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Optimization of Night Cooling of Commercial Premises Using Genetic Algorithms and Neural Networks

Emmy Dahlström[1], Linus Rönn[2] and Angela Sasic Kalagasidis[3]

[1]NCC Construction, Sweden
[2]Integra Engineering, Sweden
[3]Chalmers University of Technology, Sweden

Corresponding email: emmy.dahlstrom@ncc.se, linus.ronn@integra.se, angela.sasic@chalmers.se

ABSTRACT

This paper investigates if it is possible to optimize night cooling control setpoints and ventilation schedule regarding energy consumption and indoor climate. A retail store, located in Gothenburg, was used as a case study. The investigation was done by numerical modelling and simulations. It started with development and calibration of a building energy model for the store with data collected from the field. Afterwards, the calibrated model was used in the optimization of the night cooling. Initially, a genetic algorithm was applied to find the global minimum of the problem and further refined with a local search algorithm. The optimization speed was increased by neural networks, as they can approximate results faster than the building energy model.

The study suggests that the cooling and fan energy consumption can be reduced by 16% in the studied facility, compared to the currently used trial-and-error schemes. The project concludes that the use of logged control data in combination with genetic algorithms and neural networks are 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 and improving the results.

KEYWORDS

Night Cooling, Building Energy Modelling, Genetic Algorithms, Neural Networks and Optimization.

INTRODUCTION

Cooling load has significant impact on energy cost in commercial premises in Sweden mainly due to the peaks in cooling power demand thus increasing the need for power generation. Ventilation at night with cool outdoor air is a wide-spread strategy for reducing and shifting the cooling peaks. Due to complex relations between the building's response to night cooling, the requirements on the thermal comfort and the weather, control setpoints for night cooling are often established on site, through trial-and-error methods. Hence, the opportunity for further optimization of night cooling is missed.

Monitoring of building performance in real time is becoming a wide-spread praxis due to reliable and affordable data acquisition techniques. Indoor parameters, electricity, heat and air flows are recorded continuously, on minute basis. Big data sets that are generated thereby can be used to identify opportunities for energy savings in buildings.

The purpose of the paper is to evaluate the use of genetic algorithms and neural networks with post-processed data from a building to improve the building energy simulations and to optimize the control settings for night cooling. A store from a real commercial building is used as a case study to allow verification of the modelling results against the measured data. The building in question has a SCADA data logging system of control data such as; indoor temperatures, ventilation temperatures and ventilation air-flow rates. The data are saved every third minute. The records from the SCADA-system worked as a base for calibration of a building energy simulation.

OPTIMIZATION METHODS AND SCHEMES

The work is conducted in several steps. Firstly, a building energy model of the store was created by using MATLAB (MATLAB, 2017). It is a dynamic model that considers the building's capacity to store heat, and where indoor temperature and cooling loads are calculated based on time-varying outdoor conditions, as well as ventilation, comfort and occupancy schemes (Dahlström & Rönn, 2017). This initial model was calibrated to better simulate the reality with the help of logged data from the actual building as shown in the next section. In addition, an optimization strategy was developed and used to improve the model calibration and the settings for the night cooling. This was done by means of genetic algorithms and neural networks as described below.

Genetic algorithm

The optimization method for this analysis needs to be robust as the problems that are optimized can have a number of local minima. This makes a deterministic approach for the general optimization an unsuitable choice. Instead, a genetic algorithm is used as it is better suited to find a global minimum.

Genetic Algorithms (GAs) operate in a way that can be described similar to evolution (Aria, 2015) because they involve random inputs and stochastic search. A genetic algorithm uses a pool of variable-sets that makes it possible to search for the global minimum instead of a local one as multiple potential solution are kept in the pool. A variable-set contains individual values for all the parameters that are being optimized. Each variable-set is tested by an objective function and gets an associated fitness value produced by the objective function. 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.

Neural network

Neural networks can be used to approximate the results of functions that are relatively unknown and dependent on large numbers of input (Aria, 2015). So, called shallow neural networks (MATLAB, 2018) are used in the analysis as they can approximate the fitness value for a variable-set much faster than the building energy model, thus allowing the use of a much broader genetic function with larger pools and more iterations. One simulation by building energy model took 10 seconds, which was 1500 times slower than the neural network.

Shallow 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 their respective outputs. It will then learn the relation between the inputs and the outputs and can then be used to approximate outputs with new inputs.

Optimization scheme

Two optimization schemes were developed and used in the analyses, each employing a genetic algorithm as illustrated in Figure 1. The objective function for the first genetic algorithm is running the building simulation in MATLAB and calculating the fitness value.

All the variable-sets that are tested by the first GA with their respective fitness value are used as inputs and outputs 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.

The last step in the scheme is a local search algorithm that starts from the most optimized variable-set in Step 2. The purpose of it is to check if the minimum that was found could be further improved. A local search is used, as the genetic algorithm has very likely found 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.

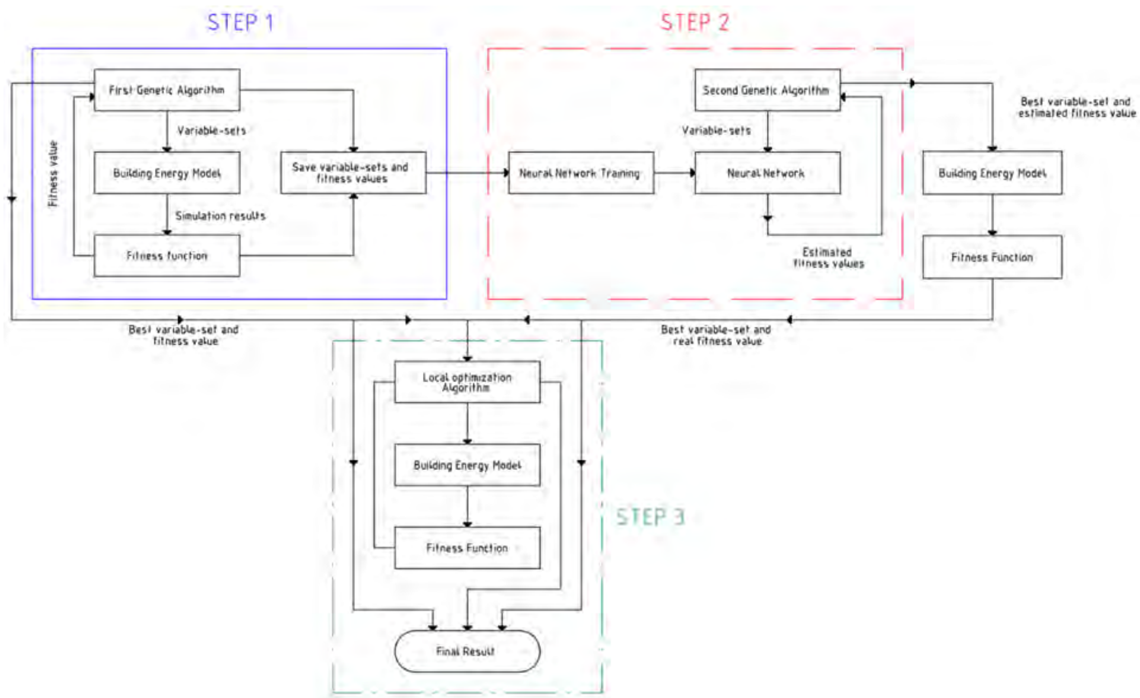


Figure 1: The optimization and calibration scheme used for the analysis.

THE BUILDING MODEL CALIBRATION

The genetic algorithms are used to calibrate different building constants such as thermal masses of interest, heat transfer coefficients between the indoor air and the interior surfaces, magnitude of internal heat loads and how they are divided between the thermal masses. The aim of the calibration is to achieve as small difference as possible between the measured indoor temperature and the simulated temperature. The model was calibrated for the entire cooling season, from May 1 to September 30, 2016. With this long calibration period, most weather conditions are accounted for.

Variable-sets and Fitness values

The calibration of the building energy model was done by making minor changes to the parameters that were initially either assumed or estimated by calculations, as the thermal masses and U-values of building envelope components, intensity of heat gains, occupancy schemes, etc. In the calibration, the fitness value is defined as a difference between the time integral of the measured indoor temperature and the simulated one, and presented in degree hours. By minimizing the difference in degree hours, the calibrated model more closely correlates with reality as the integral average between the real temperature and the simulated becomes smaller.

In the optimization of night cooling, new variable-sets, such as air flow rates, indoor and outdoor temperatures, are used instead of the building parameters that were found in the calibration. The fitness value is changed to represent the amount of energy used in the system instead of the difference between measured and simulated temperature. The energy use in the model considers the fan energy, cooling energy and the penalties, if the indoor temperature becomes too low, as described below.

To prevent the optimization 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 a thresholds value at specific times in the morning. The penalty is in form of an added energy usage. It is described as the temperature difference between the optimized indoor temperature and the threshold value, multiplied by a factor. The purpose of this is to train the system to not fall below these requirements.

Simulation of ventilation

To calibrate the building parameters the measured ventilation data was used. This made sure that the ventilation was not a changing variable in the calibration, thus providing the same conditions for each simulation. However, for the optimization of night cooling, a simulated ventilation scheme was used in order to be able to change the ventilation set-points.

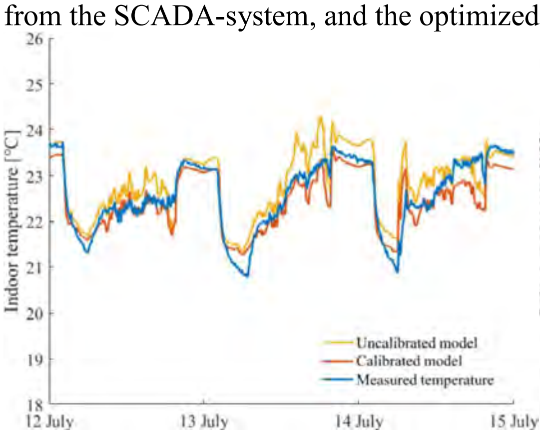
RESULTS

The calibration results show that a decrease of the degree hours between the simulated and the measured temperature is possible. Table 1 and Figure 2a shows the improvements of the calibrations.

Table 1. Mean temperature and temperature difference for the simulation before and after the calibration for the period May 1 – September 30

	Measured	Uncalibrated Model	Calibrated Model
Mean Temperature	**22.71 °C**	**22.94 °C**	**22.35 °C**
Percentile error	-	1.03%	0.34%
Degree hour difference	-	2207 °Ch	1740°Ch
Average temperature difference		0.6°C	0.47°C

Figure 2b shows the difference in indoor temperatures between the original setpoints, taken from the SCADA-system, and the optimized setpoints.



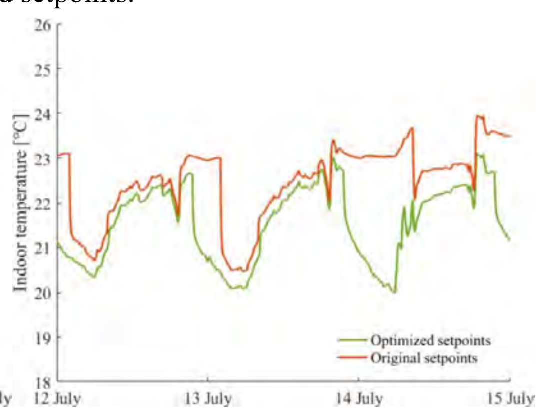


Figure 2a: To the left a comparison between the uncalibrated model, calibrated and the measured temperature for 72 hours in mid-July. Figure 2b: To the right the temperature for the facility with optimized night cooling setpoints and the original setpoints.

The main differences between the optimized and the original setpoints are; 1) the optimized night cooling is allowed to start earlier, e.g. before business hours, 2) the longer active hours of night cooling make it possible for the indoor temperature to reach lower temperatures, 3) night cooling can be active during weekends.

The optimization reduced the total energy demand for the store by 16%, but only resulted in a daytime temperature decrease of 0.22 °C. Without night cooling the energy demand and temperature increases as shown by Table 2. The original setpoints taken from the SCADA-system.

Table 2. The energy demand for the case study.

	Original night cooling setpoints	No night cooling	Optimized night cooling setpoints
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	8.55 kWh/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

An increased ventilation during night leads to a decreased daytime ventilation as shown by the table above. This also leads to an overall increase in ventilation flow. An increase of total ventilation flow does not lead to an increase in fan energy due to the quadratic specific fan power (SFP) curve. A consequence of its polynomial shape is that peak flows have a significant 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 results behave as expected, the overall mean temperature decreases with increased night-cooling but most of that decrease comes from the decrease in temperature during the night. Without night cooling the mean- and night temperature increase.

DISCUSSIONS

In the study, the use of neural network is applied in the calibration of the building energy model and the optimization of night cooling, but not tested as a control system. To use a dynamic control system such as a neural network 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 would decrease its usefulness and flexibility. To train such a control system a genetic algorithm or another algorithm could be used to optimize the weights and transfer functions of the neural network. It would then optimize towards a goal of good indoor climate and less energy use. A neural network can also potentially be used instead of a building simulation model, if sufficient measured data would be available to train the network. However, this would require a complex network and a large number of examples to train it and, thereby, making it impractical to use.

During the analysis, 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 with accuracy. Without the penalty, the neural network would make an accurate prediction but the optimization would lead to an indoor climate that would be unacceptable. Testing showed that reducing the penalty would result in a better accuracy but colder indoor climate. Therefore, for our purpose the penalty was kept high to ensure a better indoor climate even though it counter act the results from the neural network and led to less optimization and testing.

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

CONCLUSIONS

The results show that genetic algorithms can be used for calibration and optimization of building energy simulations but with some limitations regarding both. For example, 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.

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