PREDICTIVE OPTIMAL CONTROL OF FABRIC THERMAL STORAGE SYSTEMS

M J Ren & J A Wright

Department of Civil and Building Engineering,
Loughborough University,
Loughborough,
Leicestershire,
UK

ABSTRACT

Hollow core ventilated slab systems provide an effective means of utilizing the building structure as a thermal store. The optimum control strategy for the system would be one that minimizes energy costs without prejudicing the occupant thermal comfort. This paper describes an implementation of one such strategy in which the optimum operation of the plant is predicted for the next day. The controller incorporates algorithms for predicting the ambient temperature and solar radiation over the next 24 hours. The predicted ambient conditions are used with a thermal network model of the building to evaluate the energy consumption and comfort conditions for a given control strategy, the optimum control strategy being found by exercising the thermal model with a Genetic Algorithm search method.

The structure of the controller is described, together with algorithms for predicting the next days ambient temperature and solar radiation. The seasonal operation and performance of the predictive controller is also presented. The paper indicates that in relation to a conventional control strategy, occupant thermal comfort can be maintained throughout the year without excessive use of energy.

INTRODUCTION

Thermal Energy Storage Systems provide a promising approach to reducing building energy use and cost, thus restricting the production of environmental pollutants. The potential for storing thermal energy within the structure has been exploited by building engineers since the 1970's. Hollow core ventilated slab systems differ from the other fabric thermal storage systems in that they utilize the slab cores as a supply air path, which promotes greater thermal coupling between the slab and the ventilation air than would normally be achieved by a conventional exposed ceiling system. The effectiveness of the coupling is such that the ventilated slabs act as regenerative heat exchangers. During the summer, cool air is used to lower the temperature of the slab at night, so that the slab can absorb the heat from the higher temperature outside air during the day. In the winter, the slab can be used to store heat supplied from off-peak tariff heating, to be released later during peak periods. The effectiveness of these systems has been investigated previously by monitoring real buildings and by computer simulation [1,2,3,4]. This paper describes a strategy for the optimum supervisory control of ventilated slab thermal storage systems.

Conventional Control of Ventilated Slab Systems

In the conventional control of hollow core ventilated slab systems, it is usual to monitor the slab mass and or the room air temperature and to use these to dictate the time switching of the plant operation. A building at the University of East Anglia (UEA), UK, has been installed with a hollow core ventilated slab system. The supervisory control strategy for this building during the summer is described by the following rules [5]:

- night operation:

I. if during the day T_o > 15 ^oC or at 10:00pm T_{az} > 23 ^oC and 3 ^oC < (T_{az} - T_o) < 8 ^oC, then the ventilation fans are switched ON;

II. if the fans are ON and T_s < 21^oC or T_o < 8^oC, then the fans are switched OFF.

- operation during occupancy: the fans are ON to provide full fresh air ventilation at a constant rate in a range of 20-40 l/s (depending on the zone type).

T_o is the ambient air temperature, T_{az} is the zone air temperature and T_s the slab mass temperature.

Such simple rules may not fully utilize the thermal capacity of the structural mass and may sometimes waste energy. For instance, it may not be necessary to start free night cooling as early as 10:00pm to relieve the cooling load the following day. The minimization of fan operating cost can only be achieved by the optimum control of fan operating times and ventilation rates, particularly in the presence of an electricity tariff structure.

Optimal Control of Building Thermal Systems

A significant amount of research has been conducted into the optimal control of building thermal plant, but very little research has been focused on optimizing plant operation with building fabric thermal storage. Braun [6] demonstrated the potential for energy cost savings through the optimal control of building thermal storage. Though the study was of a conventional air-conditioned building, the thermal capacity of the building mass was utilized for relieving the daytime cooling load. The zone temperature setpoints over a 24 hour period were formulated as optimization variables to minimize the total energy cost while maintaining a pre-defined level of thermal comfort. The approach adopted in this paper can be generalized for the applications of the optimal control of fabric thermal storage systems. Morris, et.al [7] have also examined an approach to the dynamic optimal control of building thermal storage systems and have compared it with night setback control.

Little work has been done on the optimal control of hollow core ventilated slab systems. Due to its special air supply path, the control of this system differs from that of conventional buildings. This paper describes a controller that predicts the optimum operating schedule for a ventilated slab system for the next 24 hours.

CONTROLLER STRUCTURE

The system considered in this paper is shown in Figure 1. It contains three components: the building installed with ventilated slabs, the primary plant (chiller) and an air-handling unit (AHU). The AHU includes a heat recovery device (HRD), a cooling coil, an electric duct heater, and supply and exhaust fans. The optimum control of this building system involves minimizing the total energy cost from the chiller and AHU over a specified operating period (24 hours), without violating the occupied zones thermal comfort constraint. The optimum solution to this problem presented here, is a schedule of control operation for each hour of the 24 hour optimization period.

The potentially high number of control variables and discontinuities in the search space make this a difficult optimization problem to solve. However, the degree of difficulty can be significantly reduced by decoupling the control problem into two levels.

Figure 1, Plant Configuration

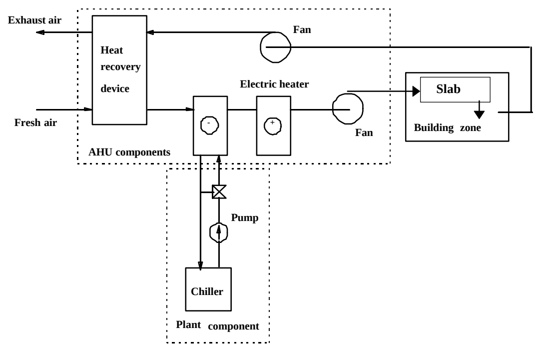
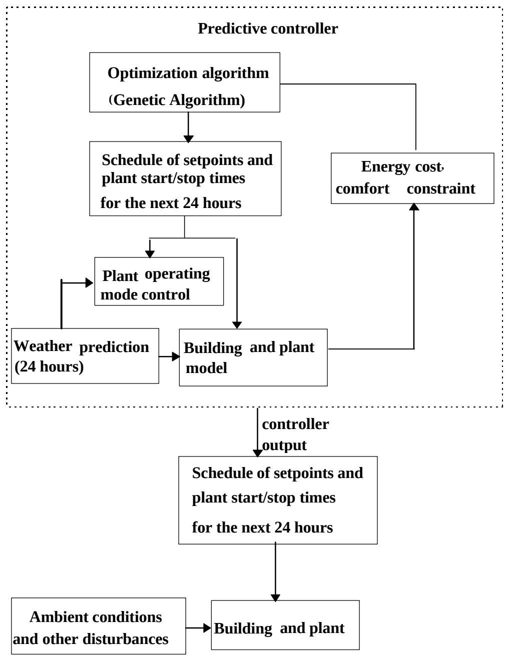


Figure 2 illustrates the control hierarchy. The high level control employs an optimization algorithm to determine a schedule of plant setpoints and operating times for the next 24 hours that minimizes the total energy cost and maintain the room thermal comfort. The low level control ensures that for a given operating point, that the plant operating mode is such that the energy consumption is minimized.

Figure 2, Control System Structure



The energy cost and comfort constraints are evaluated using a thermal model of the building and plant under predicted ambient temperatures and solar radiation. The building and plant models are an integral part of the controller. A dynamic model has been used to represent the building performance [8], whereas the plant performance is simulated by simple steady-state models.

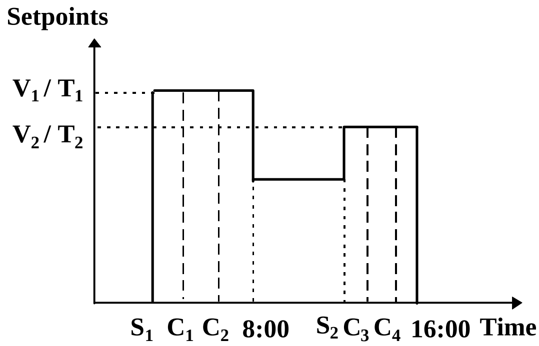
The building and plant model and the plant operating mode controller are run for each operating scheduled searched by the optimization algorithm.The optimization is run off-line, the final operating schedule is used to operate the plant over the next 24 hours. The operating schedule is used without any feedback control, although the plant operating mode is selected in each hour which to some extent, can compensate for any modelling or prediction errors.

Optimization of the Plant Operating Schedule

The high level, plant operating schedule control, is concerned with optimizing the control variables that directly influence the thermal storage over a planning period of 24 hours. Optimizing for the next 24 hours allows the daily variation of the ambient and room thermal environment, as well as the cost of electricity, to be taken into account. The dominant variables for the high level control are the setpoints for the supply air temperature and flow rate to the ventilated slab. For the optimum control of thermal storage in a conventional air-conditioned building [6], the zone temperature setpoints where selected as the control variables. This approach is not applicable for the optimal control of hollow core ventilated slab systems, since the condition of the air entering the slab has a significant influence on the thermal storage. Further, most ventilated slab control systems are open-loop to the zone condition. This is typical for highly insulated heavy weight low energy buildings which are relatively insensitive to the diurnal changes in ambient thermal conditions.

An investigation into the optimum characteristics of the setpoint schedule [9] indicated that the high level control could be represented in simple ‘time stages’. Figure 3 illustrates the control stages. S_1 signifies the start of plant operation with a supply air flow rate of V_1, C_1 to C_2 is a period of active heating or cooling during which the supply air temperature has a setpoint of T_1. No temperature setpoints are required during the free cooling (or heating) periods (S_1-C_1, C_2-8:00, 8:00-S_2, S_2-C_3, C_4-16:00), since the supply air temperature is dictated by the ambient temperature and whether the heat recovery device has been selected to be in operation or not. From the start of occupancy (8:00) to S_2 is a period of minimum ventilation rate. S_2 signifies the start of the second stage of high cooling or heating with the ventilation rate set to V_2 and a supply air temperature setpoint of T_2 during the active heating or cooling period C_3-C_4. The plant operation stops at the end of occupancy (16:00).

Figure 3, Time-Stage Plant Operating Schedule



This gives an optimization problem in 15 variables, 6 time stage variables (S_1, C_1, C_2, S_2, C_3, C_4), 4 setpoints (V_1, T_1, V_2 and T_2) and the ON/OFF operation of the heat recovery device in each of the 5 free cooling (or heating) periods. This framework makes for robust supervisory control in which the degree of start-stop operation of the plant can be constrained to be within practicable limits.

A Genetic Algorithm (GA) search method has been selected to solve the optimization problem. GA's are particularly suited to solving problems with a high number of problem variables and a discontinuous objective function [10]. The simple GA [10,11], implemented in this research has proved to be a robust technique for solving the thermal storage optimization problem.

In order to ensure that the energy cost is minimized, it is necessary to optimize the plant operating mode. The low level control is therefore concerned with the mode of operation of the plant that minimizes energy consumption of the plant in each of the 24 planning hours while meeting the supply air setpoints, passed from the high level control.

For a given supply air temperature setpoint, it may be necessary to heat or cool the ambient air to meet the setpoint. The operation of the heat recovery device may, or may not, benefit this process. The plant supervisory control variables to be optimized in each hour are therefore concerned with the mode of operation of the plant. The plant operating modes are shown in Table 1. The last three modes only apply to night operation, corresponding to full recirculation of the room extract air.

Table 1, Plant Operating Modes

Mo-de	Heat Recovery Device	Electric Heater	Chiller
1	ON	OFF	OFF
2	OFF	OFF	OFF
3	ON	ON	OFF
4	ON	OFF	ON
5	OFF	ON	OFF
6	OFF	OFF	ON
7	Recirculation	ON	OFF
8	Recirculation	OFF	ON
9	Recirculation	OFF	OFF

The optimization of the plant operating mode is undertaken by exhaustive search. However, the feasible number of operating modes can be reduced prior to the optimization by an analysis of the zone exhaust air temperature, ambient air temperature and the supply air setpoint.

THE PREDICTION OF AMBIENT TEMPERATURE AND RADIATION

Since the most significant benefit of a building thermal storage system is due to its ability in shifting the daytime on-peak cooling and heating load to the night, predicting the weather conditions for the next day is critical in determining how much of the on-peak load should be shifted to minimize energy costs. Weather predictors have been used in building design and predictive control [12,13,14]. Weather models have also been investigated for the analysis of the load calculations in design [15], and for the analysis of the stochastic properties of heating loads [16].

Each approach varies in its detail according to the application. For the optimum controller described in this paper, the weather predictor must provide a short-term forecast of climatic variables of ambient temperature and global radiation, direct radiation and diffusive radiation. The annual periodicity and seasonal effect need not be modelled separately since the forecasting is conducted daily, wherein the parameters of the weather predictor are updated to include the effect of the measured weather data from the passing day. Therefore, the annual periodicity and seasonal effect are embedded in every new set of parameters. The weather predictor has two main functions, temperature prediction and solar radiation prediction.

Temperature Prediction

The ambient dry bulb temperature is a main source of uncertain disturbances on the thermal state of the building. Temperature data can be represented as a non-stationary stochastic time-series. It has been suggested [17] that an ARMA model can sufficiently represent a non-stationary time-series through the correct selection of the parameters. The number of parameters of an ARMA model can be substantially reduced by stationalizing the raw non-stationary time-series. A combined method is described here in which the temperature data series are divided into a deterministic component and a stochastic component.

The deterministic part is calculated by an EWMA (Exponential Weighted Moving Average) model. The form of EWMA used to represent the ambient temperature is:

$$\hat{D}_{t,d+1} = \hat{D}_{t,d} + \lambda\,(T_{t,d} - \hat{D}_{t,d}),\quad t = 1,2,...,24 \qquad (1)$$

Where;

$\hat{D}_{t,d+1}$: deterministic forecast for the next day $d+1$ at time t ,
$\hat{D}_{t,d}$: deterministic forecast for previous 24 hours, day d at time t ,
$T_{t,d}$: temperature observations for the previous 24 hours, day d at time t .

The EWMA model uses exponential smoothing constant λ to give weight to the historical data. As λ increases, more influence is given in the model to the most recent observations. A study of the value of λ over a period which includes a variety of patterns in the ambient temperature, shows that $\lambda = 0.45$ can generally give good results.

The stochastic element of the model is derived from the errors in the deterministic predictions for, n, previous days $Y_t = T_t - \hat{D}_t$, (t=1,2,...,$n \times 24$). An ARMA (Auto Regressive Moving Average) model has been used to represent the stochastic element:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \phi_4 Y_{t-4} \qquad (2)$$

The study of the performance of the model indicated that a 4th order AR model is adequate. The autoregressive parameters ϕ_m , (m =1,...,4), are obtained by minimizing the sum of the squares of the residuals between the model and the stochastic component of two weeks of previously measured temperature data. The parameters are then held constant and the model is used to predict the stochastic element for the next 24 hours, $\widehat{Y}_{t,d+1}$.

The longer the lead time of the forecast, the less accurate the ARMA model is likely to be and therefore the the forecasts for the late afternoon and evening will be less accurate than for the early morning. However, although regular on-line updating of the model is possible [17], only the short term forecasts will be improved. Since the controller described here predicts the optimum control strategy only once each day, the temperature prediction models are only updated at the time of the control strategy optimization.

The complete model for the prediction of the ambient temperature is obtained by combining the prediction for the deterministic (EWMA) and stochastic (ARMA) elements:

$$\widehat{T}_{t,d+1} = \widehat{D}_{t,d+1} + \widehat{Y}_{t,d+1}\,, \quad (t = 1,2,...,24) \qquad (3)$$

Since the daily total global radiation may have important influence on the daily average temperature variations [15], the combined model could be expanded to take this into account. However, a study of the effect of this on modelling accuracy showed that this was not necessary for the short term forecasts required here.

Radiation Prediction

Like the ambient temperature, the solar radiation is non-stationary stochastic data series. The hourly sampled radiation data (global, diffuse and direct) exhibits even more random behaviour than the temperature data.

A purely deterministic model has been used for modelling the solar radiation, since the solar radiation varies randomly with such high frequency and large amplitude, that the ARMA model fails to model the stochastic variations. Two deterministic methods have been studied, the EWMA model used in the temperature prediction and a periodic function. The comparison of prediction errors between the EWMA method and periodic function shows that the EWMA model produces the greatest accuracy and has therefore been adopted to model the solar radiation.

THE PERFORMANCE OF THE PREDICTIVE CONTROLLER

The performance of the predictive controller has been investigated for a hollow core ventilated slab building derived from one located at the University of East Anglia, UK [5]. The building is well insulated with a transmittance for the external walls of only 0.2 W/m^2 K and that of the window 1.3 W/m^2 K. Five identical zones in the building have been modelled. The floor area of each zone is 4.0 m $\times$ 6.0 m with a ceiling height of 2.84 m. Each zone has one south facing external wall with a 4.2 m^2 window.

The ventilation air is introduced to the space by ceiling diffusers, which are connected to the ventilated slab air outlet. Each zone has five ventilated slabs, each of which is 4.0 m long $\times$ 1.2 m wide $\times$ 0.25 m thick. Ventilation air from the plant is divided and supplied equally to each zone. The design minimum ventilation rate during the occupied period is 2.0 air changes per hour for each zone. Occupancy is scheduled from 8:00am to 4:00pm. The electricity tariff structure 3:1 (the ratio of the cost of on-peak electricity to the cost of off-peak electricity), has been used. A set of weather data monitored in Garston, UK, in 1994, has been used as an example year over which to examine the performance of the controller.

Two elements of performance are examined here, the effect of weather prediction errors on the performance of the controller, and the performance of the controller in relation to a conventional control strategy [5]. The effects of errors in the weather prediction are evaluated by comparing the room temperatures that result from the two situations; when next days weather conditions are known (perfect prediction), and when the next days weather conditions are predicted. Three measures are used to quantify the error. The average error is quantified by the mean absolute error (MAE), while the worst error is given by the maximum absolute error (MAXAE). The bias of the error is indicated by the mean error (ME), with a negative number indicating a lower value was predicted. The same measures are used to quantify the errors in the prediction of the ambient temperature. Any errors resulting from the modelling of the building and plant are not addressed here (the same models being used to represent the building as are used within the predictive controller).

Winter Operation

The room and mass temperature profiles averaged over the month of February (the solutions for other months throughout the winter period exhibit a similar characteristic), shows that they conform to the operational strategy for most of the winter months. Generally, the mass store is pre-heated to a level that is sufficient to sustain the occupant thermal comfort throughout the occupied period, during which only minimum ventilation is used with the heat recovery device being in operation; no additional heating is necessary during this period, (the period of high electricity tariff coincides with the start of occupancy). One characteristic of the optimal control strategy is that in order to minimize energy costs, the building will only just be controlled at the comfort temperature at the start of the occupied period at around 8:00am, (sufficient thermal storage to last the day being controlled by the length of the pre-heat period). The room temperature generally increases during occupancy due to internal gains and the reduction in heat loss with higher ambient temperatures. This brings the room temperature to well within the comfort band which making the control less critical.

Table 2, indicates that during February the average error in ambient temperature prediction was over 1.6 ^{o}C, with a maximum error of 6.3 ^{o}C. However, Table 3 indicates that errors in ambient temperature prediction of this magnitude have little effect on the control of the room temperature, the mean error here being of less than 0.1 ^{o}C with the maximum being less than 0.9 ^{o}C. This is partly due to the thermal capacity of the building damping fluctuations in the external climate, but is also due to the relatively simple plant control strategy during the winter being insensitive to prediction errors. Table 4 indicates that the prediction errors in ambient conditions have led to the comfort constraint of 10.0 % PPD being violated. This occurred on an afternoon between 3:00pm and 4:00pm, when the prediction error led to insufficient thermal storage to last the day. This is a result of the accuracy in predicting the ambient conditions decreasing with the prediction period (the prediction being started at mid-night).

In comparison to a conventional control strategy [5], Table 4 indicates that the predictive controller reduces energy costs and improves thermal comfort, although greater energy use is necessary to maintain the thermal comfort. Both controllers tend to produce slightly cooler than neutral comfort conditions.

Table 2, Ambient Temperature Prediction Errors for February

Period	MAE (^{o}C)	ME (^{o}C)	MAXAE (^{o}C)
Occupancy	1.7	-0.2	6.3
24 hours	1.6	-0.2	6.3

Table 3, Room Air Temperature Errors for February

Period	MAE (^{o}C)	ME (^{o}C)	MAXAE (^{o}C)
Occupancy	0.1	-0.1	0.8
24 hours	0.1	-0.1	0.9

Table 4, Comparative performance of the Predictive Controller in February

Controller	Energy Cost (£)	Energy Use (kWh)	Mean PPD (%)	Max. PPD (%)
Conven-tional Control	46.3	332.1	15.5	21.2
Predictive control	44.4	429.9	8.9	11.4

Summer Operation

During summer operation, the optimum control strategy uses as much night free cooling as possible for relieving the daytime cooling load. For some hot days, the chiller is also operated at night to lower the temperature of the ventilated slab even more. It is only when an extremely hot day is forecast, that it is necessary to operate the chiller during the occupied period.

In the summer, the critical period for control is during the late afternoon when the thermal loads will tend to reach their peak and the thermal store is most likely to become exhausted. This is in contrast to the period near the start of occupancy (8:00am), when the room temperature is free to float within the comfort band. The temperature of the ventilated slab is at it's lowest at the start of occupancy since this is the point at which the high electricity tariff starts and therefore when the thermal store must be fully charged.

Table 5 gives the prediction errors in the ambient temperature and Table 6 the corresponding errors in room air temperature.

Table 5, Ambient Temperature Prediction Errors for July

Period	MAE (^oC)	ME (^oC)	MAXAE (^oC)
Occupancy 24 hours	2.7 2.3	0.1 -0.0	9.2 14.3

Table 6, Room Air Temperature Errors for February

Period	MAE (^oC)	ME (^oC)	MAXAE (^oC)
Occupancy 24 hours	0.4 0.4	-0.0 -0.0	1.8 2.4

As for the winter operation, the errors in weather prediction are damped by the mass of the building so that the errors in room temperature are much lower. However, the plant operation is potentially more complicated than in winter and therefore more prone to errors. There is also a greater coupling between the ambient conditions in summer than during winter. The maximum errors in room temperature (MAXAE) during July resulted from a predicted high ambient temperature causing 4 more hours of chiller operation than was necessary on one day during the month.

Table 7, Comparative performance of the Predictive Controller in July

Controller	Energy Cost (£)	Energy Use (kWh)	Mean PPD (%)	Max. PPD (%)
Conven-tional Control	28.7	142.1	6.7	19.9
Predictive control	24.2	158.3	8.0	14.4

Table 7, compares the performance of the predictive controller with the conventional control strategy [5]. The predictive controller provides closer control of the comfort conditions at a lower cost, but greater energy use. The high cost of energy of the conventional control are due to the constant use of ventilation only, no chiller is included in the conventional system (research [8], has also indicated that for systems that do not include a chiller, the predictive controller has a better performance than the conventional control strategy). The trend of both controllers is that the comfort conditions tend towards being slightly warmer than neutral. The maximum error of 14.4% in the PPD for the predictive controller was due to the weather predictor underestimating the ambient temperatures for the next day, which resulted in insufficient thermal storage to last the occupancy period.

Transitional Season Operation

The majority of system operation, for UK climatic conditions, is that of the transitional seasons between winter and summer. During these periods, active pre-cooling or heating of the thermal store is not normally required, the temperature of the room and thermal store generally controlled by the operation of the heat recovery device with the ventilation rate being kept at the minimum.

The ambient prediction errors and corresponding errors in room air temperature are similar to those during the winter operation. Due to the simple plant control strategy in the transitional season, the room air frequently floats within the comfort band.

Table 8, indicates that the predictive controller can make major savings in both running costs and energy use over a conventional control strategy. The control of comfort conditions is similar for both the conventional and predictive control, although the conventional control can lead to a higher PPD.

Table 8, Comparative Performance of the Predictive Controller in April

Controller	Energy Cost (£)	Energy Use (kWh)	Mean PPD (%)	Max. PPD (%)
Conven-tional Control	21.2	71.5	9.1	18.1
Predictive control	5.4	39.4	6.9	10.4

DISCUSSION

This paper investigates the performance of a predictive optimum control strategy for fabric thermal storage systems, in reducing energy cost and maintaining the thermal comfort in the occupied space. The structure and components of the predictive controller have been described together with the characteristics of the plant operation in each season (for the UK's climate).

In comparison to a conventional control strategy, the predictive controller has been shown to reduce energy costs. During the transitional seasons between winter and summer, the predictive controller can also reduce energy use. The predictive controller also maintains more consistent thermal comfort conditions than the conventional control strategy.

Errors in the prediction of the climatic conditions have been shown to be reduced when translated into the temperature of the controlled zone. The reduction is due to the high thermal capacitance of the building and the characteristic of the plant control strategy.

The weather prediction, and optimization of the control strategy is computationally acceptable, however, further research is required to simplify the structure of the building thermal model. The thermal model described here, relies on the the prediction and measurement of the solar radiation. Since solar radiation is not normally measured in buildings (the instrumentation being expensive), the model should be simplified and evaluated for use without the direct effect of solar radiation. Further work is also required to exam the use of the lower level plant supervisory and local loop controls, in reducing the effect of prediction errors.

REFERENCES

1. G. Allen, M. Kani, and S. Carpenter, “Mechanically Enhanced Passive Solar Thermal Storage”, *Proc. SESCI'1984, Calgary, August* (1984).
2. R. Zmeureanu, and P. Fazio, “Thermal Performance of a Hollow Core Concrete Floor System for Passive Cooling”, *Building and Environment*, **23(3),** 243-252 (1988).
3. G.L.M. Angenbroe, and H.A. Vedder, “Accurate Modelling of Air-Supplied Heat Storage in Hollow Core Slabs”, *ClIMA 2000, World Congress on Heating, Ventilation and Air Conditioning*, August, 441-446 (1985).
4. R. Winwood, R. Benstead, R. Edwards, and K.M. Letherman, “Building Fabric Thermal Storage: Use of Computational Fluid Dynamics for Modelling”, *Building Services Engineering Research and Technology*, **15(3),** 171-178 (1994).
5. R. Bunn, “Teaching Low Energy”, *Building Services Journal*, April, 19-23, (1995).
6. J.E. Braun, “Reducing Energy Costs and Peak Electrical Demand Through Optimal Control of Building Thermal Storage”, *ASHRAE Transactions*, **96(2),** 876-888 (1990).
7. F.B. Morris, J.E. Braun, and S.J. Treado, “Experimental and Simulated Performance of Optimal Control of Building Thermal Storage”, *ASHRAE Transactions*, **100(1),** 402-414 (1994).
8. M.J. Ren, and J.A. Wright, “Optimal Control of Fabric Thermal Storage Systems”, to be presented at Clima2000, Brussels, Belgium, (1997).
9. M.J. Ren & J.A. Wright, “A Ventilated Slab Thermal Storage System Model”, to be published in Building and Environment.
10. D.E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley publishing Company, Inc.
11. J.A.Wright, “HVAC Optimisation Studies: Sizing by Genetic Algorithm”, *Building Services Engineering Research and Technology*, **17(1),** (1996).
12. J. Holst, H. Madsen, & P. Thyregod, “A Method for Using Hourly Predictions of Weather Observations in Optimal control of Heat Supply to Buildings”, *Proceedings of 3rd International Congress on Building Energy Management, ICBEM*, 380-389 (1987).
13. A.K. Athienitis, “A Predictive Control Algorithm for Massive Buildings”, *ASHRAE Transactions*, **94(2),** 1050-1067 (1988).
14. T. Hartman, “Dynamic Control: The Weather Predictor and HVAC Control”, *Heating/Piping/Air Conditioning*, May, 97-101 (1988).
15. H. Yoshida, & T. Terai, “An ARMA Type Weather Model for Air-Conditioning, Heating and Cooling Load Calculation”, *Energy and Buildings*, **15-16**, 625-634 (1990/1991).
16. S. Hokoi, & M. Matsumoto, “An Analysis of Stochastic Properties of the Heating Load in an Intermittently Air-Conditioned Building”, *Energy and Buildings*, **11**, 259-266 (1988).
17. S.M. Pandit, & S.M. Wu, *Time-Series and System Analysis with Applications*, New York: John Wiley & Sons, (1983).