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Knowledge-Based versus Classical Control for Solar-Building Designs

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ABSTRACT

The present paper compares classical control systems with knowledge-based systems in the control of building designs to achieved comfort conditions. Initially the goal has been the minimization of energy usage. For this target, thermostats and PID controllers have been employed. Adaptive and ad hoc *first-generation controller implemented for the improvement of specific problems are described next. The achievement of thermal and visual comfort conditions within living and working space fits the application of fuzzy logic expert systems. The structure of a fuzzy control system is described. This paper also discusses the capabilities of the fuzzy logic expert system in the achievement of optimal resource management in passive-building designs.*

1 INTRODUCTION

Solar-building designs traditionally need the implementation of some kind of controller to ensure internal conditions approaching those intended. These controllers have the task of regulating the climate by using whatever sub-system is available and controllable, i.e. curtains, blinds, ventilation, auxiliary heating and cooling, etc. Initially the goal has been the minimization of energy usage, and simple systems like thermostats have been employed.[1,2] Subsequently more complicated tasks have been targeted, namely the achievement of thermal and visual comfort conditions within the living and working space.

As the systems grew more complicated, by adding more thermal subsystems, so the demands put on the controller rose. Consequently new techniques have been empoyed. Optimal and adaptive controllers have been applied.[3–13] Another suggested approach is the use of *ad hoc* controllers, targeted mainly at the goal of managing the available sub-systems properly, rather than minimizing the usage of auxiliary energy. These employed simple algorithms in which a degree of expertise and decision-making capabilities have been built in.[14–16] Finally advances in both hardware and software technology have made the use of knowledge-based systems feasible.[17–18] Only the latter are capable of handling fuzzy requirements, like 'comfort', particularly when coupled with the human perception of comfort.[19–22]

The present paper aims to compare these basic approaches and their assessment in the achievement of 'optimal' resource management in solar-building designs.

2 THERMOSTATS AND PID CONTROLLERS

Temperature regulation is the oldest and simplest means of improving our comfort. Thermostatic control aims at the regulation of temperature by auxiliary heating or cooling. Thermostats offer closed-loop control of a single device, i.e. either heater or cooler (Fig. 1). This type of controller achieves only two states, ON/OFF, which are fairly rapidly cycled. The cycling rate can be reduced by introducing a dead band, which has the

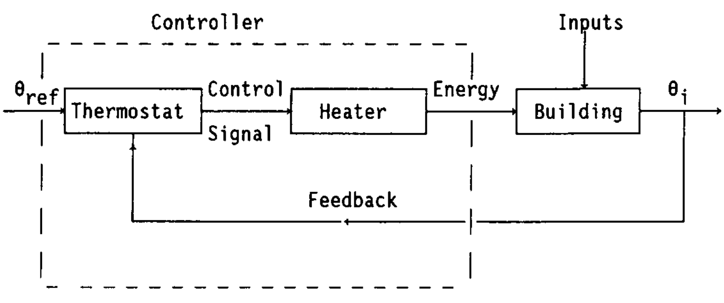

Fig. 1. Bang-bang control of a single device (θ_{ref}, desired temperature; θ_i, indoor temperature).

side-effect of increasing the temperature oscillation amplitude. In this way, temperature overshoot is likely to occur, particularly in large thermal-inertia buildings, which in turn leads to a waste of auxiliary energy.[1,2]

To reduce this problem, proportional integral differential (PID) controllers have been employed. These control auxiliary heating or cooling too, but implement an integral and a differential term, which, if they are tuned properly, reduce overshooting and temperature oscillations considerably. PID controllers are governed by the following expression:

$$u = K_{\mathrm{p}}(\theta_{\mathrm{i}} - \theta_{\mathrm{ref}}) + K_{\mathrm{I}} \int_{t_0}^{t} (\theta_{\mathrm{i}} - \theta_{\mathrm{ref}})\, \mathrm{d}t + K_{\mathrm{D}}\, \mathrm{d}/\mathrm{d}t\, (T_{\mathrm{i}} - \theta_{\mathrm{ref}})$$

The PID controllers achieve the above result at a penalty. If their gains are improperly set, instability might occur, i.e. near optimal conditions are never met, but the temperature oscillates uncontrollably between the maximum limits set by the building dynamics and the auxiliary heater/ cooler characteristics.

3 OPTIMAL AND *AD HOC* CONTROLLERS

Optimal controllers have been introduced to replace dead band thermostatic control with an optimal linear regulator scheme.[2] The improvement stems from the fact that optimal regulators process a much more accurate methematical description of the building dynamics. Although an exact building dynamics description is very difficult and leads to complicated mathematical expressions, simplified modelling is still better than no modelling, as is the case with dead band controllers. In addition optimal controllers using weather prediction algorithms and minimization criteria have been developed.[5,13] Optimal controllers need a simplified-state dynamic model for the behaviour of the building, of the following form:

$$\dot{X} = AX + BU + EW$$
$$Y = CX$$

This is the classical linear system-state space-description with external input and measurements. Matrices A, B, C, E are usually defined by employing identification techniques and are unique for each building. Vectors, X, U, W, Y are the internal system state (e.g. temperature), the control input, the random disturbance and the measured variable, respectively.

Predictive control offers in addition a system-input prediction, e.g. solar radiation prediction.[10] This knowledge can be used to modify the control decisions. Basic predictions are expressed as simplified adaptive models, or as tabulated values. In addition, other information, such as control input restrictions, can all be combined to achieve a scheme capable of controlling the present system state and calculating the effect of certain actions in the future.

All control strategies in the optimal controller approach, aim at the reduction of a mathematical index, i.e. the criterion. Following Pontryagin and classical optimal control theory, the performance index is described in the form

$$J = \int_0^T E_1(t)[\theta_i(t) - \theta_{\mathrm{ref}}]^2 \, \mathrm{d}t + K \int_0^T E_2(t) U(t) \, \mathrm{d}t$$

Improvement of the value of this performance index results from the reduction of auxiliary energy usage.[4,23] The minimization of the performance index leads to the determination of an acceptable control law.[11,12]

The performance index function has two terms: the first expresses the departure of the internal temperature from the set point; the second expresses the usage of auxiliary energy. It should be noted that, in a rather abstract way, the minimization of the performance index criterion trades off temperature departures from the set point with the usage of auxiliary energy. This is the actual role of weight factors *E1*, *E2* and *K*; *K* is actually a normalization factor. In the case where the control input is not singular, i.e. vector U is of dimension 2, then bilinear control results. For example, such a case arises if a curtain is used in addition to auxiliary heating/cooling. In all cases, the optimal control law is calculated by applying the Pontryagin maximum principle, which is widely used in optimal control theory and has been applied for the control of thermal systems.[2,4,6,7]

A problem in the whole process is that the mathematical models are unique to the particular building. To overcome this problem, real-time parameter identification techniques have been applied.[9,24] These have finally evolved into the application of even more complicated techniques, like adaptive modelling,[8] which offer in several situations considerable improvements over the classical linear optimal controllers. These techniques have been coupled with others, such as weather prediction, aimed at integrated control of all available actuators like shading, ventilation as well as auxiliary heating and cooling.

The passive-building control system of TU Delft (Delft University of Technology) and the control system of CSTB-EMP (Centre Acientifique et Technique du Batiment, Ecole des Mines de Paris) utilize weather-prediction models to estimate solar radiation, external temperature and wind speed from available measurements. Solar radiation on a horizontal plane can be approximated by a sinusoidal function of the sun's elevation, with amplitude I_{max}:

$$I_{tot}(k + k_1) = I_{max} \sin (\beta(k + k_1))$$

where I_{max} is a function of average solar radiation, k_1 is the prediction interval and β is the sunshine duration. An ARMA model is used for the prediction of the external temperature using I_{tot} as an input signal:

$$\begin{aligned}\theta_0(k) = a_0 + a_1\theta_0(k - d_1) + \cdots + a_m\theta_0(k - d_m) \\ + b_0 I_{tot}(k) + \cdots + b_n I_{tot}(k - n) \\ + d_0 e(k) + \cdots + d_n(k - n)\end{aligned}$$

where $d_i = 1 + N_i$ with $i = 0, 1, 2, 3 \ldots$ and N = number of time steps. The $e(k)$ is the prediction estimator, taken as the difference between the predicted value at time $k + 1$ and the measured value at time k. Wind speed is predicted using an AR model:

$$\begin{aligned}V_w(k) = a_0 + a_1 V_w(k - 1) + \cdots + a_n V_w(k - n) \\ + e(k) + d_1 e(k - 1) + \cdots + d_m e(k - m)\end{aligned}$$

The state of the art in optimal controller design is described in Refs 8, 9 and 11 and is the result of a CEC-sponsored PASTOR project. The systems developed can handle passive solar gains, natural or forced ventilation, auxiliary heating and cooling and lighting. The Passive Building Control System of TU Delft and the Control System of CSTB-EMP use a data-acquisition system from local controllers (TU Delft) and from meteorological stations, an adaptive controlled room model and a weather-prediction algorithm. Control is split into two levels. The first caters for optimisation and energy management. The second comprises all local controllers for each separate space (Fig. 2). The activation of the suitable lower-level controller is the result of a cost minimization function at the higher level. The following criterion is minimised:

$$J = [\theta_i(k + 1|k) - \theta_{ref}(k + 1)]^2 + ru^2(k)$$

where θ_i is the internal temperature, θ_{ref} is the reference point, and r is the weight factor for u.

The CSTB-EMP system utilises a single control-level with a weather prediction for the optimisation of solar gain systems (including shading controls) and auxiliary heaters. The Pontryagin minimum principle is applied in order to calculate the optimal control strategy.

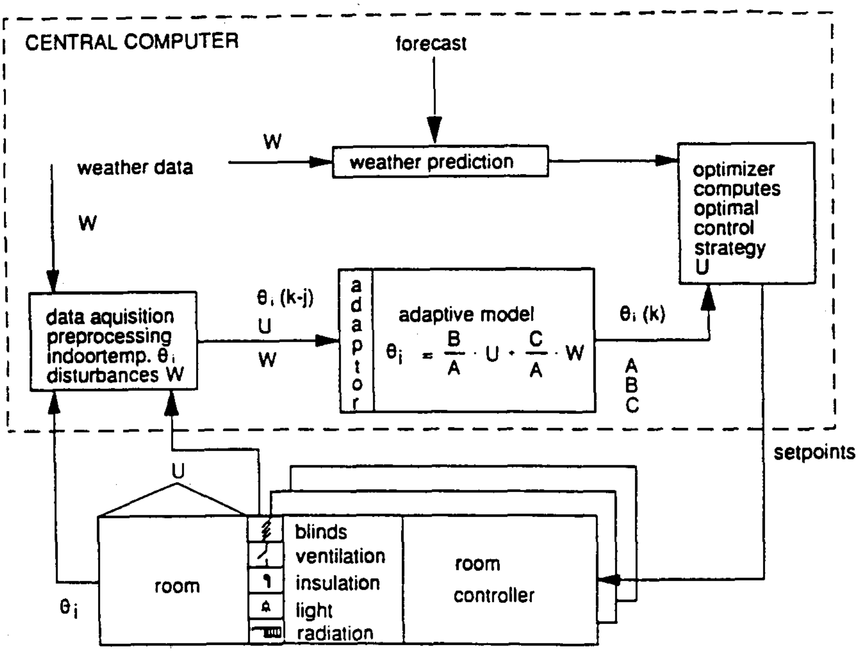

Fig. 2. General structure of the passive-building control system.[8]

Other characteristics of these systems are: (a) They use parameter-identification techniques, otherwise the systems developed could be applied only to the specific building for which they are tuned. (b) They use the 'discomfort parameter' to represent thermal comfort. Also the glare index DGI is not used to regulate visual comfort, although lighting and contrast are controlled. (c) The CSTB-EMP system consists of two temperature-regulators, operating at the same priority level; the first utilising auxiliary heating and the second ventilation. Instability may occur by the interaction of these systems, so that their set points must be set sufficiently apart.

Another system is the NAPAC-Armines (Centre d'Energique) system, described in Ref. 11. The system controls shading, auxiliary heating and ventilation. It does not use weather prediction but employs system parameter identification. The the applicable control strategy is defined by logic diagrams.

All the systems described above, either ignore thermal comfort completely, or use the term 'discomfort parameter' to estimate thermal comfort in the controlled space. The 'discomfort parameter' is defined as the weighted number of hours that the indoor temperature exceeds θ_{ref}:

$$\sum(\theta_i - \theta_{ref})n_h(°\text{Ch})$$

This is however a very limited interpretation of the thermal comfort concept, restricting it to some form of prolonged overheating. A wider-scope definition involves the thermal comfort index, defined by Fanger.[25] This index, however, involves fuzzy variables and is not suitable for handling by classical optimal-control techniques.

The practical operation of the above system has shown two major results. (a) During summer, there is no significant improvement obtained by using the advanced optimal-control systems. The simple rule 'building cooling occurs by natural ventilation if the internal temperature rises above 22°C' gives results as satisfactory as those from the advanced control system. (b) During winter, the advanced control system achieves 20% energy savings. It should be noted that the above schemes are designed and tested on fairly simple building constructions) e.g. a single room. Their adaptation for handling a more complicated building, like an office building, is not trivial and will probably require considerable effort and tuning.

Although the above techniques have improved the actual controllability of the system, they still do not overcome the set point departure/energy usage trade-off abstraction, the building modelling problems and the system operation in a manner totally unfamiliar to the user. Consequently the control laws achieved are sub-optimal in practice and can be surpassed by other heuristic, but simpler, algorithms. This has led to the development of *ad hoc* controllers, whose main target is the management of the actuators of a building in a logical and clear fashion, rather than minimizing an abstract mathematical index, as optimal controllers do.

Ad hoc controllers

These use simple algorithms, which are easily implemented using limited-memory single-chip computers. Temperature and other parameters are measured, namely humidity, both inside and outside of the controlled building. If other components are used, like thermal stores, solar collectors etc, their conditions are also monitored. The algorithm aims always to switch ON and OFF the various sub-systems in a logical and clearly understood manner. For example, if overheating is detected, then the auxiliary heater is switched OFF first, ventilation is employed as the next logical step and the ventilation switched OFF and cooling is employed as the final measure. Several of these algorithms can be stored in a fairly low-capacity memory and be implemented according to conditions in the field. In this way, no building models are required. However, the proper management of all thermal sub-systems results in near-optimal control, often more efficient than the optimal-control strategies obtained from theoretically optimal controllers.[15,16,26] *Ad hoc* controllers, due to their algorithmic nature are incapable of handling fuzzy requirements, such as comfort conditions. These need the use of more sophisticated techniques, such as the application of expert-system techniques. The implementation of logic rules in a systematic way enables the construction of more complicated algorithms than the heuristic ones implemented in *ad hoc* controllers. These are then capable of handling more complicated concepts like human comfort. On the other hand, rapid advances in hardware and software technology have increased the capabilities of microcomputer controllers considerably over the last decade. Consequently the application of expert-system techniques is economically quite feasible.

4 EXPERT SYSTEMS IN BUILDINGS

Several expert systems or knowledge-based systems (KBSs) have been developed and realised in buildings or HVAC systems.[18] Their main goals are: (a) system-state monitoring, i.e. the deduction of system state from measured quantities; (b) diagnostics, i.e. for solar radiation from available measurements and other system input, such as technician observations, and (c) design, i.e. building designer assistance to achieve stated goals. Application programs exists for fault diagnoses of several HVAC components, HVAC component selection for new designs and for energy-resource management.[3]

All KBSs used for diagnostics comprise two major subsystems: a knowledge base and an inference engine.[17] The knowledge base consists of a rule set of IF–THEN type, such as the following:

IF symptom is too-hot
    and
  thermostat-set point is correct
    and
  air-flow is good
    and
  air-flow temperature is cold
THEN the general cause is
  cooling-load size is too small (cf. 80)

The rule incorporates parameters (e.g. symptom and thermostat set-point) and values (e.g. too hot). A general cause parameter, set by application of the rule, reflects whether all rule conditions are met. The 'cf. 80' term is an uncertainty factor, reflecting the fact that even if all rule conditions are met there is only an 80% certainty that this is actually so. This uncertainty factor is introduced to allow classic KBSs to handle uncertain situations. A much more structured approach is offered by fuzzy logic expert systems, as is described later in this paper: it is designed to handle certainty factors, fuzzy variables, describe hypotheses uncertainty and obtain uncertain conclusions.

5 FUZZY LOGIC EXPERT SYSTEMS IN BUILDINGS

The above analysis shows that the development of a universal control system, without specific building models, is required. This system must have decision-making capabilities in a fuzzy environment to manage the resources, particularly in a random-input environment e.g. in cloudy weather conditions. Another important issue is the participation of the user in the determination of the environmental conditions. A fuzzy conditions problem is created because of the subjectivity of the target environmental conditions and, consequently, the use of fuzzy logic fits naturally into the problem.

Recently, the implementation of fuzzy control for an air-conditioning system has been presented. This system has two controlled variables (indoor temperature and relative humidity) and three controlling elements (cooling, heating and humidifying valves). Although the system works satisfactorily, it does not utilise the thermal-comfort concept.[29]

Fuzzy rule-based supervisors for self-tuning controllers, based on the well known generalized predictive control algorithm for HVAC applications, have also been developed. This system improves the stability and the performance of the classical controller, showing that at the decision-making level, the adaptive control schemes are rather limited.[27]

An integrated fuzzy expert system for a passive building is described in Ref. 22. This system incorporates thermal and visual comfort and can handle passive solar gains, natural or mechanical ventilation, lighting, auxiliary heating and cooling. The system developed implements a set of fuzzy rules expressing the control strategies applied in all foreseeable conditions. The fuzzy logic expert system consists actually of two, interacting, fuzzy sub-systems. The first fuzzy sub-system is used for the thermal comfort and the second is used for visual-comfort condition.[19–21] The fuzzy logic system handles naturally the user-defined comfort-level requirements, although these are usually rather vaguely defined. The expert system inputs are the PMV index, outdoor temperature, illumination and daylight-glare index. The outputs are the auxiliary heater, the cooler, ventilation window angle, shading and artificial-lighting actuator signals,

Fig. 3. Functional blocks for the fuzzy control-system.

driving the physical process actuators. The outdoor temperature is used as the input because it affects natural ventilation and PMV.

The advantages of the proposed system are the following:

(a) The system achieves integrated control for passive solar buildings.
(b) High-level control variable (PMV) is used for comfort control, instead of indoor temperature used by classical systems for energy saving.
(c) The energy consumption is within acceptable limits.
(d) The user participated in the formulation of the comfort conditions.
(e) Thermal and visual comfort are achieved simultaneously.
(f) The fuzzy system can be used for any building at no additional cost.
(g) The PMV control results in keeping the indoor temperature and the relative humidity within the ASHRAE comfort zones.

The fuzzy-system architecture

The fuzzy system consists of three functional blocks. Fuzzification (FF), inference engine (IE) and defuzzification (DF) (see Fig. 3).

The decisions on the precise quantization levels and the shapes of the membership functions are largely *ad hoc* and based on the nature of the fuzzy control variables. In this system, the membership functions of the fuzzy variables are triangular shapes, except for the comfort zone, where the PMV membership function has a trapezoidal shape.

The fuzzification block maps a real signal into the appropriate fuzzy set. Because the system is a multi-variable complex fuzzy system, the inference method used is based on the decomposition of multi-variable control rules.[28] The last functional block is a defuzzifying process, required to produce crisp actuator signals from their fuzzy counterparts. This is essentially the reverse operation of the fuzzifying process and uses the center of area method (COA).[14]

6 CONCLUSIONS

The present paper presents techniques used for the achievement of thermal comfort in buildings. The two main approaches are adaptive control and the implementation of expert-system techniques. Adaptive control in most cases interprets comfort in a rather limited manner, whereas expert-system techniques focus on the use of fuzzy reasoning. A fuzzy description of comfort conditions fits naturally into the problem. This makes it necessity to use a fuzzy logic expert system with a fuzzy rule data-base, a fuzzy logic inference engine and fuzzification and defuzzification interfaces. Although energy consumption may not be optimal, it is shown that it is satisfactory. The concept of the fuzzy logic expert system is easily expandable to more complicated buildings. Finally, a possible fusion of the two major approaches is the splitting of the control requirements in logical levels, the lower ones catered for by fuzzy expert systems. In other words the higher levels, where single-resource management ensues will implement local adaptive-controllers. The techniques presented here may well be implemented in other similar systems like greenhouses and may be easily extended in fairly complex thermal-systems as occur in centrally heated villages.

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