change as quickly as the set point. Furthermore, the cooling system in reality is not always able to maintain the set-point value and the temperature of the supply air will then be higher than the set point. To address this there have been some modification to the set-point temperature to better represent reality as it gives a better division between cooling energy and fan energy while also improving the simulated temperature.

One source of error might be the measured cooling energy and power. This because the temperature sensor before the cooling coil in the AHU is placed before the fan where the air is not perfectly mixed. Therefore, the air can have different temperatures depending on where it is measured, this resulting in an inaccurate temperature difference between the temperature before and after the cooling coil.

The results shows that there are a difference around 30% for the maximum cooling power between the model and the measured data. This is due to the differences of maximum ventilation flow since the cooling power is based on that. Nevertheless some conclusions can be drawn from the simulations regarding power demands and changes to it.

7 Optimization of night cooling

The optimization for the project uses the same optimization scheme as the calibration of the reference model, see Figure 6.2 for flow chart. However, the fitness function is changed to represent the amount of energy used in the system instead of the difference between measured and simulated temperature. The energy usage in the model takes into account the fan energy, cooling energy and the penalty, if the indoor temperature becomes too low, as described in Chapter 7.2.

7.1 Optimization parameters and boundaries

The optimization uses night cooling settings as the new variable-set instead of the building parameters that was used in the calibration. Temperature difference demand were removed due to lack of function. The function was already covered by the indoor and outdoor temperature limitations and it was never the deciding factor.

- Time: Time is divided into two parameters determining the start time and the duration of the night ventilation.

- Flow: The ventilation flow during the night ventilation is important due to the increase in power use at higher flows as shown by the SFP plots in Chapter 5.

- Outdoor temperature: Night ventilation has two start conditions based on the outdoor temperature. Firstly, the outdoor temperature needs to be below a threshold to be allowed to start the night cooling. Secondly, there is a hysteresis that creates a stop condition a few degrees below the start condition. This condition terminates the night ventilation if the outdoor temperature gets too low.

- Indoor temperature: In a similar fashion to the outdoor temperature the indoor temperate condition is divided into a start condition and a hysteresis. If the indoor temperature is above the start temperature, the night ventilation is allowed to start and will then stop if the temperature decreases below the stop condition created by the hysteresis.

In Table 7.1 the boundaries for the optimization of night cooling for both store A and B. These were based on the original settings and empirical testing.

Table 7.1: Boundaries for optimization of night cooling

Function	**Lower limit**	**Upper limit**
Ventilation schedule	Start time 21:00 Period 4h	Start time 03:00 Period 11h
Ventilation flow	Store A: 0.93m^3/s Store B: 0.66m^3/s	Store A: 2.64m^3/s Store B: 1.87m^3/s
Outdoor temperature limitation	Start condition T_{out} > 10°C Hysteresis T_{out} = 5°C	Start condition T_{out} > 18°C Hysteresis T_{out} = 12°C
Indoor temperature limitation	Start condition T_{in} > 19°C Hysteresis T_{in} = 2°C	Start condition T_{in} > 24°C Hysteresis T_{in} = 6°C

7.2 Indoor climate requirements

In order not to cool the facility below comfort levels in the morning, temperature requirements were inserted in the model. This was done by adding a penalty that starts if the temperature is below 18°C after 07:00 when the staff arrives to work, also if the temperature is below 20°C at 10:00 when customers arrive.

The penalty is in form of an added energy usage. It is described as the temperature difference between the indoor temperature and the requirement multiplied by a factor of 720 000, the factor were derived from empiric testing. The purpose of this is to train the system to not fall below these requirements, the penalty leads to problems with the neural network as explained in Chapter 10.4.

7.3 Store A- with high available thermal mass

7.3.1 Optimization parameters for store A

In Table 7.2 the optimized results from the first and second genetic algorithm as well as from the local search are presented for store A.

Table 7.2: Optimization parameters for store A

Parameter	**First GA**	**Second GA**	**Local search**
Start time Period	21:32 10.68h	03:00 10.98h	21:15 11.0h
Ventilation flow	1.52m^3/s	2.60m^3/s	1.51m^3/s
Max outdoor temp Hysteresis	16.33°C 8.67°C	14.94°C 5.08°C	16.16°C 8.66°C
Max indoor temp Hysteresis	22.70°C 5.12°C	19.13°C 5.44°C	22.14°C 4.68°C
Total energy with penalty	24.56 kWh/m^2	39.98 kWh/m^2	24.48 kWh/m^2
Total cooling energy	24.20 kWh/m^2	30.92 kWh/m^2	24.10 kWh/m^2

The second to last row includes the penalty that is used to ensure a good indoor thermal climate; penalty can be used to calculate the °Ch that the requirements were broken. The temperature requirements were reached for short periods of time for all results but the local search had a low penalty and the best energy usage. Therefore, the results from the local search is recommended and, hence, called the model with optimized night cooling. The local search was based on the result from the first GA and resulted in some slight improvements compared to the first GA. The second GA uses the neural network but it had problems to approximate the penalty so it´s result is invalid.

7.3.2 Optimization results for store A

See Table 7.3 for mean temperatures, energy, ventilation flows and max cooling power for store A.

Table 7.3: Energy and power from optimization of night cooling for store A

Parameter	Original night ventilation	No night ventilation	Optimized night ventilation
Mean temperature	22.34 °C	23.08°C	21.40°C
Day 08:00-20.00	22.32 °C	22.77°C	22.10°C
Night 20:00-08.00	22.37 °C	23.58°C	21.32°C
Cooling Energy	19.22 kWh/m^2	22.58 kWh/m^2	15.55 kWh/m^2
Difference	-	17.4%	-19.3%
Fan Energy	9.51 kWh/m^2	10.49 kWh/m^2	8.55kWh/m^2
Difference	-	10.3 %	-9.7 %
Total Energy	28.74 kWh/m^2	33.06 kWh/m^2	24.10 kWh/m^2
Difference	-	15.1 %	-16.1 %
Average Ventilation flow	1.19 m^3/s	1.11 m^3/s	1.33 m^3/s
Day 08:00-20.00	1.80 m^3/s	2.09 m^3/s	1.41 m^3/s
Night 20:00-08.00	0.59 m^3/s	0.09 m^3/s	1.27 m^3/s
Max Cooling Power	47.43 W/m^2	48.62 W/m^2	46.27 W/m^2

An increased ventilation during night leads to a decreased daytime ventilation as shown by the table above, but an increased night ventilation also leads to an overall increase in ventilation flow. This increase of total ventilation flow does not lead to an increase in fan energy due to the SFP curve. A consequence of it´s polynomial shape is that peak flows have a large increase in energy use. These peak flows are reduced with night ventilation as shown in the decrease of average ventilation flow during daytime.

The temperature for the three cases behave as expected, the overall mean temperature decreases with increased night-cooling but the majority of that decrease comes from the sharp decrease in temperature during the night. Without night cooling the temperature during the night rises above the mean value but increased night-cooling leads to a lower temperature.

In Figure 7.1 a comparison of the indoor temperature for a week in July is shown. The indoor temperature is constantly cooler with the optimized night ventilation, that corresponds well to the table above as well as the graph in Appendix E, Figure E.2. The graph also shows the difference in the ventilation strategies, the optimized night cooling starts much earlier which results in a cooler morning temperature. See Figure E.3 in Appendix E for box-plots over the indoor temperature between 07-10 in the morning. The optimized night cooling is also active during 15-16 July while the original settings does not allow it.

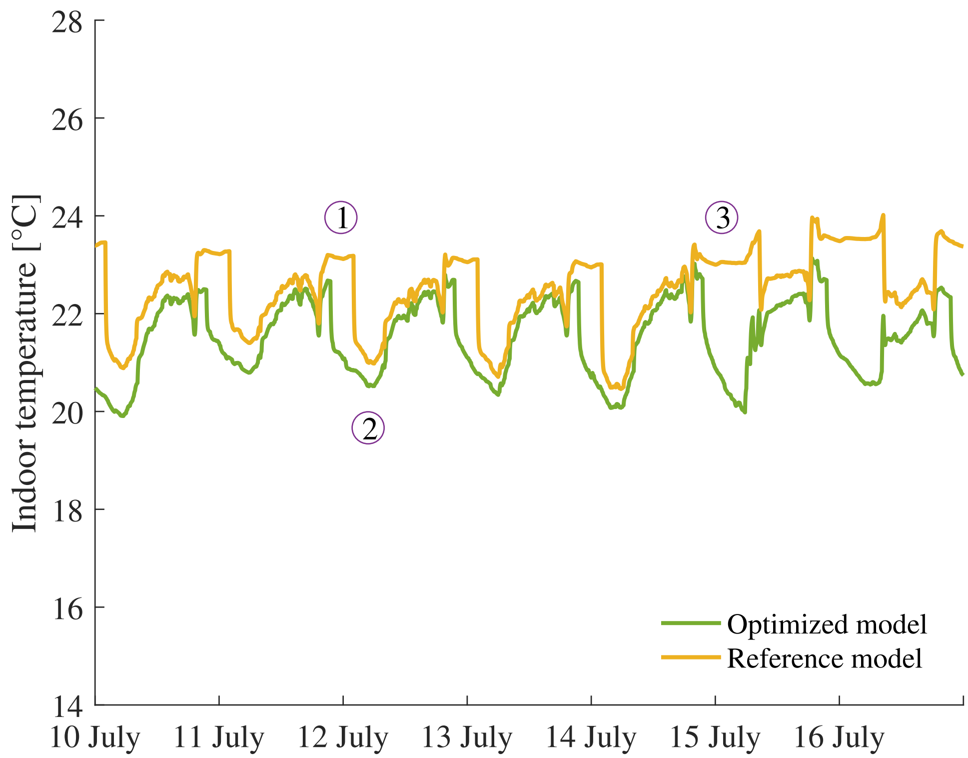


Figure 7.1: Store A - Comparison of indoor temperature over a week between optimized night cooling and the original night cooling settings.

The main differences between the optimized model and the reference model are; 1 the optimized night cooling is allowed to start earlier thus the indoor temperature is lower for the optimized model, 2 the longer active hours makes it possible for the indoor temperature to reach lower temperatures before business hours, 3 night cooling can be active during weekends.

7.4 Store B- with low thermal mass

7.4.1 Optimization parameters for store B

In Table 7.4 the optimized results from the first, second genetic algorithm and the local search are presented for store B.

Table 7.4: Optimization parameters for store B

Parameter	First GA	Second GA	Local search
Start time Period	21:53 10.85h	02:53 10.98h	21:51 10.86h
Ventilation flow	$1.54m^3/s$	$1.87m^3/s$	$1.56m^3/s$
Max outdoor temp Hysteresis	13.22°C 5.54°C	17.96°C 5.00°C	13.42°C 7.14°C
Max indoor temp Hysteresis	20.40°C 2.37°C	20.61°C 2.77°C	20.36°C 2.37°C
Total energy with penalty	35.68 kWh/m^2	43.49 kWh/m^2	35.62 kWh/m^2
Total energy	35.43 kWh/m^2	42.09 kWh/m^2	35.37 kWh/m^2

The results for store B follow a similar pattern to store A, and because of that the local search is selected as the best option for the same reason as for store A. It has the lowest energy usage and a relatively small penalty and thereby showing it will have good indoor climate in the morning.

7.4.2 Optimization results for store B

See Table 7.5 for mean temperatures, energy, ventilation flows and max cooling power for store B.

Table 7.5: Energy and effect from optimization of night cooling for store B

Parameter	Original night ventilation	No night ventilation	Optimized night ventilation
Mean temperature	22.14 °C	23.18°C	20.45°C
Day 08:00-20.00	21.93 °C	22.31°C	21.32°C
Night 20:00-08.00	22.77 °C	24.30°C	20.23°C
Cooling Energy	32.48 kWh/m^2	36.13 kWh/m^2	25.83 kWh/m^2
Difference	-	11.23 %	-20.1%
Fan Energy	8.88 kWh/m^2	9.29 kWh/m^2	9.54kWh/m^2
Difference	-	4.6 %	7.4%
Total Energy	41.35 kWh/m^2	45.42 kWh/m^2	35.37 kWh/m^2
Difference	-	9.8%	-14.5%
Average Ventilation flow	0.99 m^3/s	0.95 m^3/s	1.12m^3/s
Day 08:00-20.00	1.62 m^3/s	1.87 m^3/s	1.21 m^3/s
Night 20:00-08.00	0.36 m^3/s	0.03 m^3/s	1.05 m^3/s
Max Cooling Power	79.19 W/m^2	83.07 W/m^2	75.30W/m^2

The ventilation flows behave in the same way as for store A, an increased night ventilation decreases ventilation during the day but leads to an overall increase in ventilation.

The higher flow however leads to a larger fan energy usage in contrary to store A where the energy usage decreased. The most likely reason for this is that the SFP-curve is less inclined for store B. This has the result that maximum flow does not require the amount of energy that it would with the SFP-curve from store A.

The temperature for store B behaves in the same way as store A in terms of nighttime and daytime temperature. See Figure 7.2 for a comparison between the indoor temperature for the model with optimized night cooling and the reference model. The thermal climate will be colder during the entire days but especially the mornings. See Figure F.3 in Appendix F for box-plots over the indoor temperature between 07-10 in the morning.

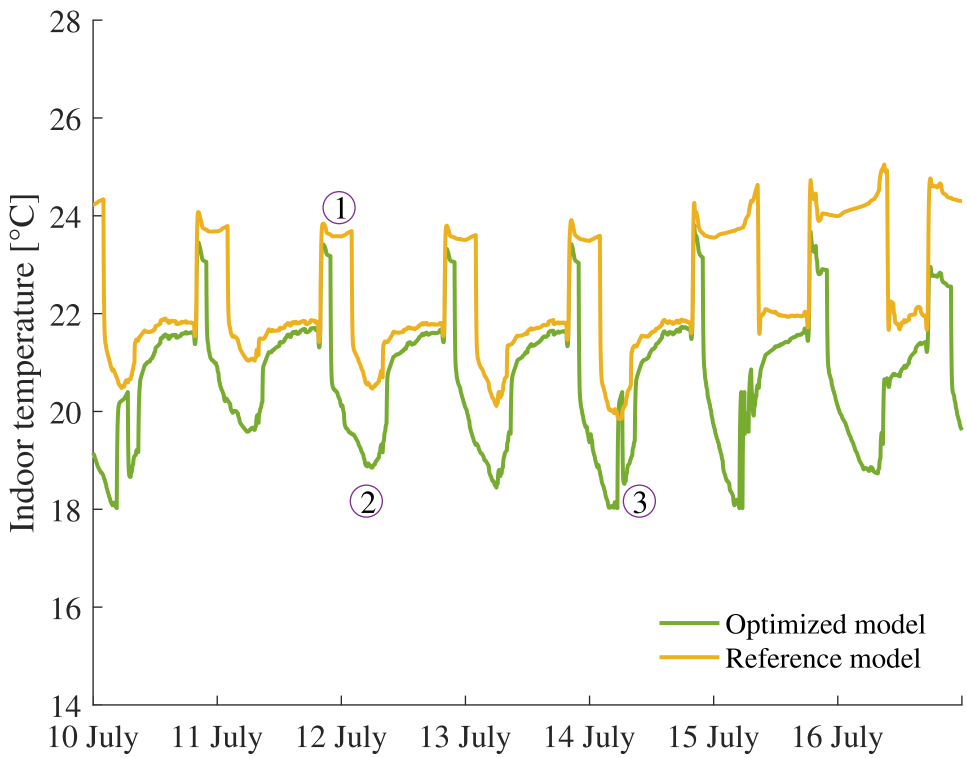


Figure 7.2: Store B - Comparison of indoor temperature over a week between optimized night cooling and the original night cooling settings.

The main differences between the optimized model and the reference model are; 1 the optimized night cooling is allowed to start earlier thus the indoor temperature is lower for the optimized model 2 the longer active hours makes it possible for the indoor temperature to reach lower temperatures before business hours 3 the indoor temperature limitation are met and night cooling stops temperature rises and reaches the start condition again and activates.

7.5 Reflections

The removal of the temperature difference demand control parameters will not affect activation of night cooling since the limitations set on outdoor and indoor temperature will cover these. On the other hand, the limitation would act as an extra safety measure when implementing the night cooling for the building.

The optimization shows that the night cooling active hours should be extended as much as possible, to maximize the energy storage in the structures thermal mass. There is a higher outdoor temperature demand for store A than store B meaning that it needs to be colder before the night cooling is activated for store B than for store A. This means that the night ventilation for store A has less of a requirement for outdoor temperature and will be active more often.

The hysteresis for the outdoor temperature shuts off the night cooling when the temperature goes below the requirements. The hysteresis could potentially be increased as lower supply air temperature should not endanger the building but it could affect the AHU. The simulation does not take into account that night cooling can use the heat exchanger to allow lower outdoor temperature and it would protect the AHU. This is a source of error since the original night cooling setting has a set point of 10 °C for the heat exchanger but this is not included in the simulation.

Store B has lower indoor temperature start point than store A; this allows the ventilation for store B to be active more often. But as night cooling is only needed when there is a large cooling need which should result in a high indoor temperature this requirement should not affect the effectiveness. Another reason for this lower requirement is explained further below.

The indoor temperature set points and hysteresis result in that the stop point for both stores is close to 18 degrees. This shows that the penalties for the temperature requirement works. This will hopefully result in a good thermal climate in the mornings. The average indoor temperature however decreases as shown in Table 7.2 and Table 7.4 and in Figure E.2 and Figure F.2.

The results also show that store B benefits from a relatively higher ventilation flow during the night than store A, due to its lower thermal mass. Store A has a lower air flow that slowly lowers the indoor temperature and the night cooling rarely shuts off. Store B however, quickly lowers the indoor temperature before being shut off as the temperature decreases below the requirement. The temperature then rises as the heat is exchanged with the thermal mass to the point that the night cooling starts again. The lower requirement for indoor temperature helps this as it allows the night cooling to start more quickly and thereby keeping the average air temperature during the night lower. Another reason for the higher flow is that SFP function does not penalize high flow in store B to the same extent as in store A.

Store A has a bigger energy saving potential with night cooling than store B. This is most likely due to that store A has a larger thermal mass compared to store B. The results shows that no night ventilation would increase the energy use both from the bought district cooling and the fan energy needed. The increase in fan energy, even though the fan is active during a shorter period of time, is due to the shape of the SFP function.

8 Sensitivity analysis

The two models with the optimized and the original night ventilation acted as starting points for the sensitivity analysis. The analysis was conducted to show how other cases would react with the ventilation strategies.

The sensitivity analysis is done by changing the following parameters:

- Thermal mass, changing the amount and accessibility of the thermal mass. This would demonstrate how a similar building with a different accessibility to the thermal mass would act.
- Internal gains, changing the internal gains could represent a change in the use of the building or a similar structure with different heat gains.
- Time schedule, reducing the period to show how a decreased ventilation period would impact the energy use. The period change could be necessary if tenants experience a bad indoor climate in the early mornings.

Table 8.1 shows the acronyms used for Figure 8.1 and Figure 8.2.

Table 8.1: Acronyms used in the sensitivity analysis

Acronym	**Comments**
Ventilation strategy	
S1	Original night cooling settings active 6 hours
S2	Optimized night cooling settings active 11 hours
S3	Optimized night cooling settings active 8 hours
Model	
X	Original building simulation model
-Q	Internal gain decrease of 10 W/m^2 during occupation
+Q	Internal gain increase of 10 W/m^2 during occupation
-C	25% less thermal mass and accessibility
+C	25% more thermal mass and accessibility

8.1 Simulation sensitivity analysis

In Figure 8.1 the energy consumption for the different cases for store A tested in the sensitivity analysis are presented.

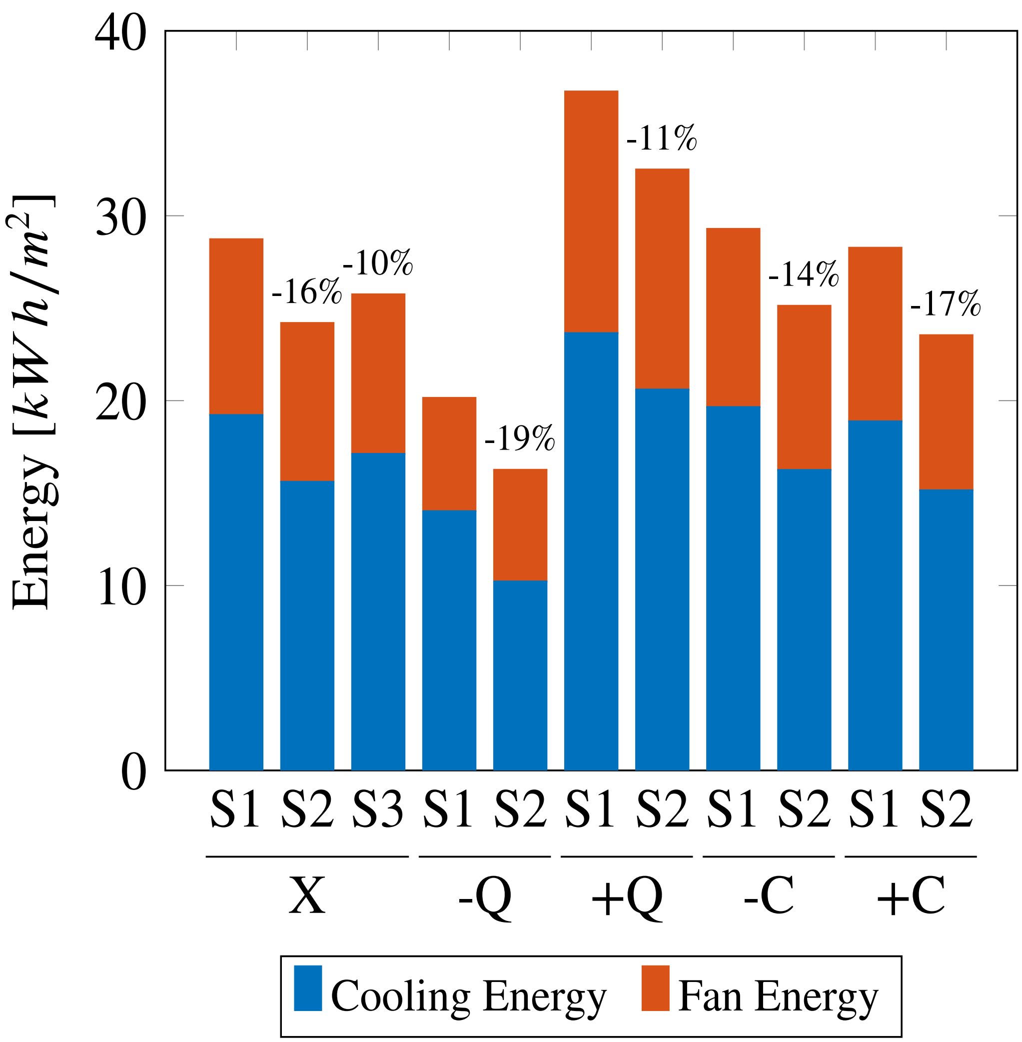


Figure 8.1: Energy consumption for the different cases for store A. See Table 8.1 for acronym explanation.

In Figure 8.2 the energy consumption for the different cases for store B tested in the sensitivity analysis are presented.

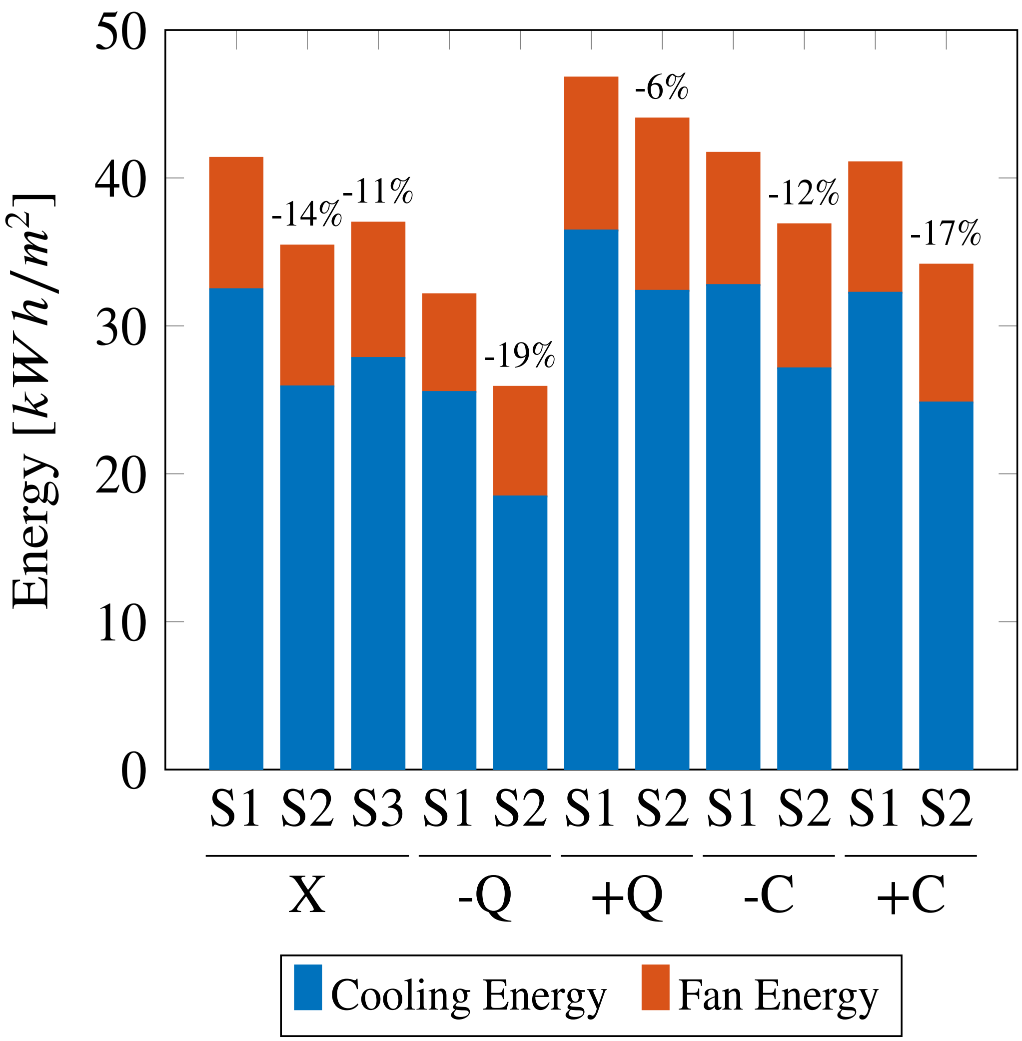


Figure 8.2: Energy consumption for the different cases for store B.

The sensitivity analysis shows that changes of the thermal mass, including the accessibility to it will have little impact on the energy usage with the original settings for the night cooling. However, with the optimized setting for the night cooling changing the thermal mass will have larger impact especially for store B. This behavior shows that in terms of night cooling larger thermal mass is only needed if the night cooling is used to the extent that it can take advantage of it. It also shows that there may be decreasing returns on increasing the thermal mass for night cooling.

With an increased internal heat load night cooling has less of a percentile effect especially for store B. This is because the amount of energy that can be stored in the thermal mass is limited and with a larger thermal load, this stored energy will be used faster.

The graph shows that the optimized night cooling would decrease the energy demand in all cases. If the thermal climate suffers during the morning due to the optimized night cooling it can be improved by the decreasing the period of night cooling and thereby of the stop time. The results of this is that the energy usage increases as shown by the bar chart above but it will increase the temperature during the morning as shown by box chart in Figure E.3 and Figure F.3.

8.2 Moisture safety

During the active hours of night cooling there will not be any risk for condensation since one of the demands to activate night cooling is that the room temperature must be higher than the outdoor temperature. Therefore, night cooling will be adding cool air in to a warm building, and warm air will have a higher moisture capacity then the cool. However, two cases are interesting to look in to:

- During the morning after night cooling had been active and the building structure is cool and ventilating with daytime air. Then the surfaces of the structure can be below dew-point temperature. Surfaces that could be cooled down faster than the thermal mass, such as steel beams can reach a lower temperature than the rest of the room therefore a risk of condensation might occur. This scenario is however unlikely since the supply air temperatures is usually between 14-15°C.

- When the dehumidifier has been running during daytime but is not active during night. This can add absolute moisture to the air but not cause any condensation.

The two cases show that there is no significant risk using night-cooling but there could be risks that are unforeseen.

9 Discussion

9.1 Reflections regarding the results

The building energy models are simplifications of the reality and the results of an energy decrease of 15% should be taken as an estimation and not as a real number of improvement. There is not a total compliance between the simulated models and the measured building data.

The studied objects are not representative for all buildings and other buildings with different building characteristics, thermal masses and internal heat gains, might result in another optimal solution. The sensitivity analysis however showed the implementation of the suggested strategies would result in a decrease of energy consumption for more cases than just the studied stores.

9.2 Validity of the Simulink models

The simulation does not take into account the thermal flow between different areas in the building. This simplification should not affect the result as the rooms should have a similar temperature but it could have a small impact on the simulated temperature that is not taken into account.

The temperature gradient in the concrete slabs, which are simplified when using a lumped model, would result in a higher heat flux during the start of night cooling and in the morning when there are big temperature changes in the building. This might cause the room temperature to be even lower in the morning and warmer during the afternoons, something that would adversely affect the indoor climate and efficiency. The simplification will also affect the amount of heat transfer during night, when the temperature difference between air and the structures thermal mass would be smaller than simulated. Thereby the energy storage potential during a night is affected and in reality is should be lower than simulated.

Because of the simplification of using lumped models with only one lump for the air, the peak power flows are hard to simulate. Since these are highly dependent on the different thermal zones of a facility. In reality, the airflow is more dynamic and changes more than the model allows. However, since the total airflow over time for the simulated models and the measured values are similar, some conclusions can be drawn from the model.

Using Simulink as the simulation software gives a lot of flexibility when modeling but does require a knowledge of the basic physics in a building. Many of the thermal loads and losses are approximated; this task also requires knowledge to make reasonable assumptions. A more simplified model is also faster to simulate and this allows for more optimization, which was important for our project. Commercial building simulation software can give better results but often require more time to run the simulation.

Our simulation does not take into account the energy that is being used for latent heating, as humidity is not included in the simulation. Using night ventilation would allow Vasakronan to increase their supply temperature to achieve even better energy efficiency.

9.3 Using AI and post processed data for optimization and modeling

In the study, the use of artificial intelligence is used in the calibration and the optimization but not tested as a control system. To use a dynamic control system for controlling the ventilation could be an option, however this would increase the "black box" effect of night cooling. Maintenance technicians and technical managers would have a harder time understanding and changing it and that may decrease it´s usefulness and flexibility. To train such a neural network a genetic algorithm or another algorithm could be used to optimize the weights and transfer functions. It would then try to optimizing towards a goal of good indoor climate and less energy use.

A neural network can also potentially be used instead of a building simulation where the neural network approximate the temperature and measured data is used to train the network. However, this could be hard requiring a very complex network and a very large number of examples to train it and thereby making it impractical to use. It would be preferable to train against a yearly basis. Although this would be hard to collect sufficient amount of measured data points to train the network properly. An alternative would be to change to a weekly basis to train on. The shortening of time period could result in a misconception of the seasonal variation of human heat gains since there are a higher loads during Christmas and sales season.

9.4 Neural Network Accuracy

The neural network was used to make an approximation of the building simulation for this project. During our project, we discovered some limitations and inaccuracies of the neural network. It was very useful and worked with good accuracy for the calibration of the building simulation. But when implementing the penalties for the optimization, the neural network had issues to function with accuracy. This is shown below in Table 9.1. Without the penalty, the neural network would make an accurate prediction but the optimization would led to an indoor climate that would be unacceptable. Testing showed that reducing the penalty would result in better accuracy but colder indoor climate, so for our purpose the penalty was kept high to ensure a better indoor climate even though it invalidated the results from the neural network and led to less optimization and testing.

Our reasoning behind the inaccuracies is that introducing the penalties leads to unexpected behavior. An example of this is a prolonged ventilation leads to lower energy use until the system gets penalties which would then quickly result in a larger energy use and a gap in the results. Other configurations of the neural network and having more example to train the network could be a solution that could handle this behavior but it is not included in the scope of this project.

Table 9.1: Neural networks accuracy

Case	NN - Approximation	Real value
Calibration - Temperature difference		
Store - A	1738.0°Ch	1737.9°Ch
Store - B	3050.3°Ch	3052.2°Ch
Optimization - Total energy		
Store - A	-55.23 kWh/m^2	39.98 kWh/m^2
Store - B	-114.95 kWh/m^2	43.49 kWh/m^2

9.5 Further studies

Further studies in this area should focus on different types of facilities and how additional cooling system will effect the result. As part of improving the simulations, other software could be used and humidity could be included to get a more accurate model. The effect of a temperature gradient in the structures thermal mass would also be interesting to include in a further study for more accurate indoor climate.

As many cooling systems are not entirely air based a further study could include a combined cooling system, with cooling baffles as a complement to the air based cooling to see how it would affect the optimization.

To further improve optimization it could include variables for start and finish to the cooling period. This could potentially increase the effectiveness of the night cooling but for this optimization normalized outdoor temperature data should be used, as there is a large difference from year to year.

10 Conclusion

The project has shown a number of general approaches for using night cooling as a way to decrease the energy usage. A clear trend is that night cooling should be active over a longer period, as it takes a long time to cool the thermal mass of the structure.

The temperature graphs and the tables in the Chapter 7 show that there are two distinct ways to control the night cooling system. The first way is to have a lower air flow that rarely shuts off, as it never causes too low indoor temperatures, as is the case in store A. The second as used in store B, has a higher flow that often lowers the indoor temperature to the point that the ventilation shuts off. Switching on and off the ventilation system during the night is undesirable. However, this behavior of the ventilation system did exist in the original settings but to less of an extent as the hysteresis is smaller for the new settings and the ventilation flow is higher. The amount of switching will be further increased as the new night ventilation has a long duration. Should the switching become a problem, it could be alleviated by increasing the indoor temperature requirement and the hysteresis so that the stop requirement still remains at 18 degrees. In addition to that, the night ventilation flow could be decreased; both of these actions should reduce number of starts and stops while still leaving an efficient night cooling.

The results also show that a building with less thermal mass such as store B has a lower outdoor temperature requirement, meaning that the night ventilation will only start at lower outdoor temperature in comparison to store A. This was expected, as it would mean that the night cooling for store B is more restricted in use.

Using no nighttime ventilation increase the energy consumption for the two stores both in terms of fan energy and cooling energy, this shows that the original night ventilation is better than none.

The results also shows that using night ventilation will decrease the morning temperature. Thus night ventilation needs to be optimized so that a good thermal climate is achieved. The sensitivity analysis shows that stopping the night cooling earlier will lead to higher indoor morning temperature while only sacrificing some of the energy efficiency.

The thesis shows that genetic algorithms can be used for calibration and optimization of building energy simulations but with some limitations regarding both. The genetic algorithm should have proper limit values. The results shows that the genetic algorithm will always favor an increase in thermal mass and because of that, it would be better to only use it for thermal load calibration. The neural network has also proved to be useful for increasing the speed of the calibration but it had problems with the optimization due to the penalties from the temperature requirements.

References

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Lain, M. & Hensen, J. (2006). The optimization of the mechanical night cooling system in the office building. In *Proc. proceedings of the 6th int conf on compressors and coolants, casta papiernicka, slovakia*.

Larsson, A. (2015). *Night cooling optimization using post processed control systems data* (Master's thesis, Chalmers University of Technology, Division of Building Technology).

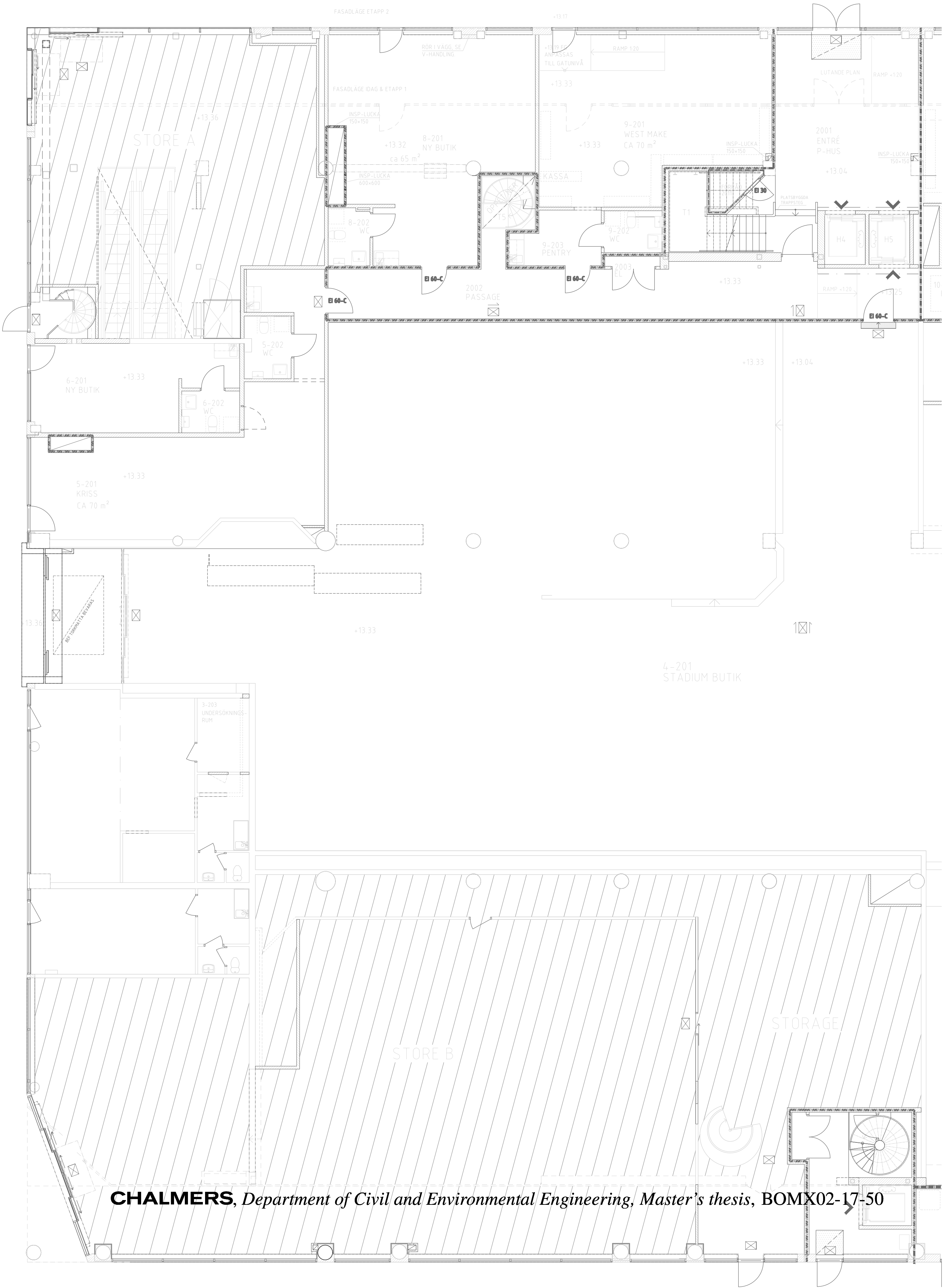
Le Dreau, J., Heiselberg, P., & Jensen, R. (2013). Experimental investigation of convective heat transfer during night cooling with different ventilation systems and surface emissivities. *Energy and Buildings*, (June).

MATLAB. (2017). Fit data with a neural network. Retrieved April 25, 2017, from https://se.mathworks.com/help/nnet/gs/fit-data-with-a-neural-network.html

A Layout and location of the stores

In the Appendix the following floor plans and maps are included

- Layout of Perukmakaren, basement floor.
- Layout of Perukmakaren, ground floor.
- Location of Perukmakaren in perspective to the urbanized area


FASADLÄGE ETAPP 2
FASADLÄGE IDAG & ETAPP 1
STORE A
+13.36
8-201
NY BUTIK
ca 65 m²
+13.32
INSP-LUCKA
150×150
INSP-LUCKA
600×600
RÖR I VÄGG, SE
V-HANDLING
RAMP 1:20
+13.33
9-201
WEST MAKE
CA 70 m²
KASSA
2001
ENTRÉ
P-HUS
+13.04
LUTANDE PLAN
T1
EI 30
H4
H5
8-202
WC
9-203
PENTRY
9-202
WC
2003
EL
2002
PASSAGE
EI 60-C
5-202
WC
6-201
NY BUTIK
6-202
WC
5-201
KRISS
CA 70 m²
4-201
STADIUM BUTIK
3-203
UNDERSÖKNINGS-
RUM
STORE B
STORAGE

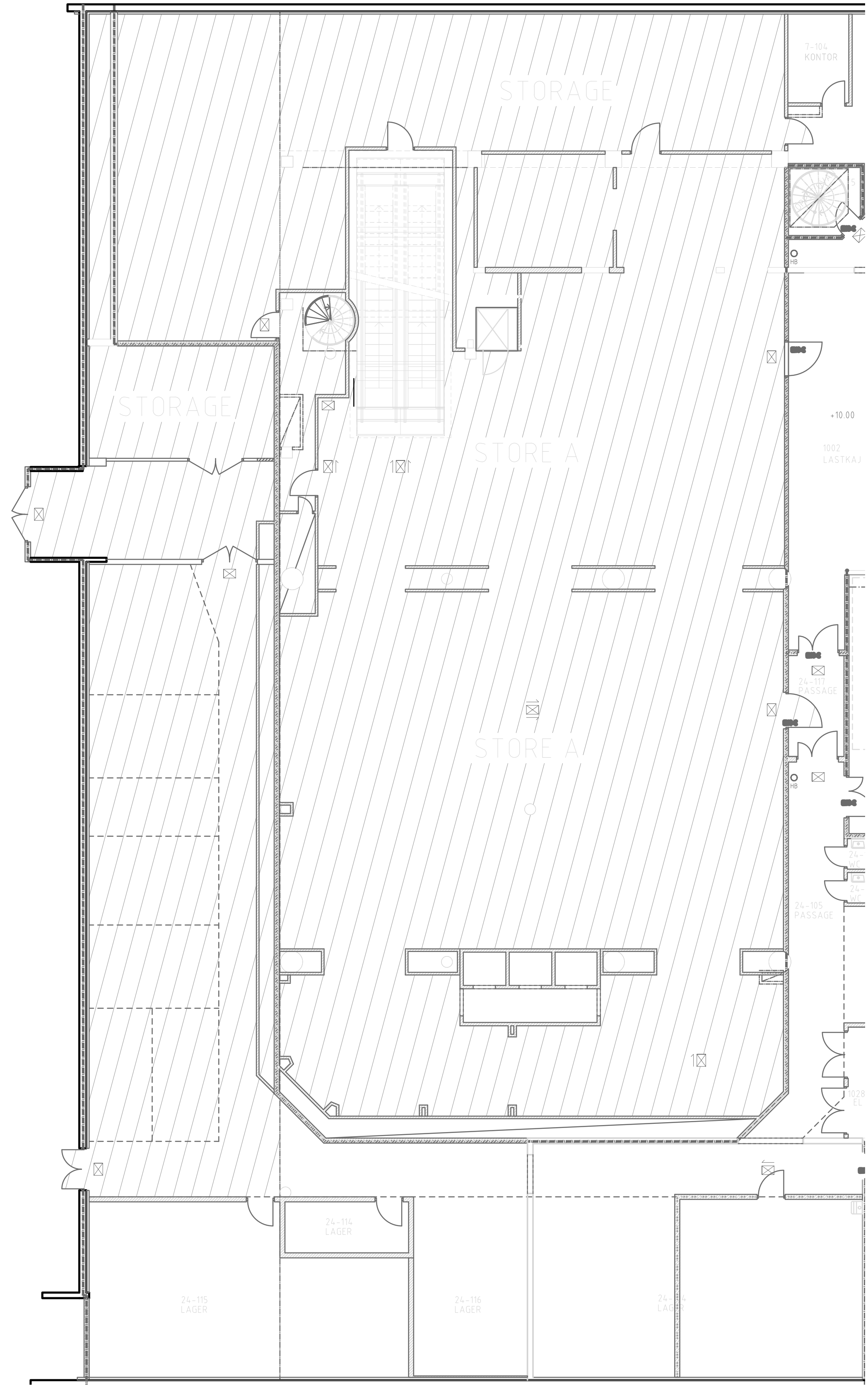

STORAGE
7-104
KONTOR
STORAGE
STORE A
+10.00
1002
LASTKAJ
24-117
PASSAGE
STORE A
24-105
PASSAGE
24-114
LAGER
24-115
LAGER
24-116
LAGER

Figure A.1: Location of the Stores, where the blue dot is store A and the red store B. The map shows that the stores are built in an urban area where shading occurs.

B Simulation indata for base models

Building properties	Store A	Store B
Geometry and construction		
Atemp	720 m^2	348 m^2
Basement floor area	600 m^2	0 m^2
Window area	North: 48.3 m^2 West: 44.0 m^2	South: 30 m^2 West: 30 m^2
Exterior wall area	56.4 m^2	23.0 m^2
U-value wall	0.25 W/m^2K	0.25 W/m^2K
U-value floor slab	1.0 W/m^2K	Not used
Infiltration	See Chapter 5	See Chapter 5
Thermal bridges	Included in U-value	Included in U-value
Thermal masses		
Air	2.81 $MJ/$°C	1.21 $MJ/$°C
Floor	202.5 $MJ/$°C	68.8 $MJ/$°C
Ceiling	82.3 $MJ/$°C	Not used
Heat transfer coefficients		
Floor	6.52 $kW/$°C	3.32 $kW/$°C
Ceiling	1.51 $kW/$°C	Not used
Window properties		
U-value windows	1.2 W/m^2K	1.2 W/m^2K
g-value windows	0.5	0.5
Solar shading	1.0	1.0
Heat loads & schedules		
Lightning Schedule	24.5 W/m^2 See Chapter 5	34.1 W/m^2 See Chapter 5
Humans Schedule	7.5 W/m^2 Weekdays 10:00-19:00 Saturdays 10:00-18:00 Sundays 11:00-17:00	7.5 W/m^2 Weekdays 10:00-20:00 Saturdays 10:00-18:00 Sundays 12:00-17:00
Solar	SMHI-data from 2016	SMHI-data from 2016

C Example codes

Example codes:

- Main script for optimization.
- Function file for calling Simulink and calculate energy consumption i.e. fitness value.
- Function file for simulation neural network and getting approximate enrgy consumption.

```
%-----------------------------------------------------------------------
%
%                    Night cooling optimizatiing
%
%                   Emmy Dahlström  &  Linus Rönn
%
% This code optimize night cooling set points for a energy model done in
% Simulink, it optimizes the set points in three steps. The program is
% linked to simulink and has two functions files, one for a calling the
% simulation done in Simulink (Ga_opt(x)) and one for neural networks
%(NN_opt(x)). It optimizes against the varible Total_Energy.
%-----------------------------------------------------------------------




% Creates global optimization variables, as simulink uses the global
% workspace instead of the function workspace
global Iter
global Total_Energy
global Input
global Night_start
global Night_period
global Airflow_percent
global Out_temp
global Out_hyst
global In_temp
global In_hyst

clear net
clc

% Defines heater for penalty
Heater=3000*20;

% Number of varibles
nvars=7;

% Creates boundary conditions, the boundaries are in the follwing order;
% start time, period, percent of air flow, outdoor temperature, hystereis
% for outdoor temperature, indoor temperature, hystereis for indoor
% temperature.

ub=[6 11  0.85  18 12 24 6];
lb=[0  4  0.3   10 5  19 2];


Input=[];
Iter=0;
Total_Energy=[];


%%  Step 1: First genetic algorithm

%Defines the number of generations and population size for the algorithm.
```

```
options = gaoptimset('Generations',3,'PopulationSize',2000);


% Defining the operative function, from function file linked to Simulink.
fop= @(x) GA_opt(x);

% Genetic algorithm dependent on opreative function, boundaries
[x,fval,exitflag] = ga(fop,nvars,[],[],[],[],lb,ub,[],[],options)



%% Step 2: Neural network and second genetic algortim

% Loads data from previous step
inputs = Input(1:nvars,:);
targets = Total_Energy;

% Create a Fitting Network with number of nodes in hidden layer
hiddenLayerSize = 30;
net = fitnet(hiddenLayerSize);

% Set up Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Train the Network
[net,tr] = trainbr(net,inputs,targets);

% Second genetic algoritm based on neural networks
% Defines the number of generations and population size for the algorithm.
option = gaoptimset('Generations',12,'PopulationSize',5000);

% Defining the operative function, from function file linked to NN.
fp= @(x_net) NN_opt(x_net,net);

% Genetic algorithm dependent on opreative function, boundaries
[x_net,fval_net,exitflag] = ga(fp,nvars,[],[],[],[],lb,ub,[],option)


Test_slut=[x;x_net]

% Tests the approximated value from nuerual networks by inserting the
% values in the Simulink model.
for i=1:2
    % Defines variables
    x=Test_slut(i,:);

    x_temp=x(1)-3;
    % x_temp is redefined due to the period blok used in Simulink
    if x_temp<0
        Night_start=24+x_temp;
    else
        Night_start=x_temp;
    end
```

```
   Heater=0;

    Night_period=x(2);
    Airflow_percent=x(3);
    Out_temp=x(4);
    Out_hyst=x(5);
    In_temp=x(6);
    In_hyst=x(7);

    %Calling for Simulink model
    SimOut = sim('Store_A_opt', 'ReturnWorkspaceOutputs', 'on');
    Comb_Energy=SimOut.get('Comb_Energy');
    Q=Comb_Energy(end);
   Total_Energy(i,1)=Q;

end

%% Step 3: Local search

Heater =3000*20;

% Defines starting point for local search
x0=Test_slut(1,:);

% Defines optimization options, minfunction and number of iterations
options = optimoptions('fmincon','MaxFunctionEvaluations',600);

% Local search algortihm with operative function linked to Simulink, the
% same as in Step 1.
[x,fval,exitflag] = fmincon(fop,x0,[],[],[],[],lb,ub,[],options)
```

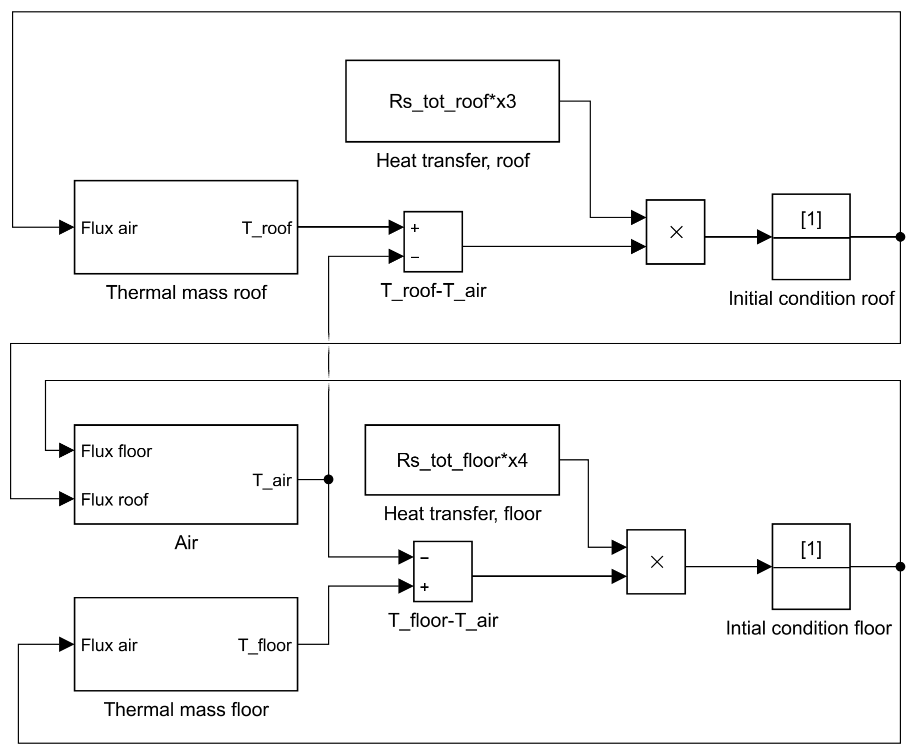
```
function Energy =GA_opt (x)
% This function file calls for a building energy model done in Simulink
% where the input is optimization parameters in a vector x and the output
% is the energy consuption from the simulated simulink model.

% Defines global variables for simulink
global Iter
global Total_Energy
global Input
Iter=Iter+1
global Night_start
global Night_period
global Airflow_percent
global Out_temp
global Out_hyst
global In_temp
global In_hyst


% Defines optimization variables

% The variable for start time is redefined due to the period blok used in
% Simulink, it can't start before midnight due to syntax

x_temp=x(1)-3;
if x_temp<0
    Night_start=24+x_temp;
   else
    Night_start=x_temp;
end
Night_period=x(2);
Airflow_percent=x(3);
Out_temp=x(4);
Out_hyst=x(5);
In_temp=x(6);
In_hyst=x(7);

% Calls for simulink model and extracs the energy consumtion for the used
% variables in vector x.
SimOut = sim('Store_A_opt', 'ReturnWorkspaceOutputs', 'on');
Comb_Energy=SimOut.get('Comb_Energy');

% The energy consumption
Q=Comb_Energy(end);

% Saves the results in matrices
Input(1:7,Iter)=x';
Total_Energy(1,Iter)=Q;


Energy=Q
```

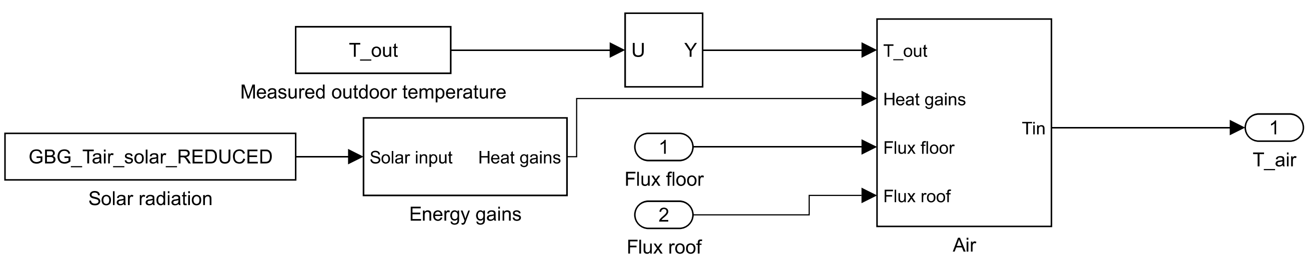
```
function fo = NN_opt(x_net,net)
% Simulating the neural network with the variable set x_net, for the
% approximated energy consumtion. fo= energy consumtion
 outputs1 = sim(net,x_net');
 fo=outputs1;
```

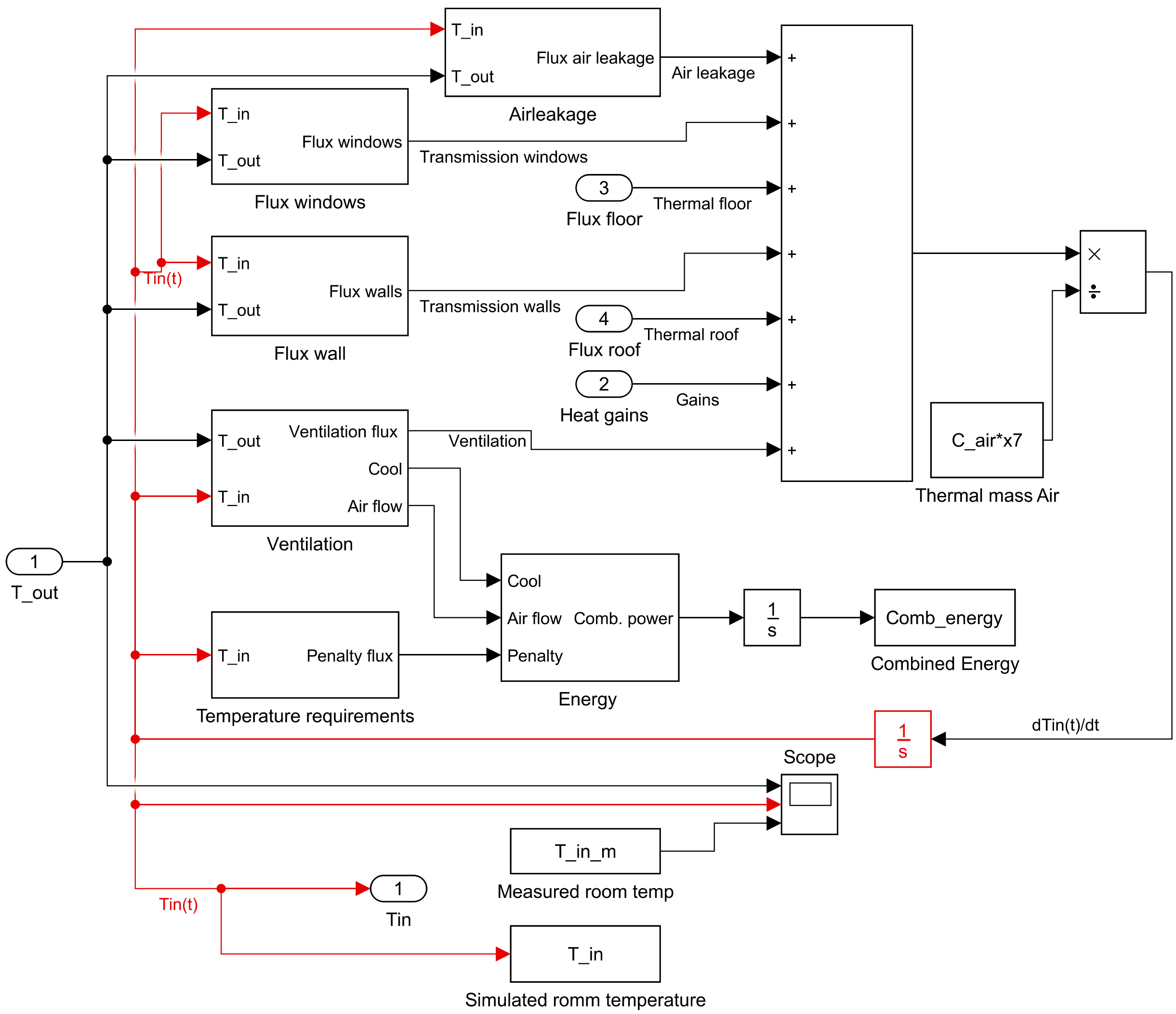
D Simulink model

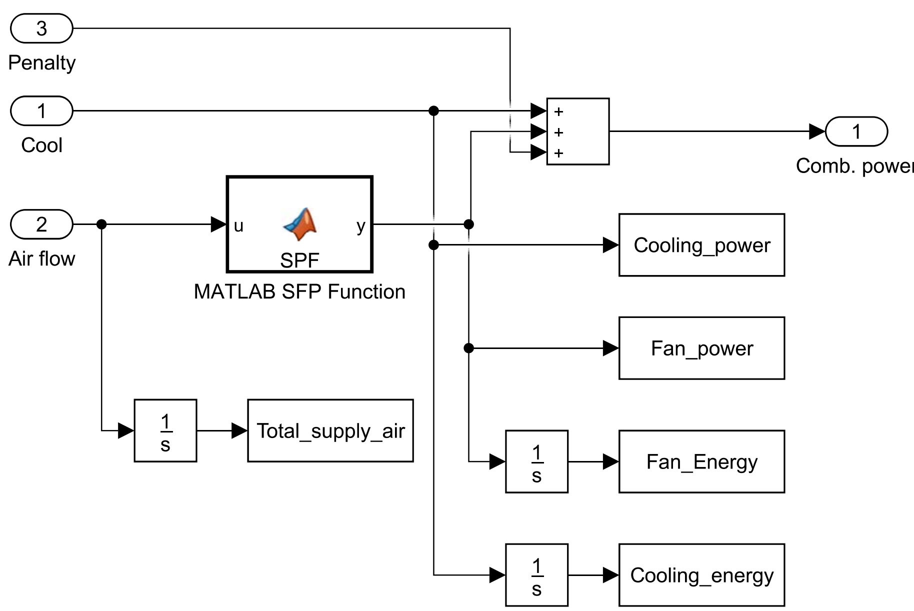
Simulink examples:

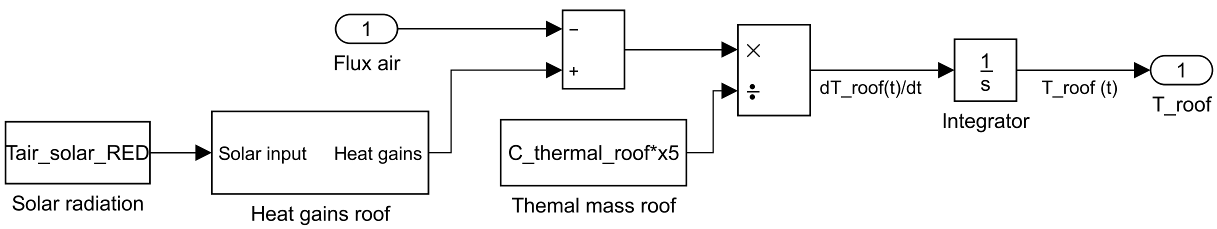
- Main page, connection the thermal masses.
- Page for air, introducing weather data.
- Heat balance equation for air.
- Energy calculation for Simulink model.
- Heat balance equation for roof.
- Heat balance equation for floor.
- Solar.
- Solar.
- Solar.
- Ventilation.
- Ventilation flow.
- Cooling.
- Cooling coil.
- Original night ventilation.
- Optimized night cooling .

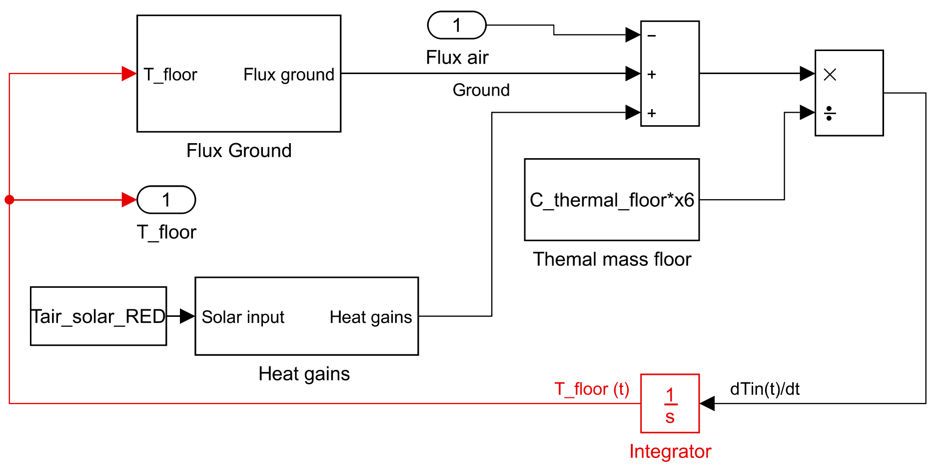

Rs_tot_roof*x3
Heat transfer, roof
Flux air
T_roof
Thermal mass roof
+
−
T_roof-T_air
×
[1]
Initial condition roof
Flux floor
Flux roof
T_air
Air
Rs_tot_floor*x4
Heat transfer, floor
−
+
T_floor-T_air
×
[1]
Intial condition floor
Flux air
T_floor
Thermal mass floor

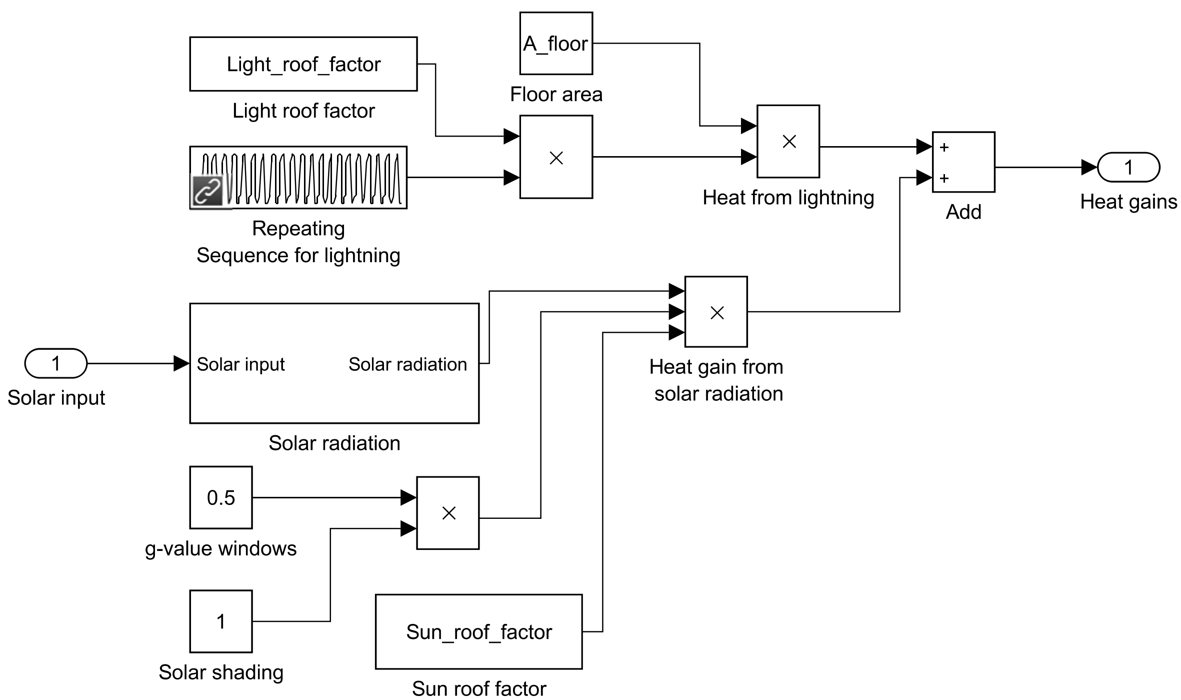

T_out
Measured outdoor temperature
U
Y
GBG_Tair_solar_REDUCED
Solar radiation
Solar input
Heat gains
Energy gains
1
Flux floor
2
Flux roof
T_out
Heat gains
Flux floor
Flux roof
Tin
Air
1
T_air

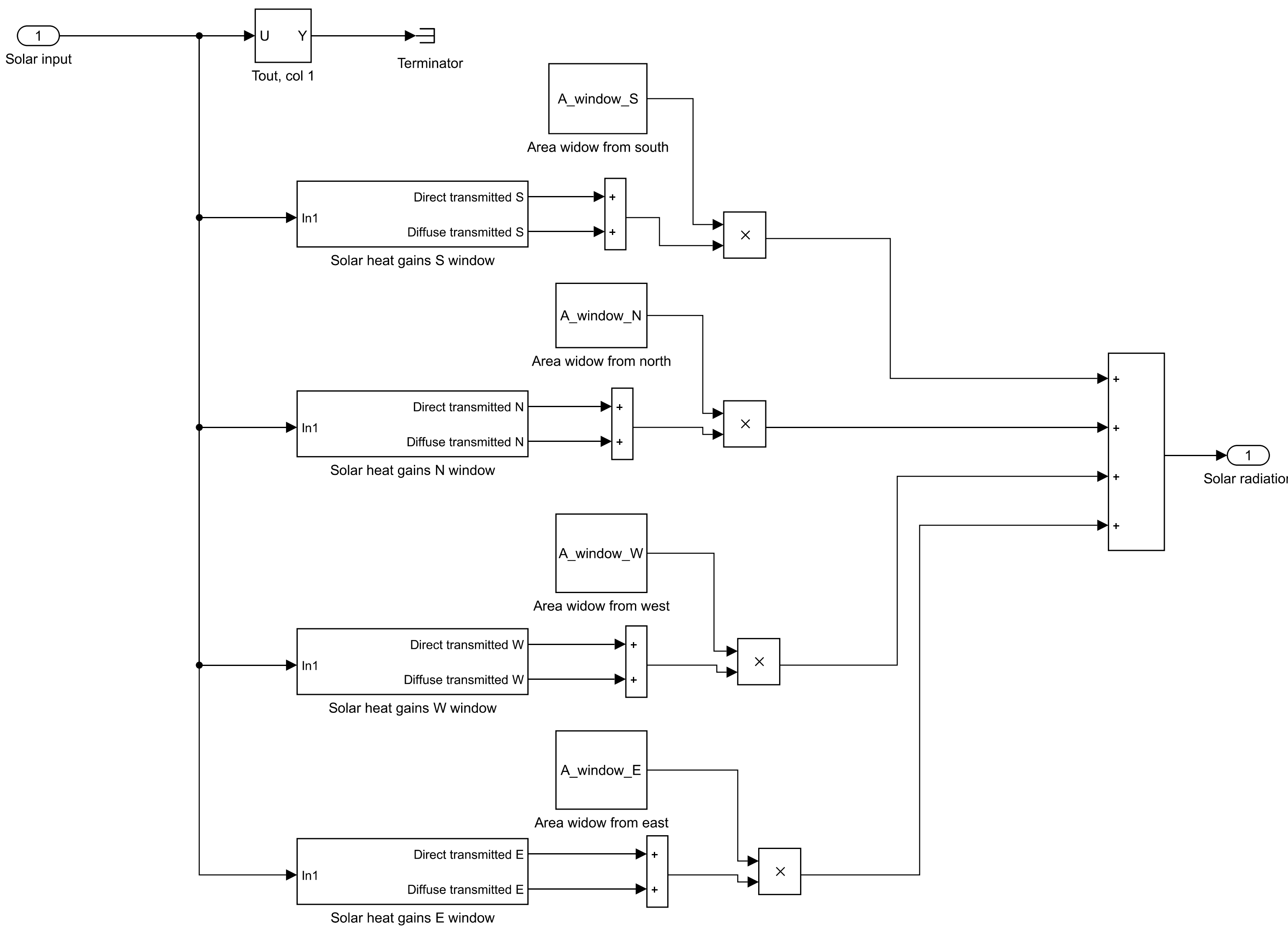

T_in
Flux air leakage
T_out
Airleakage
Air leakage
T_in
Flux windows
T_out
Flux windows
Transmission windows
3
Flux floor
Thermal floor
Tin(t)
T_in
Flux walls
T_out
Flux wall
Transmission walls
4
Flux roof
Thermal roof
2
Heat gains
Gains
T_out
Ventilation flux
Cool
T_in
Air flow
Ventilation
Ventilation
C_air*x7
Thermal mass Air
1
T_out
Cool
Air flow
Comb. power
Penalty
Energy
1
s
Comb_energy
Combined Energy
T_in
Penalty flux
Temperature requirements
1
s
dTin(t)/dt
Scope
T_in_m
Measured room temp
Tin(t)
1
Tin
T_in
Simulated romm temperature

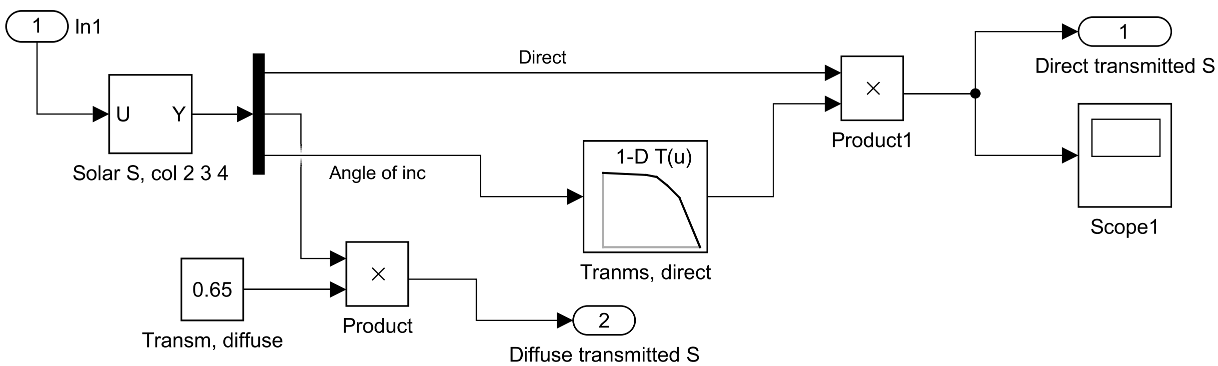

3
Penalty
1
Cool
2
Air flow
u
y
SPF
MATLAB SFP Function
+
+
+
1
Comb. power
Cooling_power
Fan_power
1
s
Total_supply_air
1
s
Fan_Energy
1
s
Cooling_energy

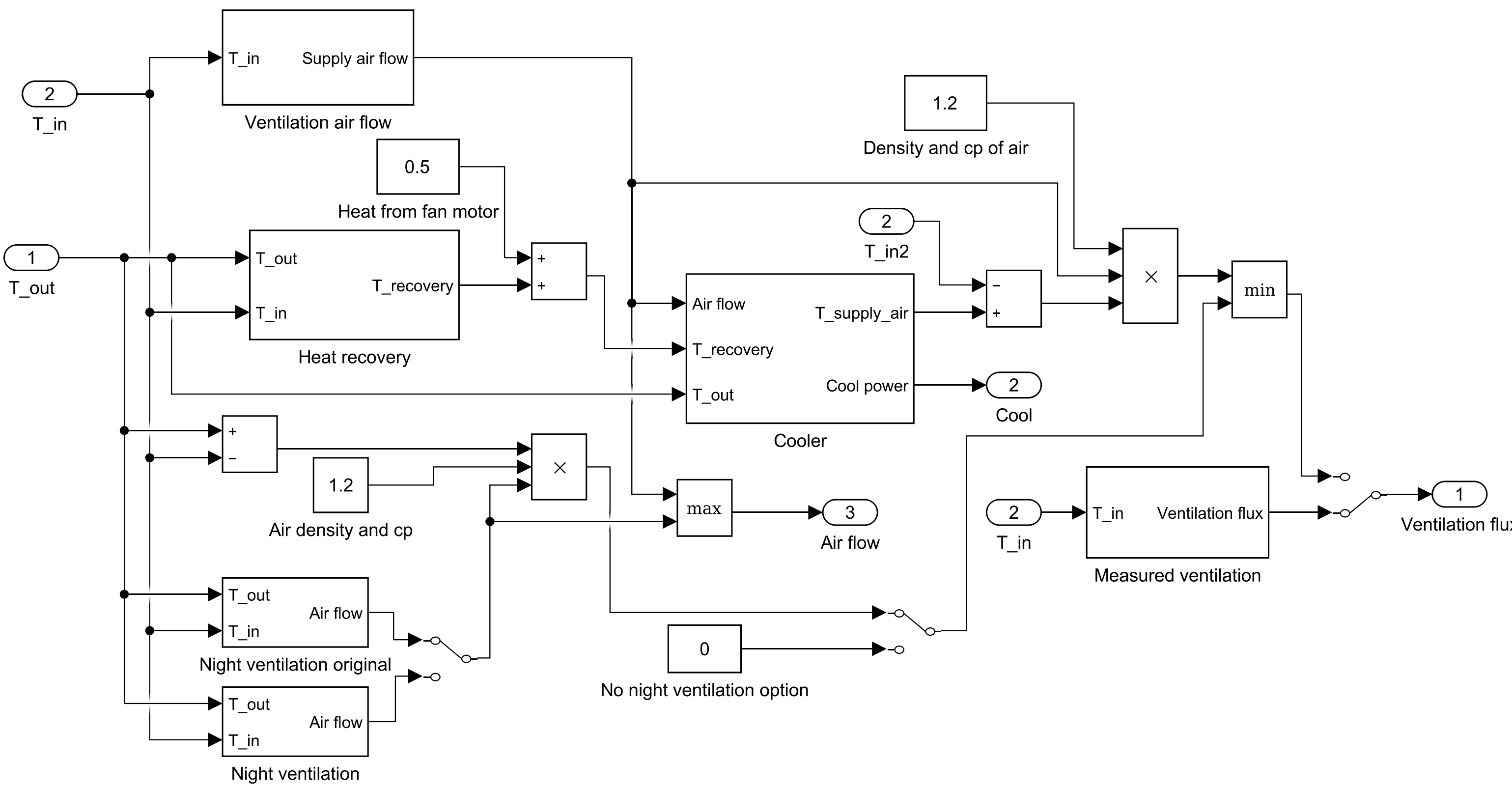

1
Flux air
Tair_solar_RED
Solar radiation
Solar input
Heat gains
Heat gains roof
C_thermal_roof*x5
Themal mass roof
dT_roof(t)/dt
1
s
Integrator
T_roof (t)
1
T_roof


1
Flux air
T_floor
Flux ground
Ground
Flux Ground
1
T_floor
C_thermal_floor*x6
Themal mass floor
Tair_solar_RED
Solar input
Heat gains
Heat gains
T_floor (t)
1/s
dTin(t)/dt
Integrator

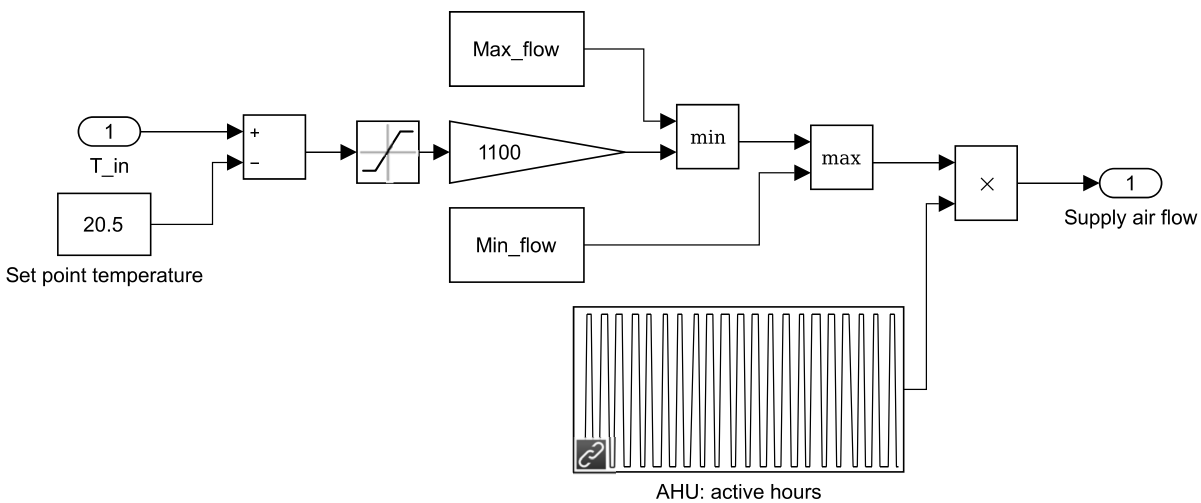

Light_roof_factor
Light roof factor
A_floor
Floor area
Repeating
Sequence for lightning
Heat from lightning
+
+
Add
1
Heat gains
1
Solar input
Solar input
Solar radiation
Solar radiation
Heat gain from
solar radiation
0.5
g-value windows
1
Solar shading
Sun_roof_factor
Sun roof factor

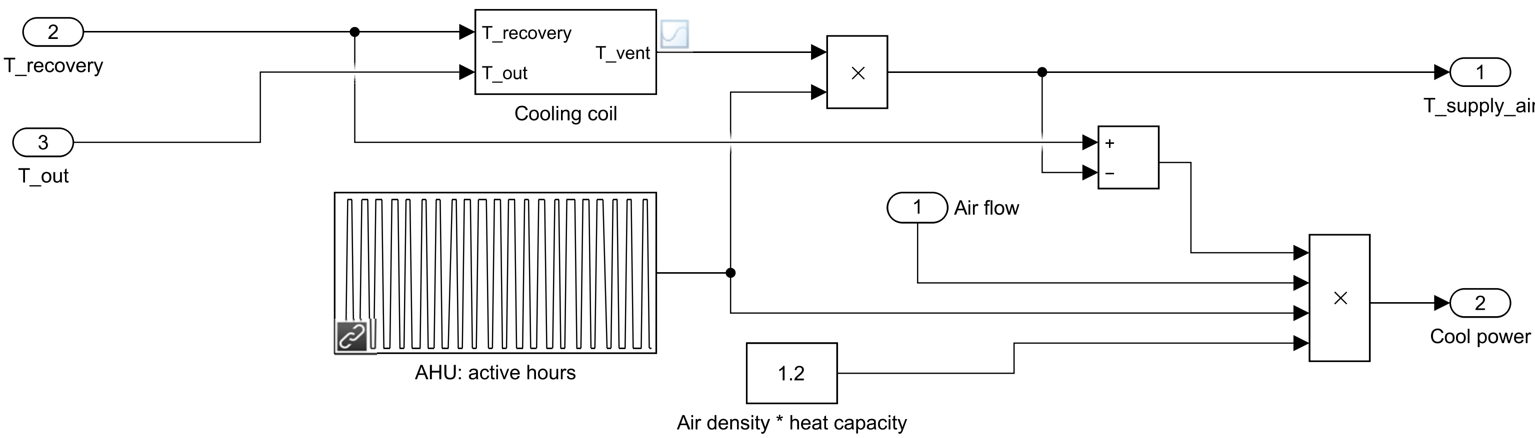

1
Solar input
U
Y
Tout, col 1
Terminator
A_window_S
Area widow from south
In1
Direct transmitted S
Diffuse transmitted S
Solar heat gains S window
A_window_N
Area widow from north
In1
Direct transmitted N
Diffuse transmitted N
Solar heat gains N window
A_window_W
Area widow from west
In1
Direct transmitted W
Diffuse transmitted W
Solar heat gains W window
A_window_E
Area widow from east
In1
Direct transmitted E
Diffuse transmitted E
Solar heat gains E window
1
Solar radiation

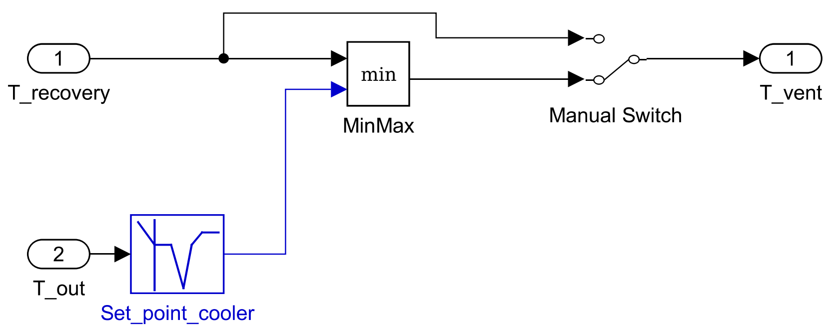

1
In1
U
Y
Solar S, col 2 3 4
Direct
Angle of inc
1-D T(u)
Tranms, direct
0.65
Transm, diffuse
Product
2
Diffuse transmitted S
Product1
1
Direct transmitted S
Scope1

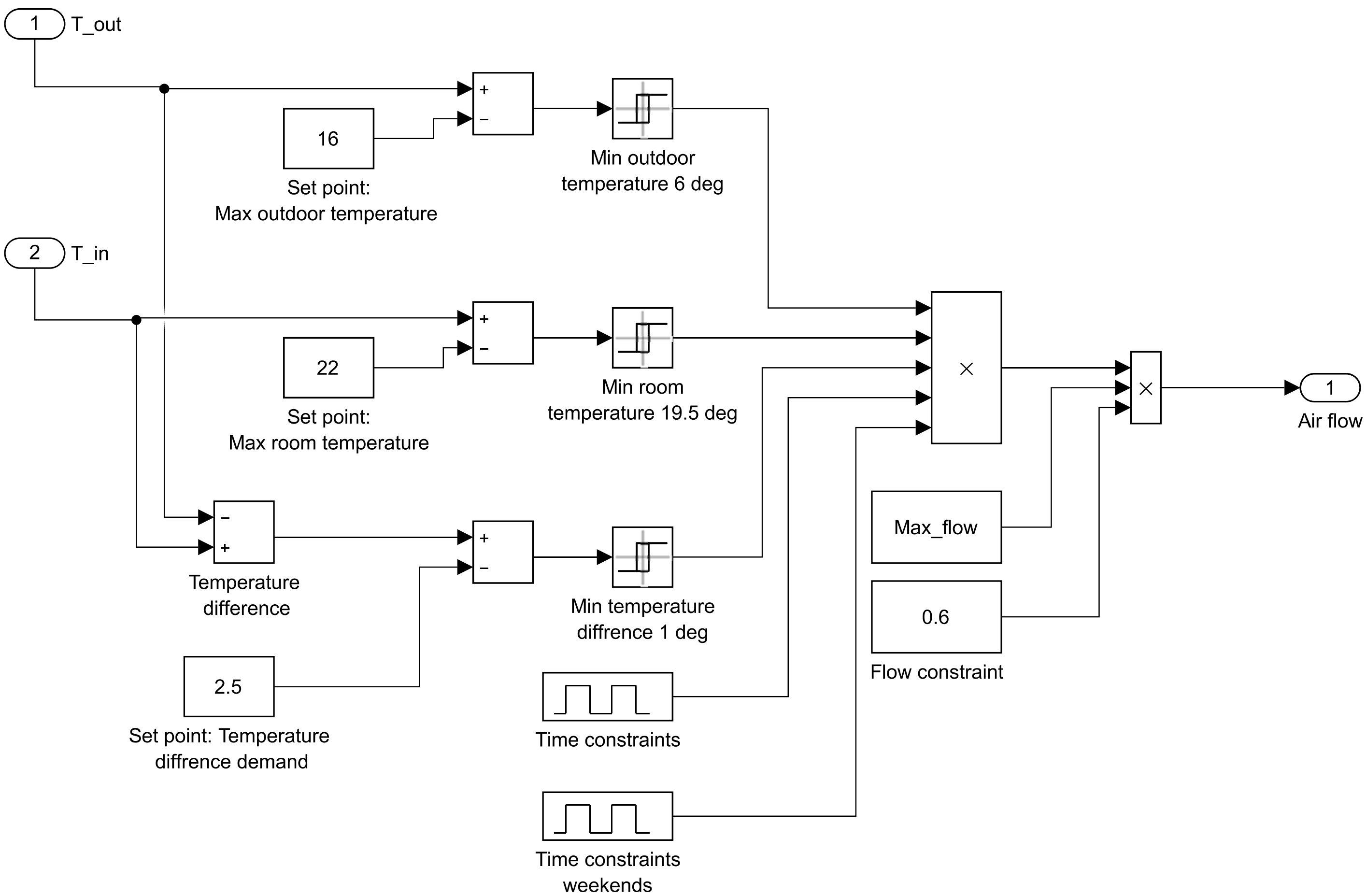


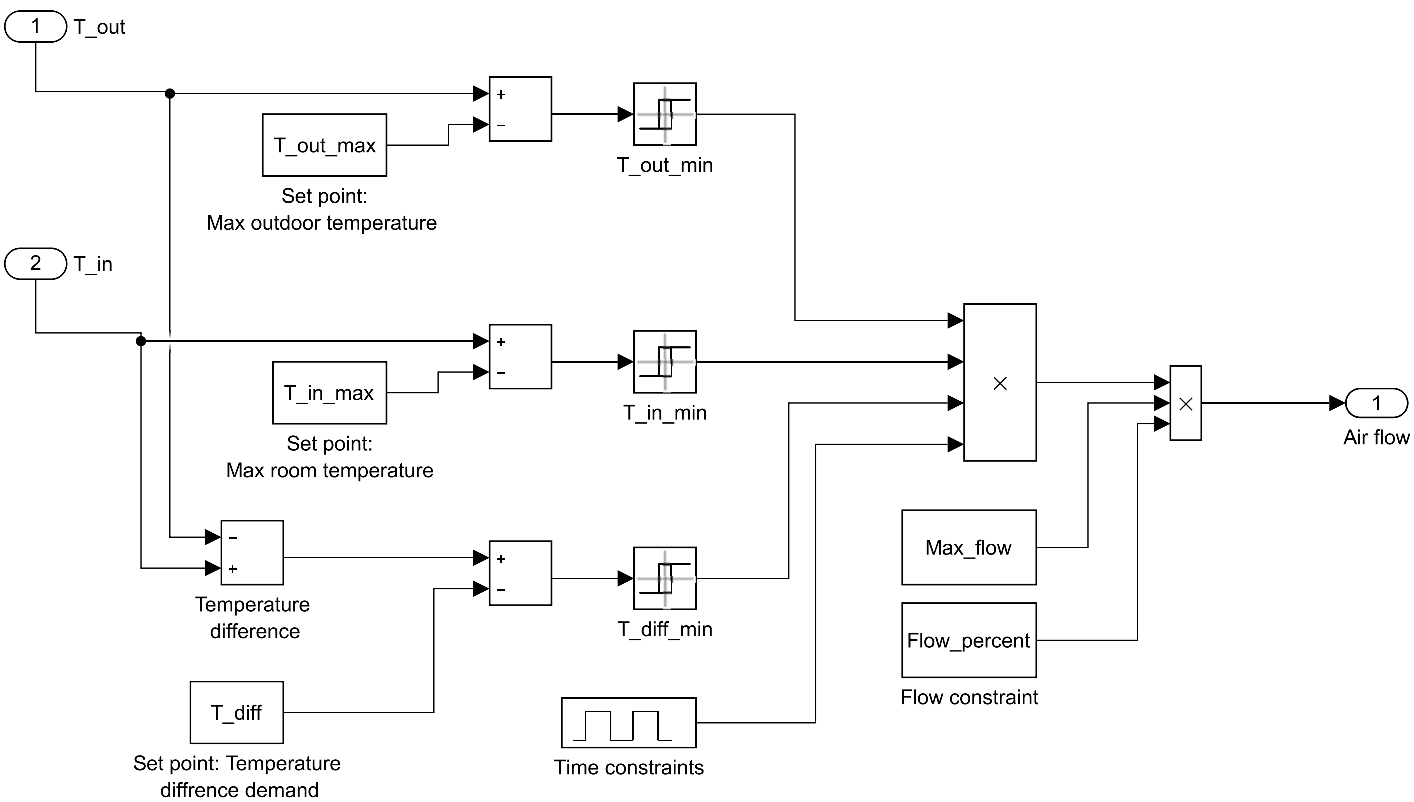
2
T_in
T_in
Supply air flow
Ventilation air flow
1.2
Density and cp of air
0.5
Heat from fan motor
1
T_out
T_out
T_in
T_recovery
Heat recovery
+
+
2
T_in2
Air flow
T_recovery
T_out
T_supply_air
Cool power
Cooler
-
+
×
min
2
Cool
+
-
1.2
Air density and cp
×
max
3
Air flow
2
T_in
T_in
Ventilation flux
Measured ventilation
1
Ventilation flux
T_out
T_in
Air flow
Night ventilation original
0
No night ventilation option
T_out
T_in
Air flow
Night ventilation


Max_flow
1
T_in
+
−
1100
min
max
×
1
Supply air flow
20.5
Set point temperature
Min_flow
AHU: active hours


2
T_recovery
3
T_out
T_recovery
T_out
T_vent
Cooling coil
×
1
T_supply_air
+
−
1 Air flow
×
2
Cool power
AHU: active hours
1.2
Air density * heat capacity


1
T_recovery
min
MinMax
Manual Switch
1
T_vent
2
T_out
Set_point_cooler


1
T_out
16
Set point:
Max outdoor temperature
Min outdoor
temperature 6 deg
2
T_in
22
Set point:
Max room temperature
Min room
temperature 19.5 deg
Temperature
difference
2.5
Set point: Temperature
diffrence demand
Min temperature
diffrence 1 deg
Time constraints
Time constraints
weekends
Max_flow
0.6
Flow constraint
1
Air flow


1
T_out
T_out_max
Set point:
Max outdoor temperature
T_out_min
2
T_in
T_in_max
Set point:
Max room temperature
T_in_min
Temperature
difference
T_diff
Set point: Temperature
diffrence demand
T_diff_min
Time constraints
Max_flow
Flow_percent
Flow constraint
1
Air flow

E Temperature plots for Store A

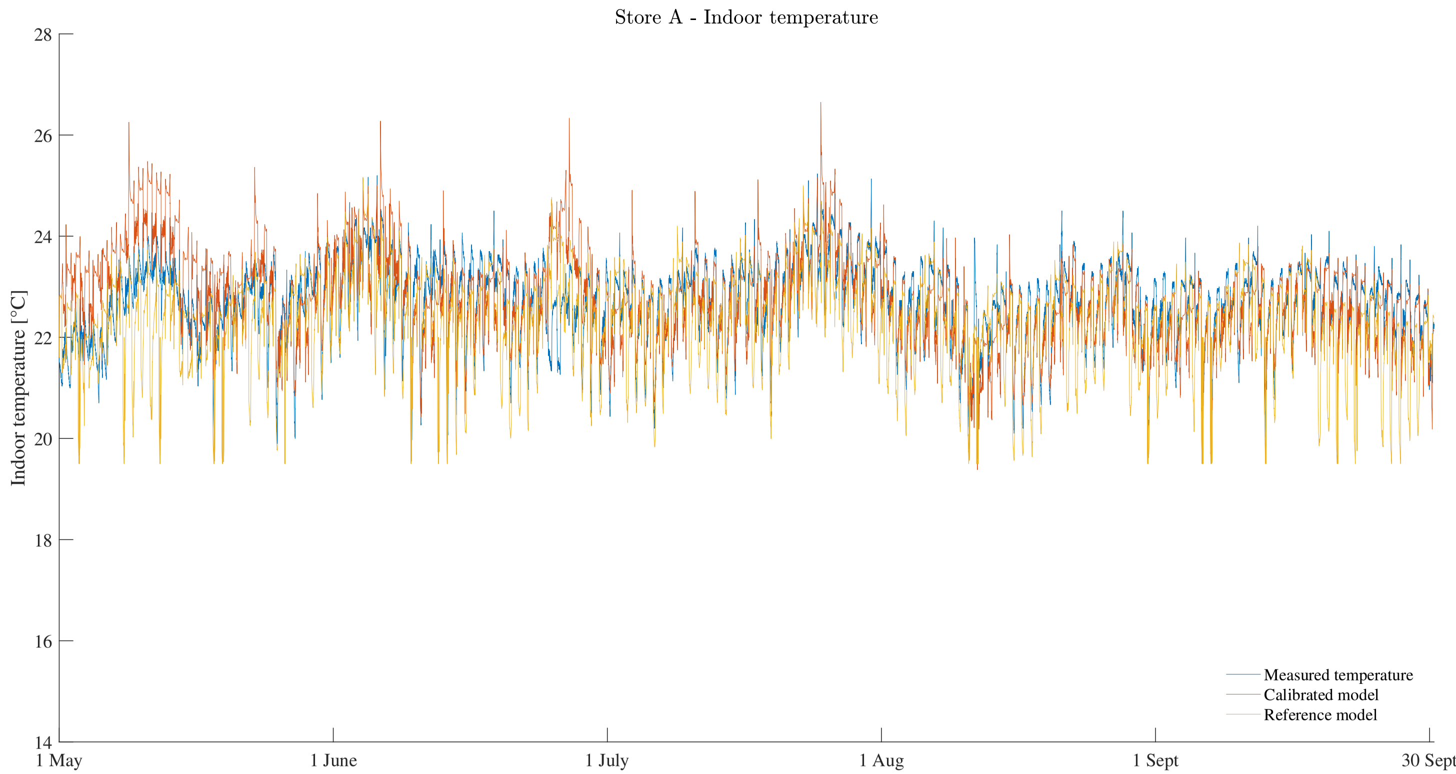


Figure E.1: Temperature plot from first of May to the last of September for store A. Where the blue line is the measured temperature, the red the temperature from the calibrated model and the yellow line the reference model.

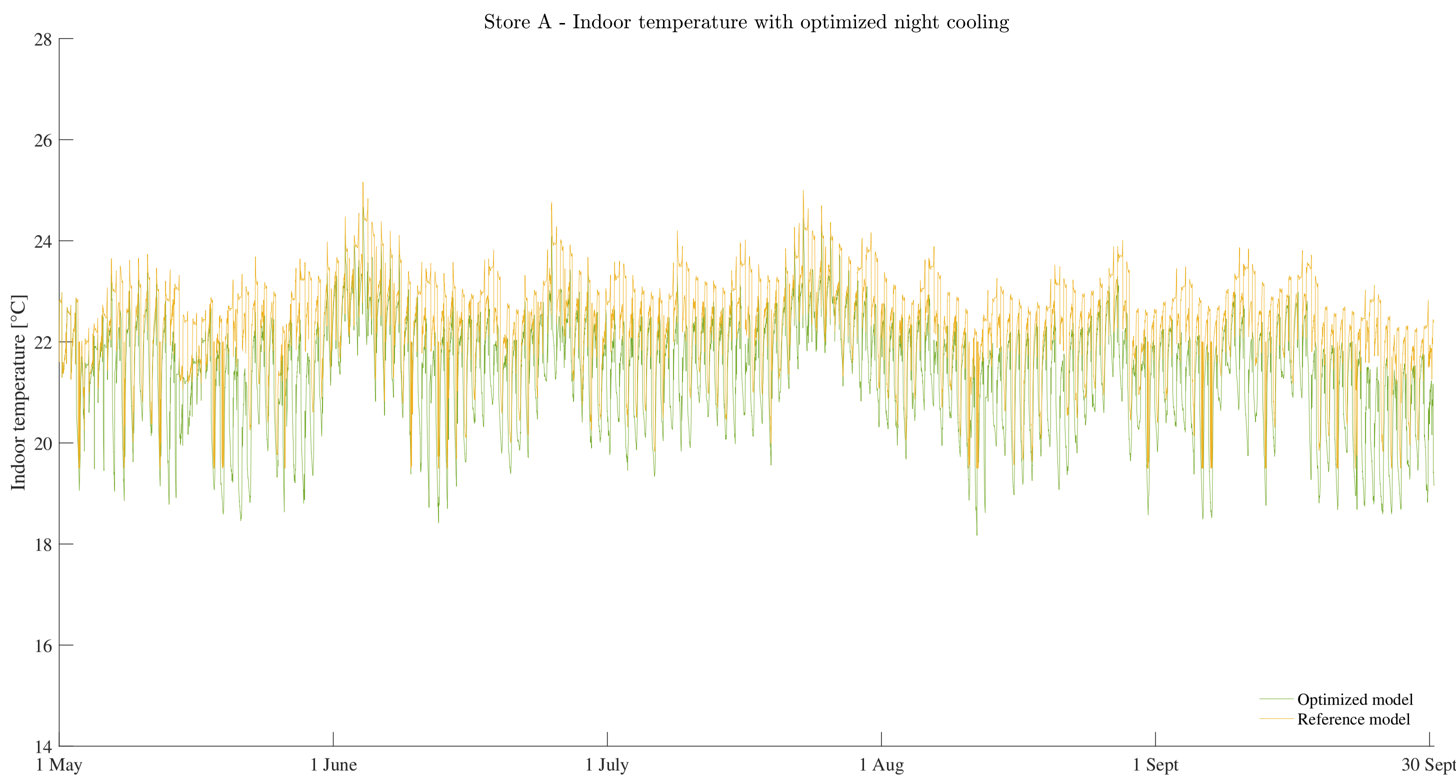


Figure E.2: Temperature plot from the first of May to the last of September, for store A. Where the yellow line is the reference models temperature and the green the model with optimized night cooling.

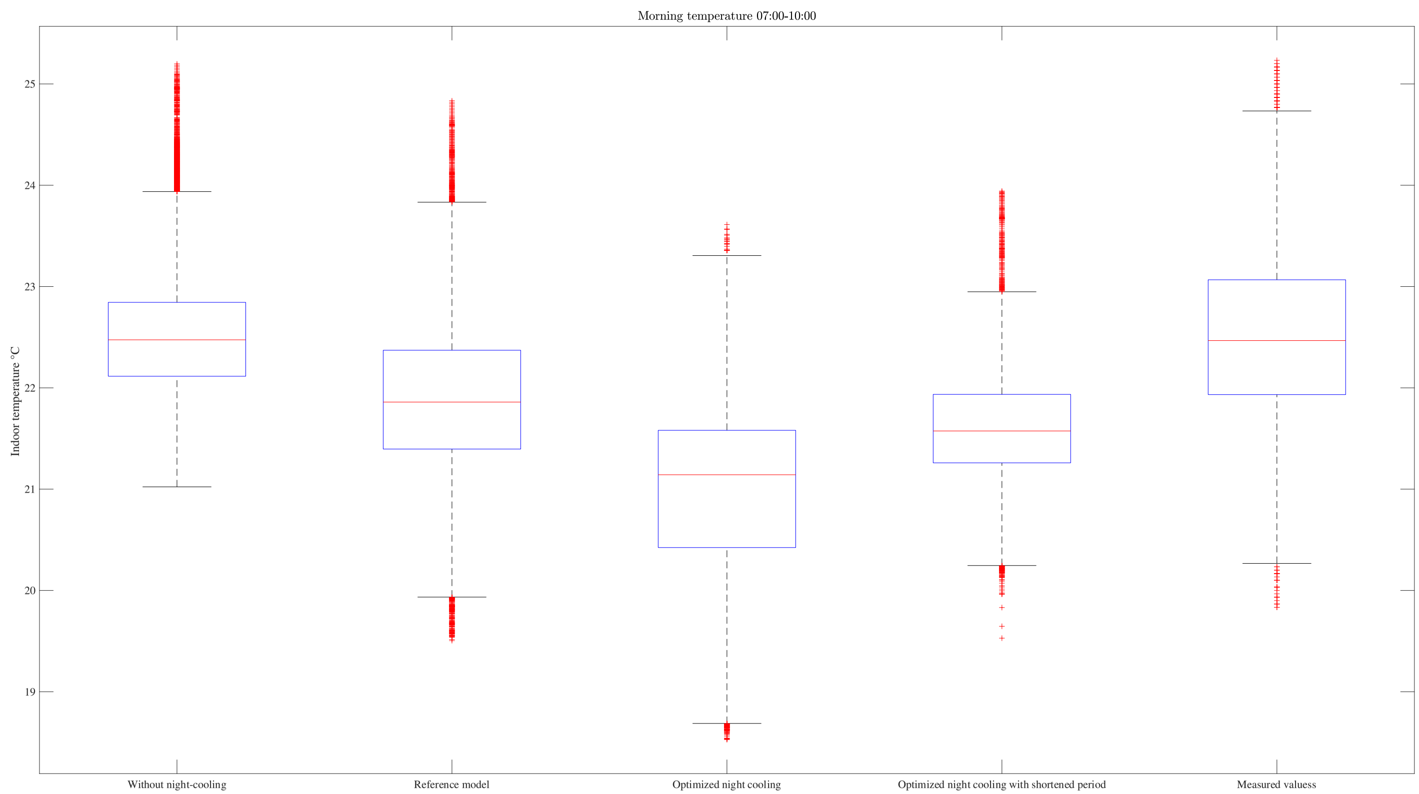


Figure E.3: Box plots over the temperature distribution in the mornings between 07:00-10:00 for store A. The blue box represent the 50% of the data, the red line the median value and the whiskers 1.5*IQR. The red dots are out layers. Box plots from the left: Without night cooling, the reference model, optimized night cooling, optimized night cooling with 3h earlier stop and the measured values.

F Temperature plots for Store B

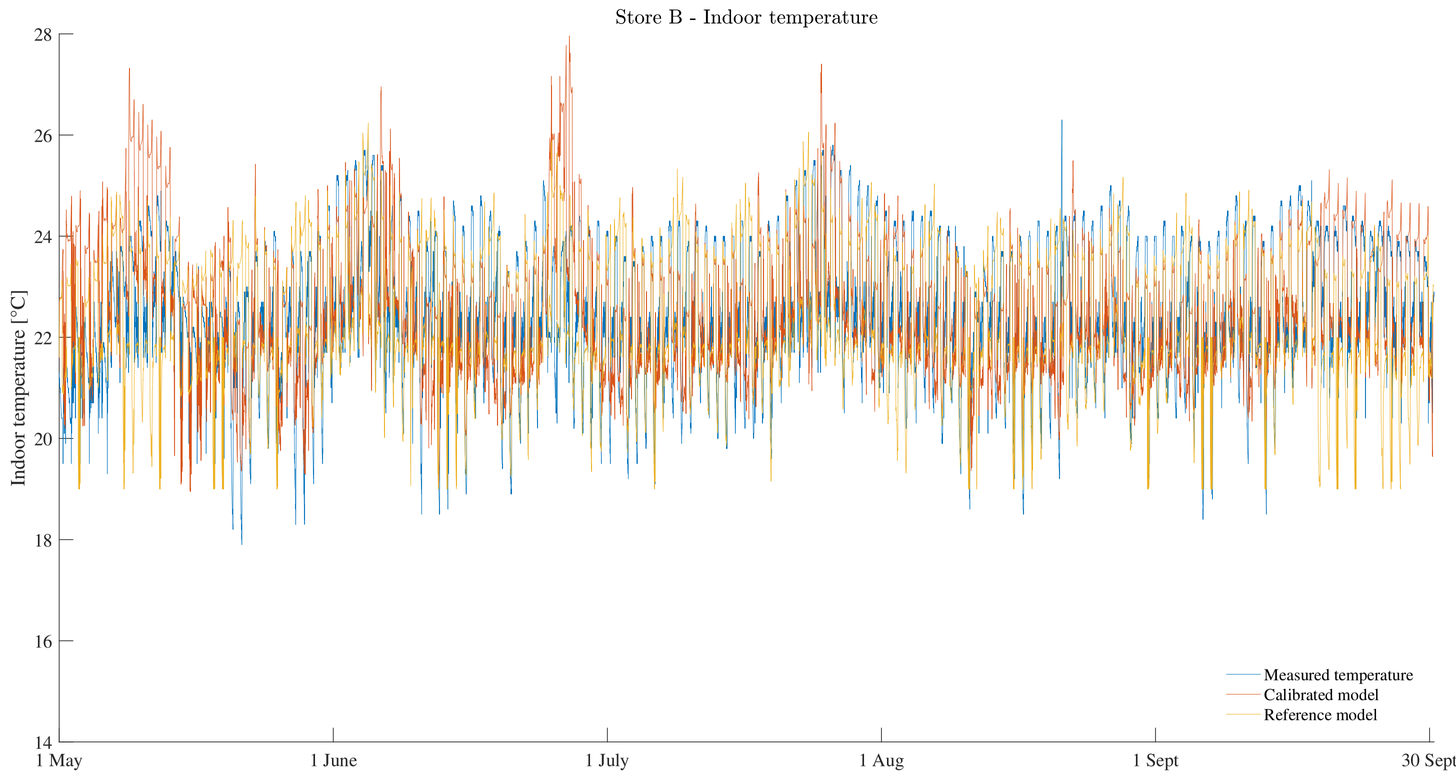


Figure F.1: Temperature plot from first of May to the last of September for store B. Where the blue line is the measured temperature, the red the temperature from the calibrated model and the yellow line the reference model.

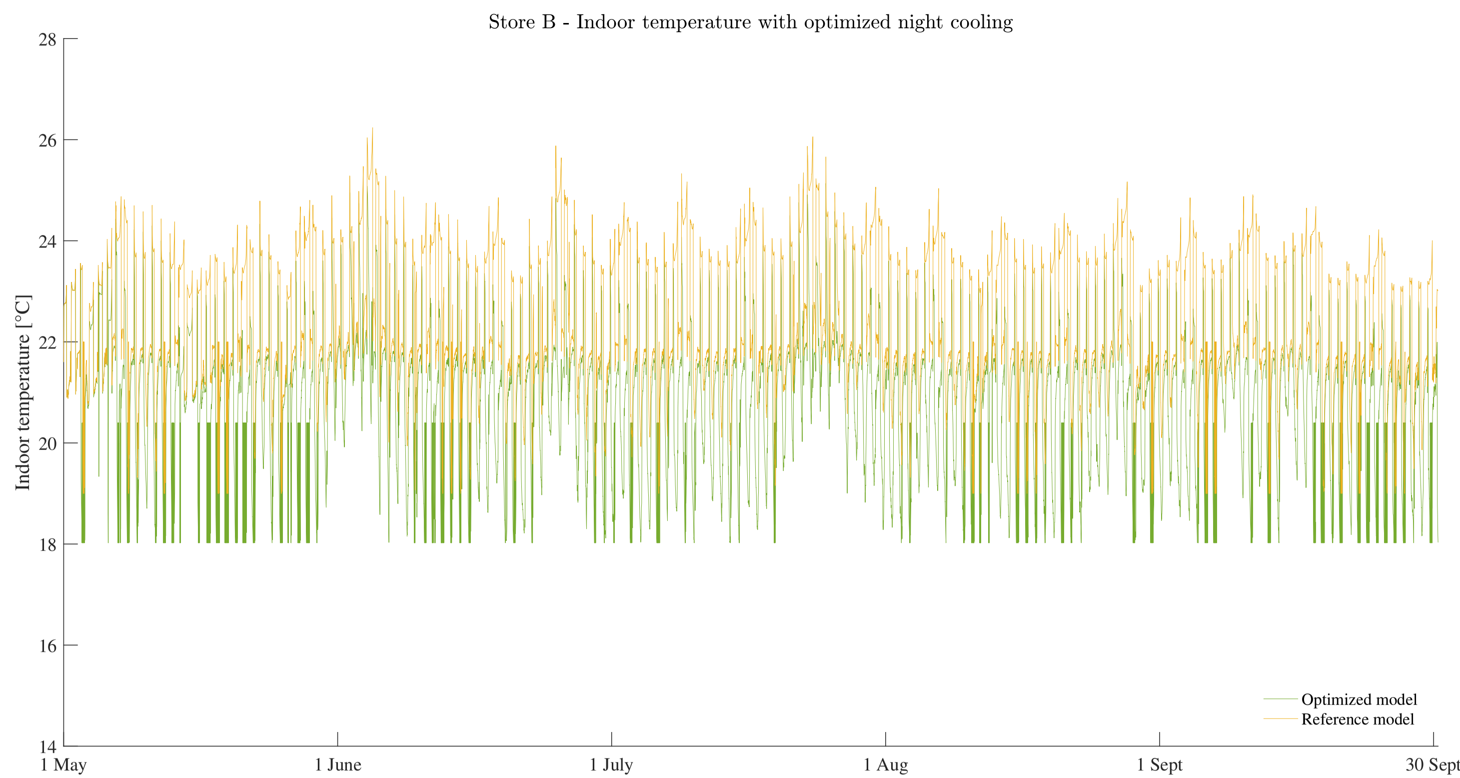


Figure F.2: Temperature plot from the first of May to the last of September, for store A. Where the yellow line is the reference models temperature and the green the model with optimized night cooling.

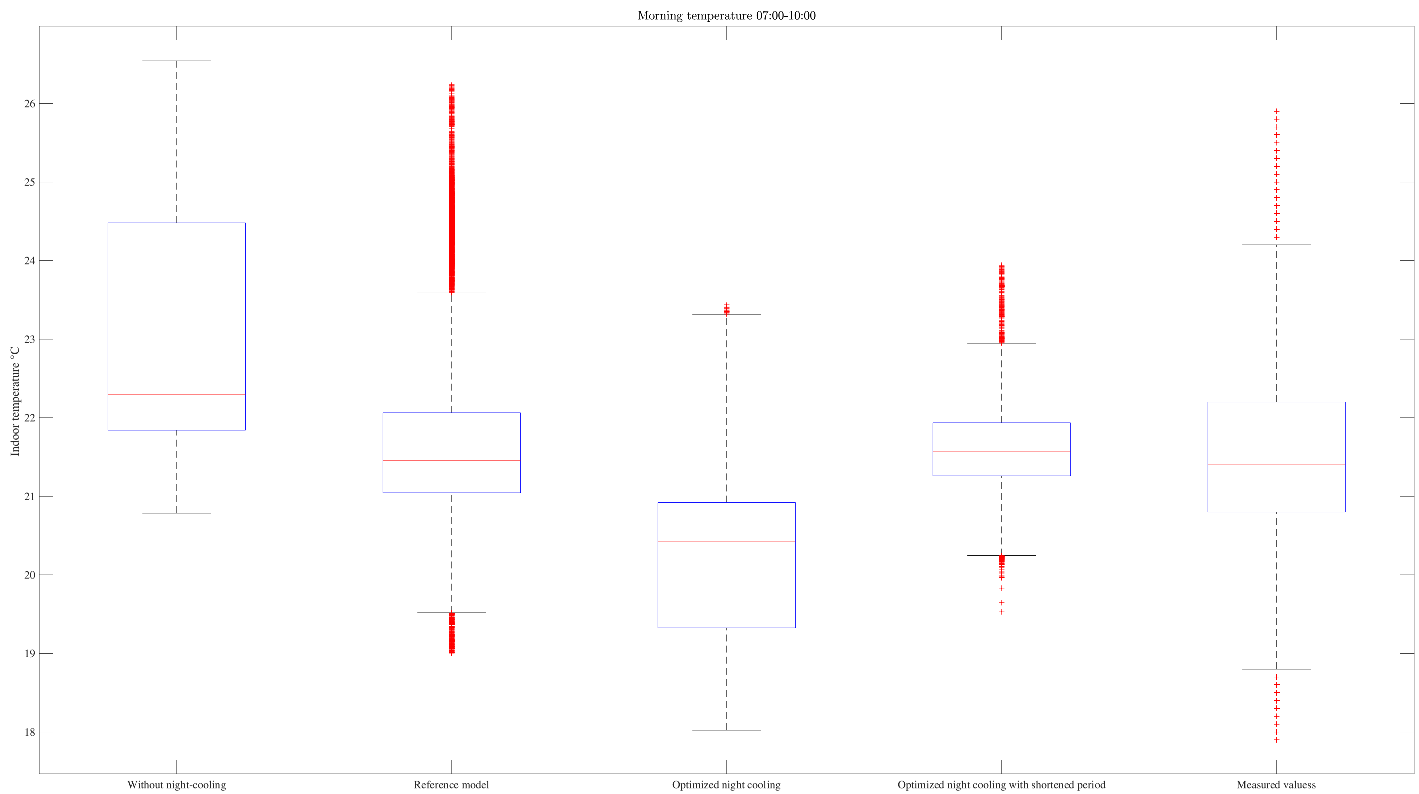


Figure F.3: Box plots over the temperature distribution in the mornings between 07:00-10:00 for store B. The blue box represent the 50% of the data, the red line the median value and the whiskers 1.5*IQR. The red dots are out layers. Box plots from the left: Without night cooling, the reference model, optimized night cooling, optimized night cooling with 3h earlier stop and the measured values.