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Intelligence in buildings: the potential of advanced modelling

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Abstract

''Intelligence'' in buildings usually implies facilities management via building automation systems (BAS). However, present-day commercial BAS adopt a rudimentary approach to data handling, control and fault detection, and there is much scope for improvement. This paper describes a model-based technique for raising the level of sophistication at which BAS currently operate. Using stochastic multivariable identification, models are derived which describe the behaviour of air temperature and relative humidity in a full-scale office zone equipped with a dedicated heating, ventilating and air-conditioning (HVAC) plant. The models are of good quality, giving prediction accuracies of $\pm 0.25\,^{\circ}$C in $19.2\,^{\circ}$C and of $\pm 0.6\%$ rh in 53% rh when forecasting up to 15 minutes ahead. For forecasts up to 3 days ahead, accuracies are $\pm 0.65\,^{\circ}$C and $\pm 1.25\%$ rh, respectively.

The utility of the models for facilities management is investigated. The ''temperature model'' was employed within a predictive on/off control strategy for the office zone, and was shown to substantially improve temperature regulation and to reduce energy consumption in comparison with conventional on/off control. Comparison of prediction accuracies for two different situations, that is, the office with and without furniture plus carpet, showed that some level of furnishing is essential during the commissioning phase if model-based control of relative humidity is contemplated.

The prospects are assessed for wide-scale replication of the model-based technique, and it is shown that deterministic simulation has potential to be used as a means of initialising a model structure and hence of selecting the sensors for a BAS for any building at the design stage. It is concluded that advanced model-based methods offer significant promise for improving BAS performance, and that proving trials in full-scale everyday situations are now needed prior to commercial development and installation. © 1997 Elsevier Science B.V.

Keywords: Facilities management; Building automation systems; Intelligent buildings; Stochastic modelling; Building simulation

1. Introduction

What are intelligent buildings? Atkin [1] stated that an intelligent building is one which ''knows'' what is happening inside and immediately outside, one which ''decides'' the most efficient way to provide an appropriate environment for its occupants, and one which responds quickly to occupants' requests. In terms of technology, intelligence in buildings is usually associated with some form of automated management system which is responsible for data gathering, decision-making and implementation. Such systems have come to be known as ''building energy management systems'' (BEMS) or ''building automation systems'' (BAS), employing digital technology to carry out the required functions. Their use proliferated throughout the 1980s, going

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hand-in-hand with the decreasing costs of microprocessors, to the extent that today they are a standard feature of many non-domestic premises. They offer the facility to monitor and to control a range of building functions, which include temperature, humidity, lighting, fire detection and security, whilst at the same time providing fault detection and alarm signalling facilities.

Just how "intelligent" are today's BAS? The answer is "not very". Intelligence in a BAS could be regarded as residing within the software used for making decisions about the actions that would be appropriate in particular situations. At present the data received from sensors and used for making these decisions are processed in a fairly rudimentary manner, frequently taking the form of simple trend plots, for example, or detecting faults merely by sending an alarm if a sensor value falls outside some expected range. The control functions that are currently employed usually consist of either on/off, or proportional, integral and derivative (PID) control methods; these are classical techniques which have been in use for many years—the only difference is that today they are implemented digitally as opposed to their former implementation in analogue format. Optimum start/stop control does represent an innovation, but there remains some considerable way to go in terms of sophistication. Thus, while performances of existing sytems might be considered by many to be adequate, there is definitely scope for improvement.

1.1. Model-based methods

In what way can improvements be made? It is certainly possible to enhance the present level of intelligence by adopting more advanced methods for treating the data which are collected by all BAS. One way would be to use model-based methods. Here, a mathematical model which describes some aspect of the building behaviour is used to forecast expected performance; this differs from the current practice of simply recording, or acting upon, instantaneously sensed information. Such models can be used in a variety of ways, such as within a fault detection strategy [2]: if the model-predicted performance and the actual performance of a building system begin to diverge beyond some statistically significant difference, then it is probable that a fault exists.

Model-based methods can also be used to control buildings and heating, ventilating and air-conditioning (HVAC) systems and there have been a number of studies in this area [3–8]. These studies have shown, mainly through simulation, that this form of advanced control is feasible. Predictive control is an example of a model-based method in which corrective action is based upon values forecasted by a model as opposed to using instantaneously measured values from the system. In this way, it is possible to reduce overshoots and undershoots about a set point, giving improved performance and the potential for energy savings. Laboratory-scale experiments have shown [9] that energy savings of 11% are possible as a result of using one form of model-based predictive control compared with the use of conventional control.

When considering model-based techniques, an important consideration is the type of model that should be employed. Often, deterministic models are used in which it is assumed that the output can be predicted exactly from a set of inputs; such models take no account of any random influences that might affect a given system. These models can be based on thermophysical properties of the building and/or HVAC plant, employing steady-state or dynamic analyses [10,11]. In practice, buildings are subject to a variety of random influences such as climatic disturbances, infiltration fluctuations, variations in occupancy pattern and appliance usage. It would seem plausible that for a BAS to operate more effectively, a probabilistic framework should be adopted for formulating the models. Stochastic models [12,13] lie within this framework, being able to handle such random influences in a convenient and compact format, and thus offer a particularly appropriate means for describing the behaviour of buildings [14].

What are the views of the BAS manufacturers towards advanced techniques of the type described? While the general consensus amongst researchers appears to be favourable, in that the advanced methods are feasible and offer potential benefits for control and other applications, there remains some scepticism amongst commercial manufacturers. This is because studies to date have been largely academic, having either a basis in simulation or appearing to be some distance removed from practical application and commercial exploitation. The argument for the advanced methods clearly needs the support that practical larger-scale demonstration can offer. Further to this, the industry needs to know whether the solutions can be easily "mapped" on to existing BAS hardware, or whether significant modifications would be necessary (the latter posing an economic hurdle to be negotiated) before widespread commercial use is possible. Finally, the question of the generality of the solutions needs to be addressed. By this we mean that the methodology must be repeatable in its application to a wide range of buildings, and must be capable of becoming a standard feature of the design process.

1.2. Objectives

The overall aim of our paper is to present the case for these advanced techniques by demonstrating their potential through practical application. In this way, it is hoped that BAS manufacturers will be convinced of this potential and will give serious consideration towards enhancing collaboration with researchers in developing this technology. In addressing the above issues, and for the purpose of this paper, we will concentrate upon the modelling and control aspects, and in particular will extend the existing work of the authors by discussing a method upon which widespread replication might be based.

Our studies are based upon practical measurements from a full-scale office zone and dedicated HVAC plant, and the specific objectives of the work are as follows.
1. To demonstrate that good-quality stochastic models which describe full-scale building zone behaviour are obtainable.
2. To show that such models can be used to improve control performance, can lead to energy savings, and can provide a deeper insight into the behaviour of building systems (specifically the effects of furnishings).
3. To show that thermophysical simulation may offer a means for selecting the sensors needed to obtain the data for modelling, and hence could lead to a general methodology which can be applied to all buildings.

We commence our discussion with a description of the test system.

2. Test system

The system employed in the study is based at Loughborough University, and consists of a test room 5.40 m in length, 3.25 m in width and 3.00 m in height. Three of its four walls are of lightweight material, partitioning it from a surrounding laboratory, whilst the fourth wall is of twin-leaf brickwork exposed to the external environment. This external wall faces south-west, and contains a double-glazed window 1.90 m wide and 1.45 m high. The floor of the room is of concrete and comprises part of the standard floor structure of the laboratory; beneath the floor is another laboratory. The ceiling is of lightweight construction, above which is the general laboratory environment. The room is representative of an "office zone" within a commercial premises in that three of its walls, its floor and its ceiling adjoin internal environments at a similar temperature to the test room, with the "heavyweight" wall being subjected to climatic influences. Initially the office zone was devoid of carpet and furniture; at a later stage the zone was carpeted and furnished to determine the effect on system behaviour. The office zone is served by a dedicated direct-expansion HVAC plant which provides heating, cooling and humidification to maintain the room conditions at the required levels. Sensors and actuators sited within the plant and office are interfaced to a digital computer via 12-bit analogue-to-digital and digital-to-analogue converters, permitting data logging together with direct digital control of the office environment, exactly as in a BAS. By utilising appropriate software, it is possible to operate the system such that data are generated about plant and zone performance, the data being used for developing a mathematical model which describes the system behaviour; the model can then be used as part of an advanced model-based control strategy. Both conventional and model-based control methods can be implemented via the digital computer to regulate the office zone conditions. Fig. 1 illustrates the office zone and HVAC plant and shows the arrangement of the sensors. Full details

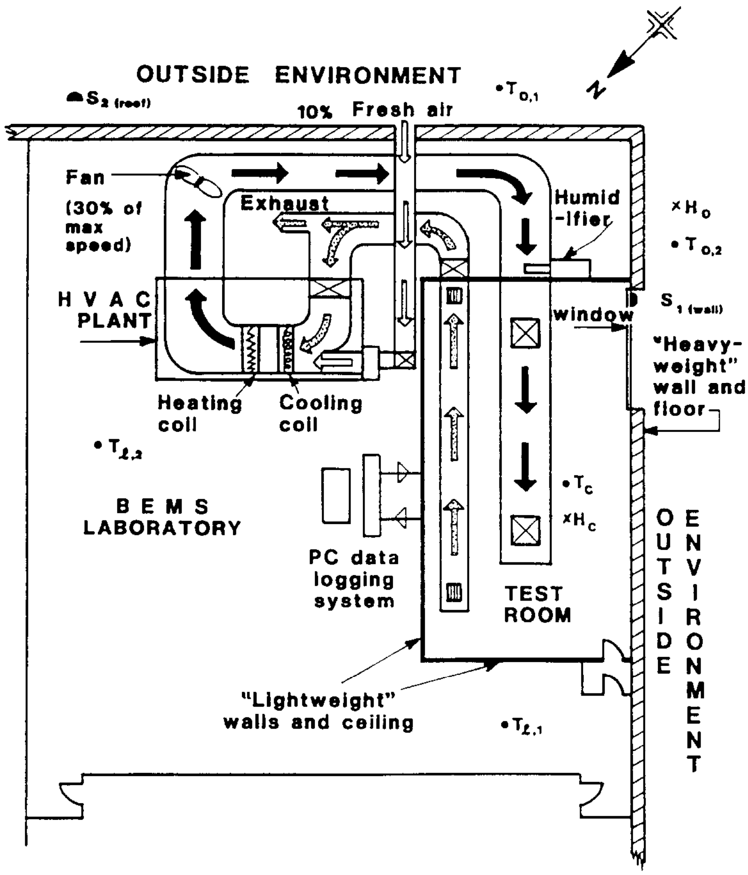


Fig. 1. Office zone test system and position of sensors.

regarding the test system and instrumentation may be found in [9].

3. Modelling and validation

3.1. Modelling technique

The test system is subject to stochastic disturbances brought about by the external climate, consisting chiefly of variations in outdoor temperature, solar irradiance and infiltration; occupancy-induced disturbances were absent in this system. The office and plant were thus modelled as a 3-input/2-output system in the presence of climatic disturbances (Fig. 2). The inputs are the heating, cooling and humidification powers, and the outputs are the office air temperature and relative humidity. System identification [13,15] was used to obtain a mathematical model from the input/output data. The technique is complex, and its application to the test system has been fully described elsewhere [16]. However, for convenience, a brief summary of the procedure is presented here.

Various system trials are needed in order that the collected data contain sufficient information to produce an accurate model; to do this, it is necessary to "excite" the system across its full operating range. The trials include the following operations.

1. Single input step response tests; these provide fundamental information about the system, such as the dominant relationships between inputs and outputs, dominant time constants and system delay times.

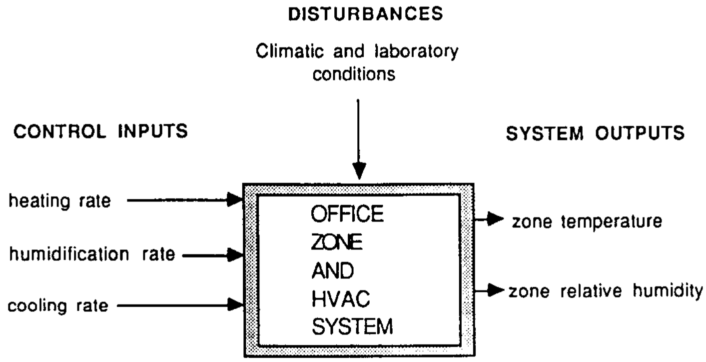


Fig. 2. Block diagram of office zone system.

2. Single input pseudo-random binary sequence (PRBS) response tests; these excite individual inputs through their full range of frequencies so that all resulting system modes contribute to the data collected. The data obtained can then be used to yield a model structure; hence, the number of parameters in each term needed to categorise a particular system can be established.
3. Multivariable PRBS trials; here, all inputs are driven simultaneously in order that the cross-coupling and interaction effects between different loops can be obtained and hence a multivariable model deduced.
4. Modelling; using the model structure from 2, the full multivariable model can be derived by performing a least-squares minimisation.
5. Model validation; using further data from trials, the model is validated by comparing actual measurements with model predictions.

For the office zone and associated HVAC plant, the application of the above procedure gives the following normalised model for describing the temperature behaviour inside the office zone:

$$\begin{aligned} T_c(t) = {} & (1.61z^{-1} - 0.64z^{-2} + 0.02z^{-3})T_c(t) \\ & + (0.004z^{-1} - 0.006z^{-2})H_c(t) \\ & + (0.22z^{-1} + 0.07z^{-2} - 0.26z^{-3})W(t) \\ & + (-0.62z^{-1} + 0.36z^{-2} + 0.19z^{-3})C(t) \\ & + 0.04z^{-1}H(t) + 0.006z^{-1}T_1(t) \\ & + 0.001z^{-1}T_o(t) + 0.015z^{-1}S(t) \\ & + (1 - 1.36z^{-1} + 0.48z^{-2})V_1(t) \qquad (1) \end{aligned}$$

Similarly, the normalised moisture behaviour of the office zone was found to be modelled by:

$$\begin{aligned} H_c(t) = {} & (1.54z^{-1} - 0.58z^{-2} + 0.02z^{-3})H_c(t) \\ & + (-0.04z^{-1} + 0.003z^{-2})T_c(t) \\ & + (-0.71z^{-1} + 0.37z^{-2} + 0.29z^{-3})W(t) \\ & + (-4.02z^{-1} + 3.73z^{-2})C(t) \\ & + (3.29z^{-1} - 2.42z^{-2} - 0.49z^{-3})H(t) \\ & + 0.01z^{-1}T_1(t) + 0.01z^{-1}T_o(t) \\ & + 0.002z^{-1}H_o(t) - 0.09z^{-1}S(t) \\ & + (1 - 1.24z^{-1} + 0.32z^{-2})V_2(t) \qquad (2) \end{aligned}$$

for $t = T, 2T, 3T, \ldots$, where T is the sampling interval (equal to 5 minutes); T_1 is the laboratory air temperature and T_c is the office zone air temperature in °C; H_c is the office zone relative humidity in %rh; W is the heat input rate and C is the cooling rate, in kW; H is the rate of energy input in kW to produce moisture for the office zone; T_o and H_o are the external air temperature in °C and relative humidity in %rh, respectively; S is the solar irradiance in W m^{-2}; V_1 and V_2 are white noise processes of variances 0.02 (°C)^2 and 0.18 (%rh)^2, respectively; z is the difference operator, where $z^{-1}f(t) = f(t-T)$. The normalised variables in the models can be converted to their true values by re-introducing the means which were removed in the identification procedure, giving constant terms in Eq. (1) and Eq. (2). In this way, the models can be used at different operating conditions, although there will be a reduction in prediction accuracy. Note that Eq. (1) and Eq. (2) were derived for the office in an unfurnished condition, as would often be the case when a BAS is commissioned in an actual building.

3.2. Validation

Having obtained the stochastic models, it is necessary to validate them by comparing the predictions from the models against a set of measured data. Such data can be the same as that used in modelling but is usually different from that used in the modelling process. In our case, the data used in the modelling process corresponded to an average office zone temperature of 19.2 °C and to an average relative humidity of 53.0% rh. For predictions up to 15 minutes ahead, the forecasting accuracies of the models were found to be within ±0.25 °C in 19.2 °C for air temperature and to within ±0.6% rh in 53.0% rh for relative humidity, respectively. These prediction accuracies are remarkably good, and show that the models are suitable for immediate control purposes. Corresponding prediction accuracies when forecasting up to 100 minutes ahead were ±0.55 °C and ±0.75% rh, respectively. Since 100 minutes is of the same order as the dominant time constant in the office zone, the results further show that the models can also be used in steady-state system analysis. Fig. 3 and Fig. 4 illustrate these prediction accuracies and compare the cases where the same data and different data are used to validate the models. In addition, comparisons were made with a simple piecewise constant approximation, that is, the next value of office zone air temperature or relative humidity is

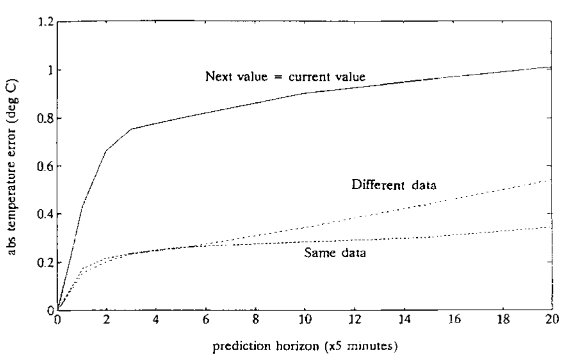


Fig. 3. 20-step-ahead temperature prediction errors.

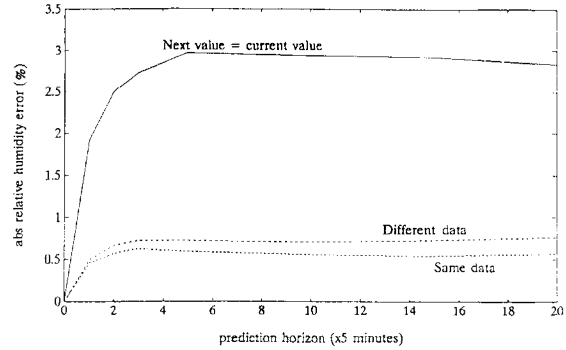


Fig. 4. 20-step-ahead relative humidity prediction errors.

assumed to be equal to the current value; the latter effectively corresponds to having no predictive model at all. The superiority of the model-based approach is clearly evident from these findings. Additional testing of the models was carried out by investigating their prediction accuracies for a period up to 3 days ahead; these were found to be ±0.65 °C and ±1.25% rh, respectively, thus showing that the models can also be useful for providing strategic information about the system which in turn could be used in future scheduling. The full validation process is described in Virk et al. [17] and Loveday et al. [18].

The above results are considered to be exceptionally good, showing that good quality models are obtainable for building systems using the stochastic identification technique. The models presented can describe building zone/HVAC plant behaviour to a high precision when used under conditions similar to those encountered during the identification trials. Note that in the above cases the terms V_1 and V_2 have been assumed to be zero, so that the stochastic nature is deemed to be absent (no "noise") and that a deterministic model is sufficient for prediction purposes. The models can also be used under different conditions but the prediction accuracies can of course deteriorate. In these circumstances it is advisable to utilise an on-line identification scheme so that the models remain in tune with any changes and thus maintain good forecasting accuracy. Note also that the exceptional prediction accuracies described above have been achieved under conditions of limited disturbances (climate-driven only), and with no occupants in the office zone. When these (stochastic) effects are present to a greater extent, prediction accuracies will be poorer; however, this can be improved by using additional terms in the models. The data for these terms can be obtained by deploying extra instrumentation (to monitor occupancy levels, for example), and/or by using mathematical models of the occupancy patterns; in this way the occupancy effects can be predicted more closely.

However, we have clearly demonstrated that good-quality models are obtainable, and the next stage is to investigate their potential in a variety of applications. This we describe next.

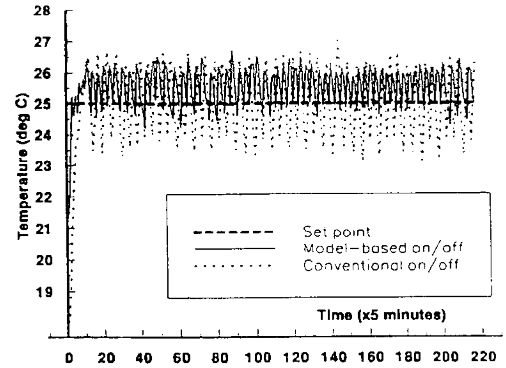


Fig. 5. Temperature regulation comparison for the office zone.

4. Utility of models

Stochastic models of the type derived can be put to a variety of uses. We now investigate in detail their potential from three points of view: control performance, energy consumption, and as a metric for gauging building system behaviour in general.

4.1. Control performance and energy consumption

The model-based approach can be implemented via a range of control methods, in all of which the model is used to design the control signal to be applied to the system. The control methods range from minimum variance, pole placement and optimal control to adaptive and robust designs. To demonstrate the potential of the model-based concept, we test and assess the simplest strategy—conventional on/off control—in comparison with a corresponding model-based version, namely predictive on/off control. Both control algorithms have been given elsewhere [19], but essentially the predictive method tests both the "on" and the "off" states to determine which gives the smaller prediction error at the next sampling instant, the predictions being based on the use of Eq. (1). The conventional on/off strategy employs a hysteresis of ± 1 °C for the zone temperature control. For zone temperatures above the upper threshold, the control signal is set to the "off" state, whereas for zone temperatures below the lower threshold the control signal is set to the "on" state. For zone temperatures within the hysteresis band the control signal is kept at its previous state.

Both control methods were digitally implemented on the test system, and were compared in terms of the air temperature regulation in the office zone and the corresponding energy usage, for a set point of 25 °C. Fig. 5 shows the comparison of office zone air temperature regulation, and Table 1 compares the errors and normalised energy consumptions over the test period of 18 hours. It should be emphasised that the energy figures presented here have been normalised with respect to the internal/external air temperature difference for the test room; in this case the energy figures in Table 1 correspond to a temperature difference of 5 °C.

From inspection of Table 1, it is evident that the model-based approach achieves superior temperature regulation (30% improvement) as compared with the conventional method, together with a reduction in energy consumption of about 17%. Other features worth noting are the d.c. offset for the model-based on/off controller results, and the larger temperature output swing of the standard on/off controller (of about ± 1.5 °C). Clearly, both these effects are undesirable and need addressing before a realistic implementation, in order that the achievable results will be acceptable. The d.c. offset problem is due to the imbalance in the on/off states of the input, that is, the temperature gain when the input is "on" is different from the temperature loss when the input is "off". At steady state, such a controller will continually switch from "on" to "off" at successive sampling instants leading to control system "dither". It is the averaging effect of the dither which is causing the d.c. offset observed in Fig. 5. If such an offset was a problem in an on/off controlled application, then it is possible to deal with the on/off imbalance in a number of ways. Essentially, these methods redress the balance, such that the average becomes centred. The balancing can be achieved by

Table 1
Comparison of on/off controllers for the office zone

Type of on/off controller	Σ (errors)^2 (°C)^2	Normalised energy usage (kWh)
Conventional	189.0	41.0
Model-based predictive	130.7	34.0

appropriate re-sizing of the heater, time-proportioning of the heater output, or extending the on/off control strategy to include proportional control. The sizeable temperature oscillation is a function of the hysteresis adopted in the conventional on/off strategy. A 1 °C hysteresis, as used, is the conventional value adopted in commercial BAS. If the hysteresis is reduced, then the output regulation would be improved, but at the expense of increased controller switching activity. Such activity can be a problem in practical systems as it gives rise to increased wear and decreased reliability. Therefore, a compromise must be reached between hysteresis, temperature output swing and controller activity. We believe that the solutions presented here, because they are based on commercial norms, achieve this balance; however, if one aspect is more important than the others, then the design can be biased accordingly.

The results presented in this part of our study demonstrate the significant potential offered by the model-based approach if it were to be implemented in a BAS. However, while these results might appear to be exceptionally good, it should be remembered that in this particular test zone stochastic disturbances were limited to those of the external climate. During the trials, these disturbances were not particularly large, and hence very precise performance is possible, as seen. This is because the situation is essentially deterministic, permitting accurate predictions and tight control regulation.

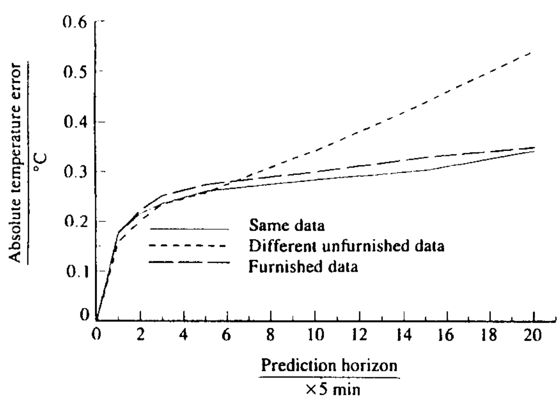
In practice, the disturbances that would be introduced by the presence of occupants together with their actions in the form of appliance usage, window-opening and door-opening, are likely to be much more significant and can have a potentially large effect on the dynamic behaviour of the building system. Under such occupancy conditions, the results can be expected to be much poorer than those suggested by the tests described here. It is possible that energy savings of the order of 10% will be more likely, as observed in other laboratory studies [20], where large-magnitude stochastic disturbances were applied to a test cell in the form of randomly induced mechanical ventilation.

Further investigation of the model-based approach for control in full-scale buildings is therefore required over a range of realistic situations where occupancy and other stochastic disturbances of appropriate magnitude and frequency are present. Nevertheless, the results presented demonstrate the significant potential offered by the model-based approach to the control of building environments. These aspects are discussed further in Section 6. We next investigate the potential of models as a means for monitoring building system behaviour in general.

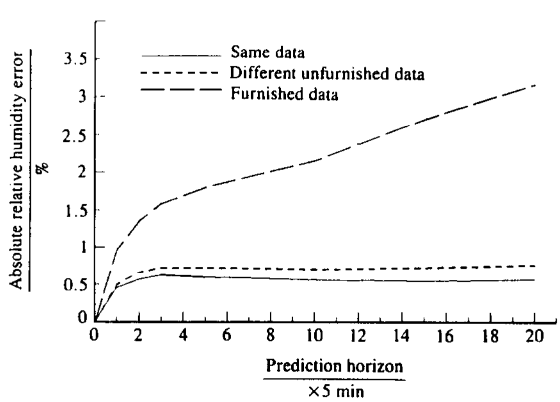
4.2. System behaviour

The models in Section 3.1 were identified for the situation where the office zone was completely devoid of carpeting, furniture and fittings (a situation which is frequently encountered during the commissioning phase of a BAS); it has been shown that the predictions from the models are accurate when dealing with the zone in this unfurnished state. However, what if zone conditions were to change? How accurate would then be the predictions from the models? In order to investigate this situation, the zone was carpeted by covering its entire floor area with a hessian-backed, polyester/woollen pile carpet; no underlay was used. The zone was then furnished by adding the following items: a standard solid wooden office desk and steel-framed upholstered chair, a matching three-seater settee and armchair of PVC-covered lightweight upholstery, and two standard metal filing cabinets (both empty). These alterations may be regarded as "passive", that is, no heat-generating items were installed. Step tests were then carried out on the furnished zone which revealed that no significant change had occurred in the dominant time constants as compared with the unfurnished situation. This is thought to be because the furnishings added were "lightweight" and passive in nature, and thus no major changes had effectively been made to the zone thermal response. An alternative explanation is that carpeting the floor causes it to behave in a more thermally "lightweight" manner and that this might have been balanced by the added thermal mass of the furnishings. The models given by Eq. (1) and Eq. (2) and obtained for unfurnished conditions—the "unfurnished" models—were then used to predict air temperature and moisture behaviour in the furnished zone.

The results are shown in Fig. 6(a) and (b). It can be seen that while air temperature in the furnished zone remains well-predicted by the unfurnished model, the same cannot be said for relative humidity.



(a) Temperature



(b) Relative humidity

Fig. 6. (a) k-step-ahead temperature prediction errors for the unfurnished model (no noise). (b) k-step-ahead relative humidity prediction errors for the unfurnished model (no noise).

Here, predictions from the unfurnished model of moisture behaviour in the furnished zone are poor. To fully confirm this finding, further models were identified for the furnished zone, and predictions of temperature and relative humidity using the "furnished" models were compared as above. This is more fully described in Virk et al. [17] where the results showed that the furnished model is able to predict temperature and moisture behaviour with good accuracy whether the zone is furnished or unfurnished.

The explanation proposed for these findings is that carpeting and furniture possess moisture absorption properties, and that their addition to the test zone significantly alters the dynamic moisture behaviour of the zone. Since identification of the furnished model included such moisture-dynamic effects, the model is able to predict for both furnished and unfurnished situations. However, the unfurnished model is unable to accurately predict relative humidity behaviour because such moisture dynamics would have been largely absent during its identification.

There are several conclusions which can be drawn from these findings. First, for accurate modelling, all dynamic effects must be present during the identification phase. Second, if a new effect subsequently "enters" the system, then prediction accuracies can suffer. This can be used as a "detector" of a change in the system, and can form the basis for a system fault detection technique, for example. Third, as far as a BAS is concerned, it is necessary to have some level of carpeting and furniture present at the commissioning stage if model-based control of relative humidity is contemplated.

The work described here has served to illustrate a further use of stochastic models for buildings, namely, that they can be used to monitor and detect changes in building system behaviour. Further work is needed before this can form an on-line basis for building/HVAC fault detection or for detecting the presence of an intruder, to give two examples, but the authors are currently pursuing this aspect. Having established the potential offered by model-based techniques for buildings, we now turn to the question of their widespread adoption, and in particular how the model-based approach might be replicated for any building.

5. Wide-scale replication

The identification of the stochastic models described earlier required the use of input/output data from the office zone/HVAC system, which in turn meant selecting those variables that needed to be measured and then installing the appropriate sensors. If the technique for obtaining and using a model is to become commonplace for buildings, then it will clearly be necessary to adopt some standard approach for selecting the variables and hence the sensors with which to equip the BAS. While in some cases this can be decided intuitively, it is not a reliable approach, and so a more methodical basis must be devised. Even with on-line self-adapting stochastic models, it will still be necessary to "initialise" a model structure with the relevant variables. With this in mind, we now investigate the potential of thermophysical simulation as a selection tool.

For any system, the system output variables will respond to variations in the input variables, but there will be certain input variables to which the output responses will be most sensitive; it is these inputs which will be the key variables to monitor, and which will be the ones to be incorporated in a model. By using a thermophysical simulation model it is possible to simulate the thermal behaviour of the office zone system, and using sensitivity analysis, to rank input variables in terms of their influence on the outputs (office zone air temperature and relative humidity). The rankings may then be compared with those found from the stochastic model identification process. We concentrate this part of our study on one output only—office zone air temperature—as a first step towards assessing the potential of this technique.

5.1. Ranking from identification

As part of the process for identifying the stochastic model given by Eq. (1), it was necessary to test a number of models before selecting the one which gives the best "fit" to the data. The "goodness of fit" is measured in terms of the "loss function" which is the sum of the squares of the errors between the model-predicted value of air temperature and the actual measured value; the lower the value of the loss function, then the better is the fit of the model to its data set. The ranking of the input variables in terms of their influence on the output (office zone air temperature) was determined by removing one input variable at a time from the model (Eq. (1)) and then computing the corresponding loss function. Comparison of the loss functions reveals the strength of influence of any particular variable against the remaining variables. Table 2 shows the loss functions as each input variable listed is eliminated, together with its corresponding ranking.

Table 2
Loss functions and ranking from identification

Eliminated variable	Loss function	Influence ranking
Heating power	0.540	1
Cooling power	0.309	2
Laboratory air temperature	0.095	3
Solar irradiance	0.089	4
Humidification power	0.085	5
External relative humidity	0.078	6
External air temperature	0.071	7

It can be seen that elimination of the heating power term results in the highest value of loss function, indicating that heating power has the strongest influence on the office zone air temperature, and so on.

5.2. Ranking from simulation

The office zone was modelled using the computer program BRE-ADMIT [21]. The program is based on the admittance procedure [22] in which the internal temperature of a zone is determined from an assumed single-cycle sinusoidal external temperature variation of period 24 hours. The procedure defines the parameters of admittance Y ($\mathrm{W\,m^{-2}\,K^{-1}}$), time lag (hours) and decrement factor, which arise as a result of heat storage effects within the building fabric. Though less rigorous than the fully dynamic building simulation programs [23], it offers a quasi-dynamic analysis for comparing building designs which has the advantage of being relatively straightforward to understand and inexpensive to use by architects and building services consultants. Table 3 lists the thermophysical properties of the office zone which were used in the BRE-ADMIT program, where the U-value is the thermal transmittance of a building element.

Table 3
Office zone thermophysical properties

Element	U-value ($W\,m^{-2}\,K^{-1}$)	Y-value ($W\,m^{-2}\,K^{-1}$)	Time lag (hours)	Decrement factor
External wall	1.53	4.45	7	0.48
Internal walls (three)	0.44	0.45	0	1.00
Ceiling	0.41	0.41	0	1.00
Floor	2.37	4.52	6	0.46

The following input variables were selected for sensitivity analysis: external air temperature, solar absorptivity (applicable to the external wall only), heating plant power, and cooling plant power. Though it was possible to change further input variables in the BRE-ADMIT program, those selected corresponded to the variables monitored in the actual system. To use the program, it was necessary to define a "hybrid" external temperature t_h, comprised of the surrounding laboratory air temperature t_l and the actual external air temperature t_a, weighted in terms of U-values and areas, as:

$$t_h = (U_{int} A_{int} t_l + U_{ext} A_{ext} t_a)/(U_{int} A_{int} + U_{ext} A_{ext}) \tag{3}$$

This is because the program is designed to model cuboidal zones as stand-alone single enclosures surrounded on all sides (except the floor) by an external environment. Here, U_{int} and A_{int} are the average U-value and total area, respectively, of the three internal walls, the floor and the ceiling which enclose the office zone, while U_{ext} and A_{ext} are the average U-value and total area, respectively, of the external wall/window for the zone. This led to the following expression for t_h:

$$t_h = 0.698 t_l + 0.303 t_a \tag{4}$$

A sinusoidal variation of cycle 24 hours (as required by the admittance procedure) was impressed upon t_h with a mean value of 13.18 °C and a swing (peak to mean) of 1.38 °C. Climate data relating to a day in November were employed for subsequent comparison of simulation output with measured data. A ventilation rate of 0.25 air changes per hour was used, together with "no plant" operation, the zone being simulated as free-running in the first instance. Comparison of simulated and measured office zone air temperatures showed good agreement, but a simulated heating plant power of 0.25 kW was necessary in order to fully match the measured and simulated behaviour. The set of simulation input data thus derived was adopted as the "standard" condition upon which the sensitivity analysis was carried out, for the free motion.

Two further standard conditions were defined. These corresponded to a heating plant power of 2.5 kW and to a cooling plant power of (−)0.91 kW; these corresponded approximately to the averages of the ranges for heating and cooling powers employed in the stochastic identification work. Note that to observe the effects of these plant inputs it was necessary to modify the original BRE-ADMIT program by extending the limits of the permitted zone air temperature range. This resulted in the modified versions of the program, which we called BREAMOD 3 and BREAMOD 4, used for comparatively assessing the effects, on zone air temperature, of changes to input variables. For the ranges of operation applicable to the original program BRE-ADMIT, no difference was observed between the outputs from BRE-ADMIT, BREAMOD 3 or BREAMOD 4.

The technique of differential sensitivity analysis [24] was adopted. This technique offers the advantages of being simple to perform, quick to use when the number of inputs is small, and is capable of producing the individual input sensitivities directly. It was therefore used to find the effects of variations in each input to the simulation model. Changes of −10% and +10% were made to the standard values of the input variables. By decreasing, as well as increasing, the value, it was possible to determine whether the model was behaving properly, that is, whether the zone air temperature increased with increasing external air temperature and with increasing solar absorptivity, and vice versa. Corresponding changes in the zone air temperature were then deter-

Table 4
Rankings from simulation

Controllable inputs	Ranking	Uncontrollable disturbances	Ranking
Heating power	1	"external" (laboratory) air temperature	1
Cooling power	2	solar absorptivity (irradiance)	2

mined, and the magnitudes of the changes were used to rank the input variables in terms of their influence.

For the free-running condition, changes of -10% and $+10\%$ were made to the external air temperature (taken as the hybrid temperature, standard value 13.18 °C) and to the solar absorptivity of the external wall (standard value 0.8). For the conditions of zone heating and zone cooling, changes of -10% and $+10\%$ were made to the plant standard input powers of $+2.5$ kW (heating) and $(-)$0.91 kW (cooling). The full set of results is presented in [9].

5.3. Results

For the free-running condition, external air temperature was found to have a greater influence on zone air temperature than does the solar absorptivity. For the condition of cooling plant input, the order of influence (from most to least) is: external air temperature; cooling power; solar absorptivity. This result is based on the standard values stated earlier. It should be noted that if the standard value for cooling power is raised only a little to $(-)$1.3 kW then the cooling power ranking becomes higher than that of the external air temperature.

Table 4 presents the rankings obtained by the simulation approach, where the inputs to the system have been categorised as "controllable" and "uncontrollable". Here, the controllable effects represent the heating and cooling inputs to the system, while the uncontrollable effects are caused by disturbances which are beyond direct control.

For direct comparison with the results from the identification procedure (Table 2) it is necessary to note that in the thermophysical simulation:

1. the external air temperature is made up of approximately 70% laboratory air temperature and 30% actual external air temperature—this corresponds mainly to "laboratory air temperature" in the identified model;
2. the level of solar irradiance to which the office zone was subjected is directly proportional to the value of solar absorptivity—thus solar absorptivity corresponds directly to "solar irradiance" in the identified model.

Although the rankings were dependent to some extent on the values selected for the larger magnitude standard figures, by categorising the variables as "controllable inputs" and "uncontrollable disturbances", the rankings obtained by simulation are seen to be in agreement with those found from the identification process.

These findings are encouraging since they demonstrate that thermophysical simulation may potentially be used as a means for determining which variables are likely to have the biggest influence on the outputs for any particular building system, and thus as a method for initialising the model to be employed in a model-based building management strategy; consequently, simulation would offer a means for selecting the sensors for the BAS. More work is needed to fully explore this approach before it can be proven and then adopted as a standard practice. For example, repeatability of results for a range of situations, the extent to which the choice of simulation model affects the findings, and the way in which standard values are assigned to the inputs all need to be thoroughly investigated. The authors are actively pursuing this research theme.

6. Extension to multi-zone occupied buildings

In Section 5, an assessment has been made of the potential offered by thermophysical simulation as a method for setting up the advanced model-based approach for any building while at the design stage. In addition to the latter developments, the wider adoption of the advanced model-based technique will also require that multivariable stochastic identification is extendable to multi-zone occupied buildings. In this section we describe the prospects for, and important aspects encountered in, extending the advanced modelling technique to such buildings.

The results described in Section 2, Section 3 and Section 4 have concentrated upon an unoccupied single-zone facility subject to tight experimental constraints. It is these restrictions which, in the main, have been responsible for the remarkably good model predictions that we have reported in this paper. Clearly, the methodology needs to be extended to more realistic situations, where multiple zones are present, together with a relaxation of the "no-occupancy" constraint. The latter, in turn, implies not only the presence of people, but also the effects of their activities, such as appliance usage, door/window opening and lighting operations. It is important that the preceding results should be extended to these everyday conditions, and that the results remain of good quality. Once this has been achieved then BAS manufacturers will be more likely to invest in this technology, thereby giving rise to true pro-active management of facilities.

We are currently investigating the potential of the stochastic predictive modelling technique for occupied multi-roomed office buildings. To do this, two additional research facilities have been established, one at Bradford University, and the other at Portsmouth University. Each facility consists of a three-zone office with its own dedicated variable air volume (VAV) HVAC system. Both plants consist of a main air-handling unit (with pre-heat, cooling and humidifying facilities), and one VAV box (with terminal re-heat) for each of the three rooms. All the rooms are occupied and are subject to appreciable solar gains due to significant areas of glazing. The total floor areas of the Bradford and Portsmouth research facilities are approximately 50 m^2 and 100 m^2, respectively. Both are of heavyweight construction, and are subject to the external climate (on one facade (south-west) for the Bradford facility and on two facades (west and south) plus the roof, for the Portsmouth facility). Full details of the extendability of the previous controlled single-zone work to the more realistic multi-zone environments will be available in due course. However, early results from trials and analyses of recorded data suggest that there is every possibility that the quality of the earlier model predictions can be maintained, but that to do so will require extra sensors or software models to provide a measure of the additional disturbances (see, for example, Virk et al. [25,26]).

Important aspects already observed in the multi-zone case are as follows:
1. significant interactions exist between rooms (both for temperature and for relative humidity);
2. occupancy has a major effect;
3. the large glazing areas have a major effect, not only on solar gain but also on heat loss, which, although obvious, is directly observable in the identified stochastic model, raising its importance ranking within the model.

Full results of this work will be published during and after the conclusion of the current EPSRC-funded contract (reference GR/J/46326), due to end in Autumn 1997.

7. Conclusions and future developments

This paper has shown that, for buildings, it is possible to obtain stochastic models which are capable of predicting accurately the air temperature and relative humidity within a zone. When used in a model-based predictive on/off control strategy, they have been shown to save energy (possibly 10%) in comparison with the conventional on/off control regime, and to give improved temperature regulation. In work published elsewhere, the predictive control technique has also been shown to offer improved performance in comparison with PID control [20,27,28]. Such models have also been shown to give the building operator a deeper insight into the way in which the building behaves; this has been demonstrated with respect to the role played by the models in highlighting the effect of furnishings on the moisture behaviour within a zone. A major conclusion from this is that it is necessary to have some level of furnishing within a zone when commissioning a model-based method for the control of relative humidity. In addition, an initial investigation has been reported into the development of an approach for replicating the model-based method in any building. The results are sufficiently encouraging as to warrant further investigation.

There is little doubt that model-based methods hold out the promise of significant improvements to the way in which buildings are managed and operated. Such models, if operated in an on-line way, can offer further versatility of application, which includes self-commissioning and fault detection. Once the BAS for a particular building has been instrumented (the sensors perhaps having been pre-selected at the design stage via simulation), input/output data can be used to identify the model in an on-line way using the recursive generalised least-squares method [15]. Such a model is able to self-adapt as conditions change, and thus to provide a self-commissioning and self-tuning capability which ensures optimal performance over a wide range of operating conditions. A solution of this kind would go a long way towards alleviating the problem of long commissioning times currently associated with BAS.

A model of the type described can also be used for fault diagnosis. A fault detection and isolation facility can be obtained by the use of state-space techniques to construct a state observer. The observer can be used with the on-line model to produce a failure-sensitive filter [29], and the filter can be designed so as to detect faults which are common to HVAC plant installations (typically wiring faults, wrongly-piped sensors and valves, and non-actuation of valves and dampers). Statistically significant differences between predicted and actual behaviour can then be used to signify the presence of particular fault types.

This paper, in placing in context the level of "intelligence" of today's buildings, has dealt principally with stochastic models obtained from statistical identification techniques. However, there are other model types and modelling methods available—models based on neural network and fuzzy logic methods, for example. The potential offered by these techniques is still under investigation (see for example, Hepworth et al. [30] and Dexter and Trewhella [31]).

While BAS offer the means to implement advanced solutions, there remains much more that can be done in this application area before full advantage is taken of the information technology revolution. In the 1980s, the trend was towards "high-tech" buildings, where the application of technology and significant levels of servicing were used to provide a building internal environment which was effectively "divorced" from the exterior climate. The 1990s, however, has seen a change in building design towards a more harmonious co-existence with the natural environment. Here, for example, the aim is to minimise the building energy needs by the use of natural processes, such as stack-driven ventilation and/or "coolth" storage within the structural mass. These types of buildings offer significant challenges in the design of control systems, since essentially the servicing is being driven by random climatic effects. It is here where the advanced techniques such as stochastic model-based control will come into their own. Successful proving trials of the new techniques in realistic situations is now the next step along the road towards the truly intelligent environmentally benign buildings of tomorrow.

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