INTEGRATED SMART CONTROL OF HEATING, COOLING, VENTILATION, DAYLIGHTING AND ELECTRICAL LIGHTING IN BUILDINGS

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ABSTRACT

The present energy consumption of European Buildings is higher than necessary, given the developments in control engineering. Optimization and integration of smart control into building systems can save substantial quantities of energy on a European scale while improving the standards for indoor comfort. Many tools are available for the simulation of one or some of the following aspects: (1) heating, cooling and indoor thermal comfort, (2) ventilation and indoor air quality, (3) daylighting, electrical lighting and light quality, (4) installations, local control and fault detection, (5) Genetic optimized Neuro-Fuzzy control. The interaction between these aspects, however, is very relevant and cannot be neglected. Therefore, an integrated software tool is required. TNO together with the University of Delft develops such an integrated tool partly within the EU-Joule project EDIFICIO. This paper describes the first version of this new tool.

KEYWORDS

Integrated Building Control, Predictive control, Smart Control, Heating, Daylighting, Electrical Lighting, Simulation tools.

1. INTRODUCTION

The purpose is to save energy for indoor climate control while improving the indoor comfort. To achieve this, an integrated predictive adaptive controller is required.

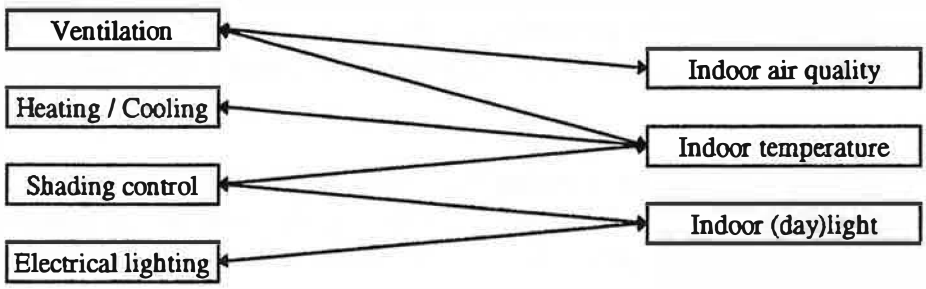

Figure 1: *Relevant relations of actuators and indoor climate related variables.*

All relevant indoor parameters should be controlled **integrated** to address the relevant cross-relations between the different actuators and controlled variables adequately (figure 1).

The control should be **predictive** in order to benefit from the building dynamics. The indoor temperature and indoor air quality have dynamic responses and it is possible to optimise energy use and indoor comfort by predictive control (Ferguson 1990; figure 2).

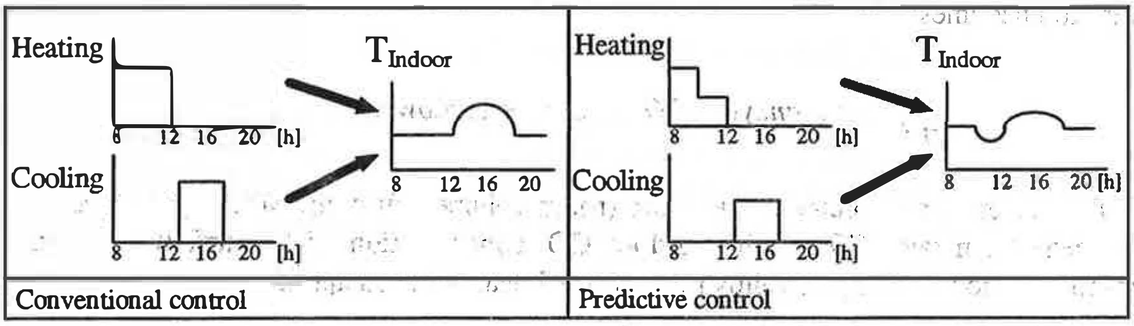

***Figure 2:** Example demonstrating thermal comfort improvement and energy use reduction by predictive control, temporarily decreasing heating below the set point.*

The smart controller should be **adaptive** in two ways: (1) the controller should adapt to the specific application, room and building-specific properties as thermal mass, window size, and building installation etc. To support this a building and installation model is utilised within the controller, automatically adapted by matching the responses of the real building. (2) the controller must adapt to the occupant, both in a direct way, by direct response and in an indirect way, by structural controller adaptation to the analysed occupants preferences.
Incentives are required to stimulate the occupants to decrease energy use to balance the structural adaptation to the occupants preferences supported e.g. by providing the occupant information on energy use indicating high - average - low energy use.

2. BUILDING MODEL FOR CONTROLLER DESIGN AND TRAINING

Since the controller is self learning, automatically adapting to the specific building, installation and climate, detailed modelling is of less importance. The focus is on flexible design and optimisation of smart control systems including Neural, Fuzzy control and Genetic Algorithms. Therefore, Matlab and Simulink are used as platform.

The controller controls heating and cooling power, electrical lighting power, ventilation rate and solar shading position. Building model inputs are annual climate files, occupation patterns and window properties. Outputs are comfort and energy use. The comfort depends on the indoor temperature, the (day)light properties in the room and the indoor air quality. The controller will be optimised toward maximum comfort and minimal energy requirements.

2.1 Indoor air quality

Three different contaminant sources affecting the indoor air quality can be distinguished: (1) People, producing CO_2 and other bio-effluents. CO_2 can be used as an indicator for bio-effluents produced by people. The production rate depends on the number and activity level of the occupants (Bearg, 1993). (2) The interior (e.g. furniture, carpets) produce VOC's (volatile organic compounds). The production rate depends on the temperature, but is highly depending on the specific furniture, carpet etc. VOC's can be measured using VOC sensors (Bearg, 1993). (3) Activities, such as smoking cause unpredictable and difficult to measure contamination (many possible substances). A practical solution is to control the ventilation based on the measured CO_2 levels.

The outdoor CO_2 concentration and CO_2 generation rates per person in office buildings can be assumed constant (Bearg, 1993). The incoming air is assumed to mix sufficiently with the internal air to take the concentration as an internal state. The model used for the indoor CO_2 concentration becomes:

$$CO_2(t) = \frac{1}{\text{Veff}} \int (occupancy(t) \cdot CO_2 gen.rate + airflow(t) \cdot (CO_2 out - CO_2(t))dt$$

Here *Veff* is the effective volume of the room (room volume - furniture volume), *CO_2 gen.rate* the CO_2 generation rate, *CO_2out* the outdoor CO_2 concentration. If the airflow is assumed constant for a period of time, the following Laplace linear function applies :

$$CO_2(s) = \frac{occupancy(s) \cdot CO_2 gen.rate + airflow \cdot CO_2 out}{Veff \cdot s + airflow}$$

The time-constant τ = Veff / airflow. That is, for a room of 70 m^3 and a maximum airflow of 0.2 m^3/s (approx. 10 ACH), the minimum-time-constant τ is 350 sec.

2.2 Indoor temperature

The building model includes a second-order dynamic model (figure 3). The total heat gain Q in the room due to heating and solar transmittance can be added, having solely a direct effect on the air and the inner parts of the wall (Madsen, et al., 1995). In addition, the heat flows due to occupancy, ventilation and electrical lighting can be added to the total heat gain.

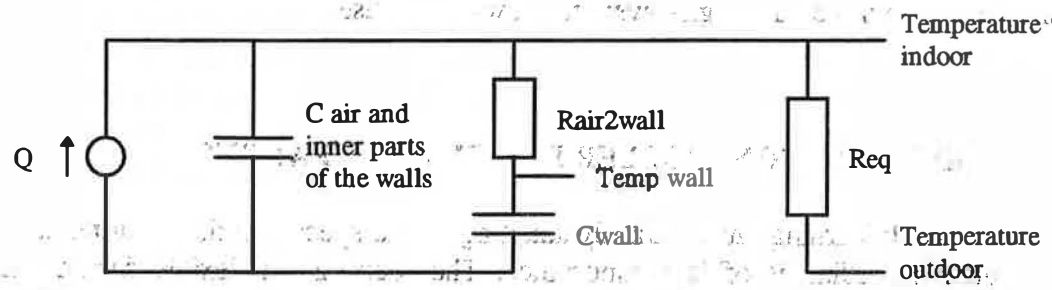

Figure 3: Building model.

The model (figure 3) contains two time constants (typical example τ_1 = 26 min and τ_2 = 154h). The response-time decreases substantially if ventilation is included (see response speed CO_2 model). Inclusion of ventilation also introduces strong non-linear effects.

The total solar transmittance through the window(s) is computed using hourly climate data and the solar angle dependent solar transmittance, computed using the Advanced Windows Information System WIS (Bakker, et al., 1996). The occupation is generated with standard weekly patterns with random variation.

2.3 Daylight

The daylight is also modelled based on the climate data, the solar azimuth and altitude. With WIS (Bakker, et al., 1996), the angle dependent visual transmittance is computed. The possible diffuse fraction is assumed angle independent. The pre-processed luminance's and illuminaces of the separate, 100% dimmable electrical lighting systems is superposed to the solar visual transmittance. A combination of electrical light and daylight is computed resulting in a minimal desk Illuminace of e.g. 500 Lux, maximum luminance ratios between window, table and back of the room and minimum electrical energy for lighting. In addition, for the non-occupied state, the shading is controlled to save heating or cooling energy.

3. INTEGRATED CONTROLLER PERFORMANCE INDICATION

To optimise or self-adapt the controller's performance, the quality of the controller is expressed in an overall cost function. The cost function expresses the energy use and relevant discomfort aspects. The cost functions for these aspects are added with different weights to obtain one number indicating the controllers performance, enabling optimisation of integrated control.

$$J = \int (W_1 \cdot U + W_2 \cdot f_1(T) + W_3 \cdot f_2(CO_2, VOC) + W_4 \cdot f_3(light)) \cdot dt$$

Here W_i are the weights, U is the used energy, $f_1(T)$ is the cost function for the temperature, $f_2(CO_2,VOC)$ is the cost function for the air quality and $f_3(light)$ is the cost function for light. The function is integrated in time. The weights of comfort will be zero if the room is in the non-occupied state and no occupation is predicted. A minimum temperature can be given to the cost function to ensure minimum temperature e.g. before entering, also depending on the predicted occupation schema.

The sensor costs for the measurement of the most important air contamination in offices, CO_2 are relatively expensive (approx. 500 - 1500 ECU) but are expected to decrease rapidly in prise (Jones, et al., 1997). The most often used cost function for CO_2 concentration is a step-function at e.g. 800 PPM. VOC and other contamination's mainly from the interior are a problem if the building is not ventilated for a longer time. This can be avoided by ventilating before people enter the room, if low ventilation rates are used during the night. The user must always be able to adapt the ventilation rate because of the unpredictable and unmeasured contamination.
To avoid sick building effects and oscillations, the user should observe that the system reacts directly also for ventilation control.

Usually more complicated expressions are used to qualify the discomfort for variations in temperature (e.g. Predicted Mean Vote-PMV. (Fanger 1970, ISO 7730 1994)). If an adaptive system is utilised, a less complicated expression is required to satisfy the users preferences, using for instance a quadratic cost function.

User requirements can change rapidly. This must result in an adaptation of the cost function. It is important that the controller reacts fast to these adaptations. The user interface is also very important and should be extremely user friendly and simple.

4. CONTROLLER STRUCTURE

Figure 4 shows the controller's structure determining the best airflow rate of the ventilation, the cooling and heating power and the position of the blinds. Adequate interfaces to interface the controller with local controllers are required and are not shown here.
The 'adaptive building model' (see figure 4) will predict the indoor temperature, IAQ, the lighting and the energy use that will occur after a set of control actions. The 'cost function'

determines the quality of the predicted control actions to be optimised. The 'cost function' adapts to the user demands communicated by the 'user interface'. The 'search engine and the action generator' searches for the future control action path with the best (lowest) cost function. Many control action paths are tested along a search path. The best found control action path will be executed to control 'the real building'. For the next control step the controller searches the best control path for the current situation using the 'search engine' etc.

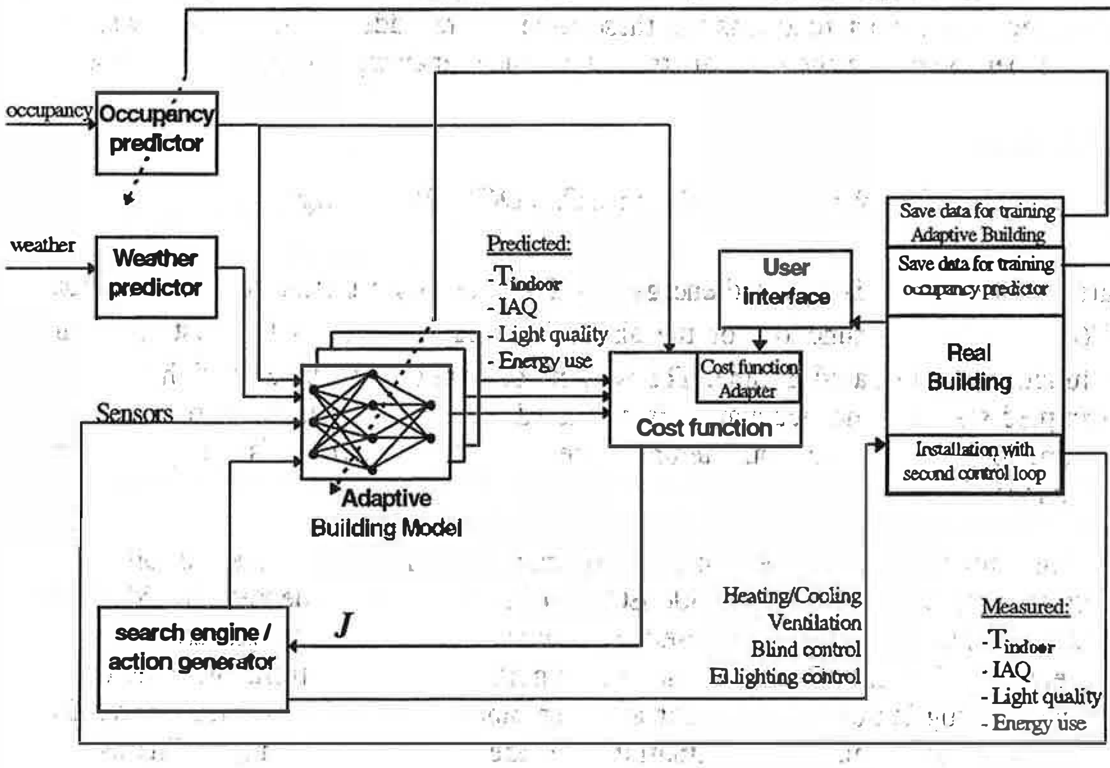

***Figure 4:** Controller objects and structure.*

For the prediction of the building behaviour, a weather prediction block is utilised. To calculate the cost function for a control action path, the occupancy of the room has to be predicted. This can be done with a neural network like in Hittle et al., 1996. It is also possible to use the weather of the day before (Ferguson, 1990) and a fixed pattern for the occupancy (e.g. working days from 8:00 till 18:00) to simplify the predictions.

If the occupancy prediction is fixed pattern, it must be trained using some measured data of occupation. Also the 'adaptive building model' must be trained with data from the 'real building' or real building model to enable to use this controller in several different buildings and to adapt to changing situations in the building where the controller is installed.

The main drawback of this model based predictive controller is the large size of the search space for the 'search engine and action generator' due to the many possible control actions. At present, possibilities are explored to use approximate feedback linearization, linearizing the internal model. Utilising linearized models, well-known and relatively fast optimisation techniques are feasible (e.g. quadratic programming).

5. FUTURE WORK

The performance of the controller can be firstly evaluated with the building model, but later it must also be tested in a real building. As the simplified model can affect the performance of the controller, it should be evaluated against real buildings.
The design of the user interface is extremely important for the acceptance by occupants, and for adequate feedback from the occupant enabling adequate adaptation to the particular situation (building type, orientation, country, climate).

6. CONCLUSION

Model based predictive control seems to be an adequate approach to realise an integrated, predictive, adaptive controller able to handle the model complexity (non-linearity) and multivariable systems.

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