FUZZY MODEL-BASED FAULT-TOLERANT CONTROL OF AIR-CONDITIONING SYSTEMS

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ABSTRACT

The paper describes the development of a supervisory control scheme that adapts to the presence of degradation faults and minimises any resulting increase in energy consumption or deterioration in occupant comfort. Since there is a high degree of uncertainty associated with the results of any fault identification scheme in information-poor systems of this type, the supervisory control scheme uses fuzzy models to predict fuzzy measures of the overall performance and a fuzzy decision-maker to determine the most appropriate set-points. This fault-tolerant control scheme is being developed and evaluated using a detailed computer simulation of a multi-zone, variable-air-volume, air-conditioning system. The fuzzy models relate the performance of the air-handling unit and the chiller to the supply air and chilled water temperature set-points, and to fuzzy measures of the amount of air-side and water-side fouling.

Results are presented that demonstrate the ability of the fuzzy models to predict the performance and show the effect of both water-side and air-side fouling on the performance. Problems associated with training the fuzzy models are also discussed.

INTRODUCTION

There has been much recent interest in the development of fault detection and diagnosis techniques that are suitable for use in building environmental control systems [Hyvarinen and Sarki, 1996].

The detection of abrupt faults, such as a broken fan belt, necessitates immediate manual intervention to eliminate the cause of the fault. Other, so called degradation faults, such as air or water-side fouling, will result in a gradual deterioration in the performance of the air-conditioning system [Pape et al., 1991, Rossi and Braun, 1996]. In some cases the control strategy can be modified so as to adapt to the presence of a fault. Such fault tolerant control schemes [Patton, 1997] are capable of continually re-optimising the overall control performance as the size of the degradation fault increases.

Estimating the size of degradation faults is particularly challenging in air-conditioning systems where sensor bias and estimation offsets are significant [Ngo and Dexter, 1999], and no training data are available from the actual plant that is typical of faulty operation. In practice fault diagnosis may have to be based on qualitative descriptions of the behaviour of the plant in the presence of faults [Dexter, 1995; Glass et al. 1995] and only imprecise estimates of the size of the fault will be generated.

Supervisory controllers optimise the performance of air-conditioning systems by changing the values of the set-points for the local controllers. Some supervisory schemes use mathematical models to predict the performance and an optimiser to find the best values of the set-points [Curtiss et al. 1994]. There are often significant uncertainties associated with the definition of the control objective [Dexter and Trewhella, 1990], the estimation of the cooling demand [Henze et al., 1997] and the models used to predict the performance. In such cases, precise optimisation is unnecessary and suboptimal rule-based supervisory control schemes may be more appropriate [Keeney and Braun, 1996; Drees and Braun, 1996].

This paper describes the development of a fuzzy model-based fault tolerant supervisory control scheme. The basic scheme is first described before the approach used to generate the fuzzy models is explained. Results are then presented that demonstrate the sensitivity of the performance to the presence of both degradation faults and set-point changes.

FUZZY MODEL-BASED SUPERVISORY CONTROL

The basic scheme (see Figure 1) consists of a fuzzy objective function, a fuzzy decision-maker and one or more fuzzy models.

The fuzzy models are used to predict the performance of the air-conditioning system for particular values of the set-points, operating conditions and sizes of the faults. Each model consists of a set of fuzzy IF-THEN rules. The number of fuzzy sets used to describe inputs and outputs of the models

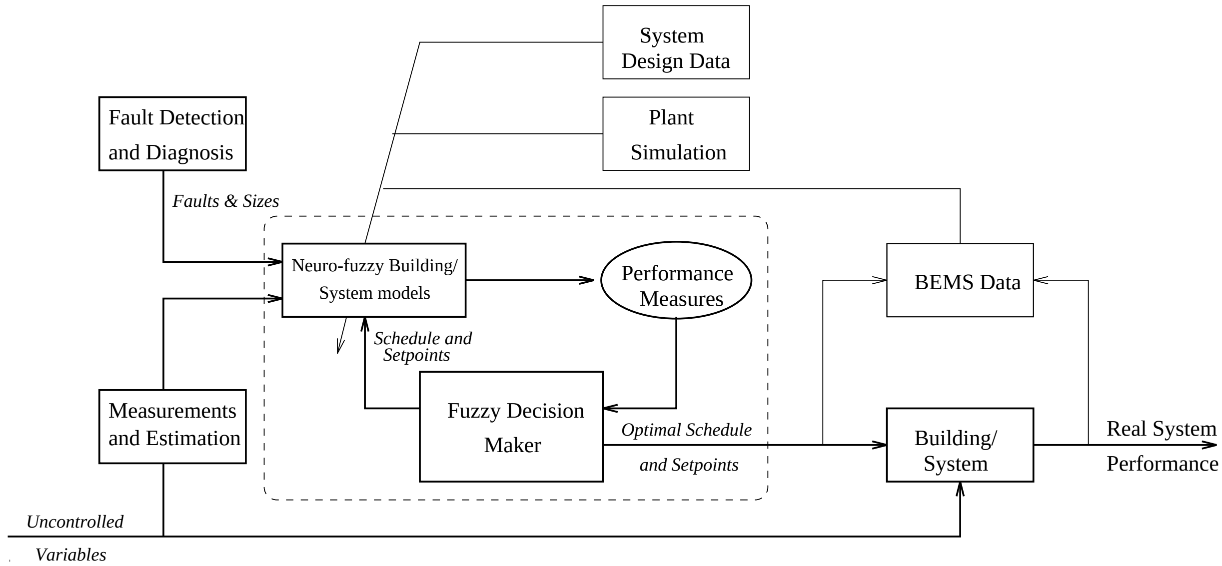

Figure 1: Fuzzy model-based supervisory control

is chosen to reflect the uncertainties associated with their measurement or estimation. The fuzzy objective function includes fuzzy estimates of both the power consumption and the control performance. The two terms are combined using a fuzzy weight and fuzzy arithmetic. The fuzzy decision maker compares the fuzzy objective function to a fuzzy goal function (centred around zero) to determine the degree to which the goal is satisfied. The set-points producing the fuzzy objective function which best satisfies the goal are then applied to the plant. The procedure is repeated at regular intervals (for example, every hour).

The current version of the supervisor uses two steady-state fuzzy models. One relates the power consumption and speed of the supply fan to the supply air temperature set-point for a given cooling demand, operating conditions and amount of air-side fouling. The other relates the power consumption of the chiller and the position of the cooling coil valve to the chilled water and supply air temperature set-points for a given cooling demand, operating conditions and amount of water-side fouling. The fuzzy objective function includes a fuzzy estimate of the total electrical power consumption and a fuzzy indicator of the control performance (it is assumed that, if the set-points are chosen so as to meet the demand for cooling, a fuzzy measure of the proximity of the cooling coil control valve to its fully open position, and a fuzzy measure of the proximity of the fan speed to its maximum value, are satisfactory indicators of the control performance).

GENERATING THE FUZZY MODELS

A Max-Product identification scheme is used to estimate the rule confidences of the rule in each of the fuzzy models from training data generated by computer simulation [Ngo and Dexter, 1999]. The cooling coil/chiller model has six inputs (supply air flow rate, inlet air temperature and humidity, supply air and chilled water set-points and amount of water-side fouling) and two outputs (power consumption and cooling coil valve position). The supply fan model has two inputs (supply air flow rate and the estimated amount of air-side fouling) and two outputs (power consumption and fan speed). The use of both high and low precision fuzzy models is being examined.

The training data are generated by simulating the steady-state behaviour of the VAV air-conditioning system, over its full operating range, using the HVACSIM+ simulation package. To reduce simulation times, open-loop experiments were performed in the case of the cooling coil. The control valve was step from its fully closed to fully open position in 5% increments at each set of operating conditions. Water-side fouling was introduced by adding a calcium-carbonate layer to the inside of the chilled water pipes in the simulated cooling coil. Air-side fouling was introduced by increasing the flow resistance in the ductwork.

Figure 2 compares the defuzzified value of the chiller power predicted by the high precision fuzzy model with the data used for training for different supply air and chilled water temperature set-points, a constant supply air mass flow rate and

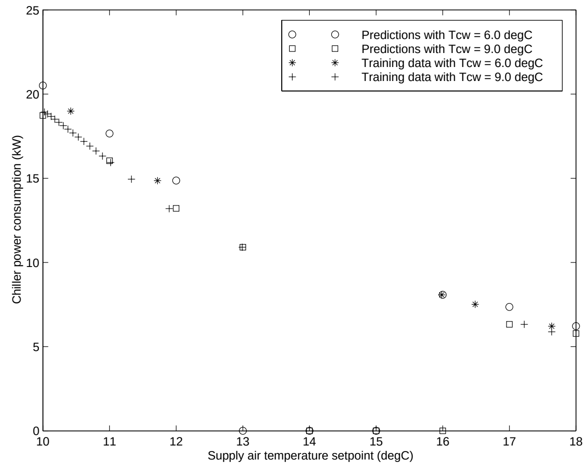

Figure 2: Comparison of predicted and actual chiller power

no water-side fouling. The high precision fuzzy model used eight fuzzy sets to describe the supply air flow rate, six to describe inlet air temperature, five to describe the inlet air humidity, nine to describe the supply air temperature set-point, four to describe the supply chilled water set-point, three to describe the water-side fouling, six to describe the power consumption of the chiller, and five to describe the position of the control valve.

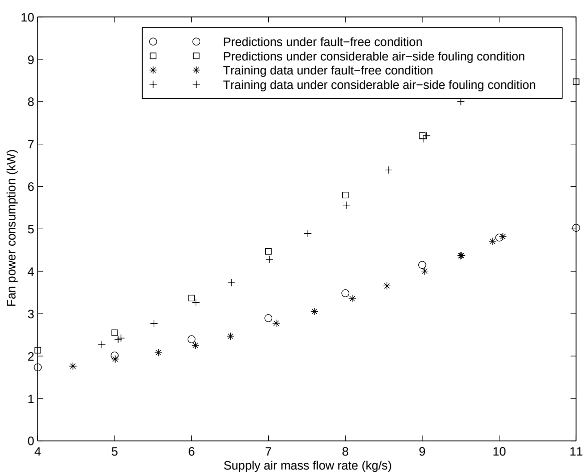

Figure 3: Comparison of predicted and actual fan power

The high precision fuzzy model is able to predict the power consumption of the chiller to better than ±1.0 kW. It should be noted that the chiller power is not very sensitive to variations in the chilled water temperature set-point. The missing training data for supply air temperature set-points between 13^{o}C and 16^{o}C are a result of the highly non-linear characteristic of the oversized cooling coil control valve used in the simulated air-handing unit.

Figure 3 compares the fan power predicted by the high precision fuzzy model with the data used for training at different supply mass flow rates, when there is and is not air-side fouling. Once again the predictions are generated by a high precision fuzzy model that uses eight fuzzy sets to describe the supply air flow rate, four to describe the air-side fouling, nine to describe the power consumption of the fan, and five to describe the fan speed.

The high precision fuzzy model is able to predict the increased power consumption of the supply fan resulting from the air-side fouling with reasonable accuracy. It should be noted that the fan power is not very sensitive to changes in the supply air flow rate when there is no air-side fouling.

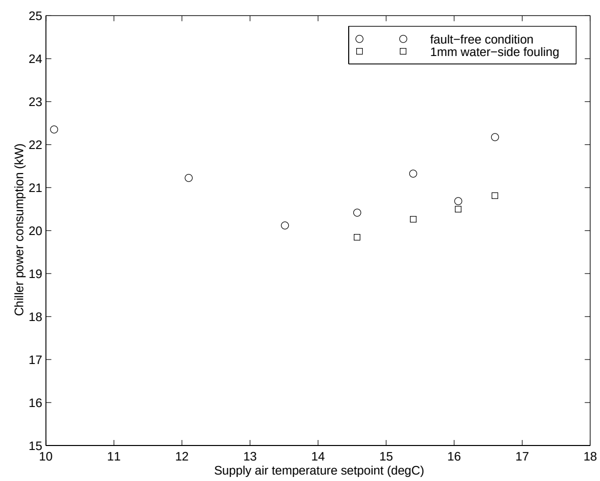

Figure 4: Sensitivity of chiller power to set-points and water-side fouling

SENSITIVITY OF PERFORMANCE TO DEGRADATION FAULTS AND SET-POINT CHANGES

The predicted chiller power, with and without 1mm of water-side fouling, is plotted against the supply air temperature set-point in Figure 4, for the case when the chilled water supply temperature set-point is high (9^{o}C), there is a high cooling demand ($60kW$), and the humidity of the inlet air is low (humidity ratio = 0.009). Data are only plotted for those values of the set-points that do not cause the cooling coil control valve to move to its fully open position.

When there is no water-side fouling, the minimum value of the chiller power occurs at a supply air temperature set-point of approximately 14^{o}C. It should be noted that the water-side fouling reduces the number of supply air-temperature set-points that are feasible but has relatively little effect on the power consumption of the chiller.

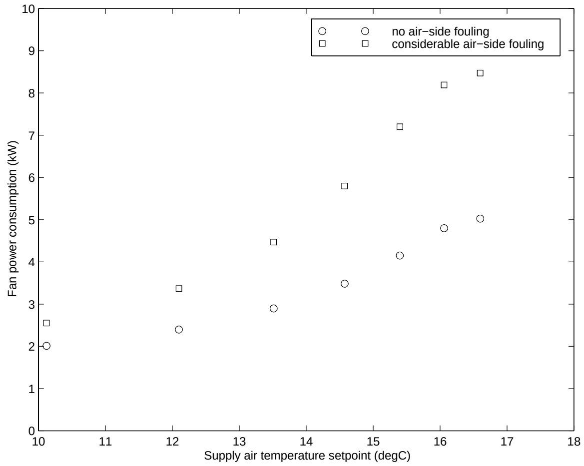

Figure 5: Sensitivity of fan power to set-points and air-side fouling

The predicted supply fan power, with and without air-side fouling, is plotted against the supply air temperature set-point in Figure 5 for the case when there is a high cooling demand ($60kW$). The air-side fouling results in a significant increase in the power consumption of the fan at high supply air temperature set-points.

The predicted total power consumption, with and without air-side and water-side fouling, is plotted against the supply air temperature set-point in Figure 6 for the case when the set-point of the chilled water supply temperature is high (9.0^{o}C), there is a high cooling demand ($60kW$) and the humidity of the inlet air is low (humidity ratio = 0.009). As before, data are only plotted for those values of the set-points that do not cause the cooling coil control valve to move to its fully open position.

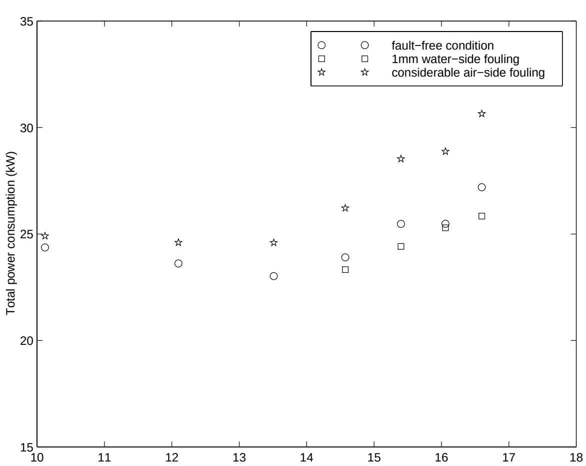

Figure 6: Sensitivity of total power to set-points with and without fouling

Set-point changes result in relatively little variation in total power when there is no fouling. The supply air temperature that minimises the total power consumption is approximately 14^{o}C at these operating conditions. The lowest feasible value of the supply air temperature set-point should be used when water-side fouling is present.

FAULT TOLERANT CONTROL OF A VAV AIR-CONDITIONING SYSTEM

A six zone VAV system was simulated [Haves et al., 1998]. The simulated portion of the building consists of three floors plus a basement, approximately 15m high, 26m long, and 16m wide. Representative internal and external heat gain profiles were developed separately for each of the six zones, and weather data from a typical summer day was used in the simulation. The internal heat gains have three sources: human occupants; office equipment and miscellaneous appliances; and electric lighting. External gains, due to the external ambient air temperature and insolation, are represented as a sol-air temperature. During the whole 24 hours' (from midnight to midnight) simulation period, the outside air damper is at its minimum position due to the enthalpy-based economizer control algorithm and the high outside air enthalpy.

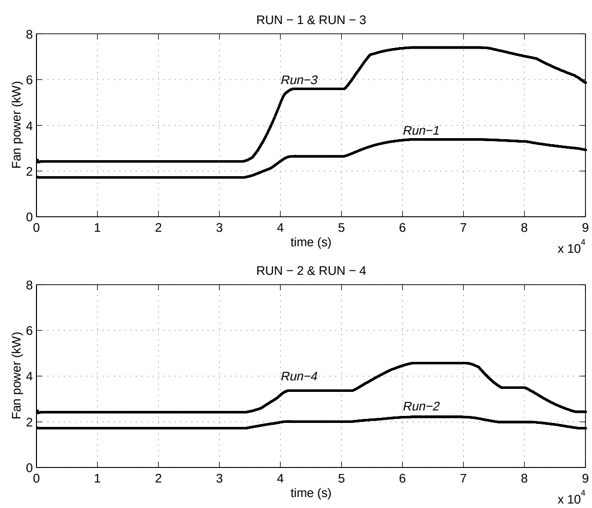

Figure 7: Fan power consumption: with and without air-side fouling

Two typical operating conditions were simulated and compared to see the effect of changing set-points on the system energy consumption. The details are given in Table 1

In Run-1, Run-3 and Run-5, the supply air temperature set-point was set at a value (16.5^oC), above which the thermal comfort in the largest zone could no longer be maintained throughout the occupancy period. The chilled water temperature set-point was set to the highest value

	$Tsup = 16.5^oC$ $Tcwi = 8.0^oC$	$Tsup = 13.5^oC$ $Tcwi = 6.0^oC$	$Tsup = 16.5^oC$ $Tcwi = 4.0^oC$
Fault-free	Run-1	Run-2	–
Air-side fouling	Run-3	Run-4	–
Water-side fouling	Run-5	–	Run-6

Table 1: Summary of the simulated cases

(8.0^oC) that allowed the supply air temperature to be maintained at the set-point value through the occupancy period. In Run-2 and Run-4, the supply air temperature set-point was set at the highest value (13.5^oC) that would ensure that the supply air flow was at its minimum value through the occupancy period. The chilled water supply temperature was set to the highest value (6.0^oC) that allowed the supply air temperature to be maintained at its set-point value throughout the occupancy period.

Air-side fouling

Figure 7 illustrates the impact of air-side fouling on the supply fan power consumption by comparing faulty (Run-3 and Run-4) and fault-free operation (Run-1 and Run-2). Clearly, air-side fouling significantly increases the fan power.

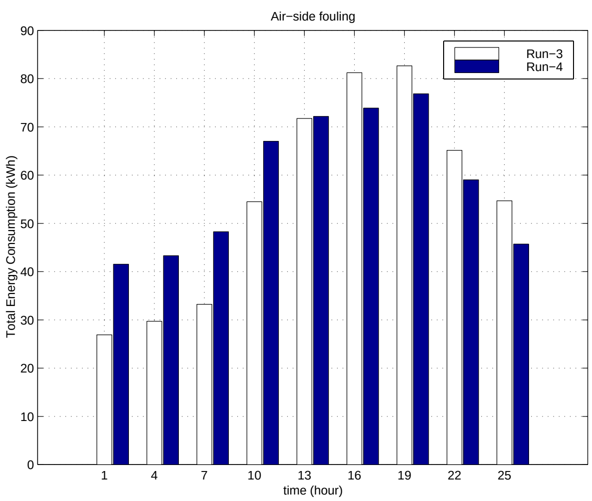

Figure 8: Three hourly total energy consumption

For example, comparing Run-1 and Run-3 (with the same set-points), fouling only increased fan power consumption by about 50% at the beginning of the simulation period, when the air flow rate was small, while by more than 100% during the peak load period when the air flow rate was at its maximum demand. It can also be seen from Figure 7 that the same amount of air-side fouling had a much greater influence on the fan energy consumption in Run-3 than in Run-4, since it had a higher supply air temperature set-point, and thus required a higher air flow rate. Figure 8 shows the total energy consumption for Run-3 and Run-4. In both cases, the thermal conditions in the zones were within the comfort region at all times.

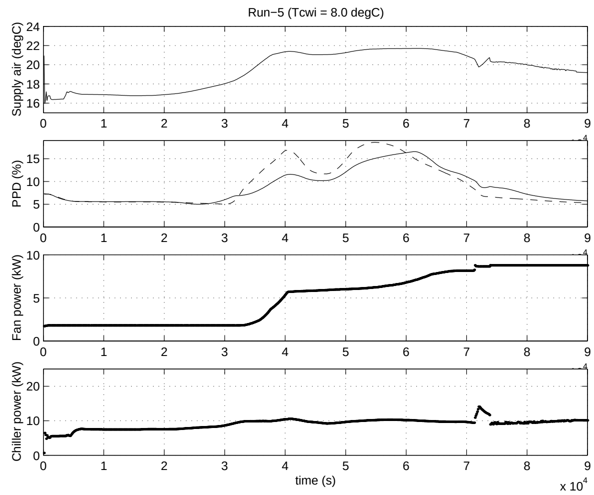

Figure 9: Operation with 1 mm of water-side fouling ($T_{cws} = 8.0^oC$)

Water-side fouling

Figure 9 shows the effect of $1mm$ of water side fouling on the control performance. The supply air temperature set-point (16.5^oC) could not be maintained when the set-point for the chilled water supply temperature is 8.0^oC (Run-5). However, satisfactory supply air temperature control and zone comfort is observed (see Figure 10) when the chilled water temperature set-point is reset to 4.0^oC (Run-6).

CONCLUSIONS AND FUTURE WORK

The total cost of operating the fault-free system is relatively insensitive to the choice of set-points since, in this particular system, the supply fan and the ductwork are oversized and the COP of the chiller changes very little as the supply water temperature varies. However, both set-points must be varied with operating conditions to ensure no loss of control, and the total power consumption is sensitive to the choice of the supply air-temperature set-point when there is significant air-side fouling.

Although low precision fuzzy models will be less accurate than those used here, they will also be less sensitive to missing training data. Fault tolerant control based on fuzzy models that use

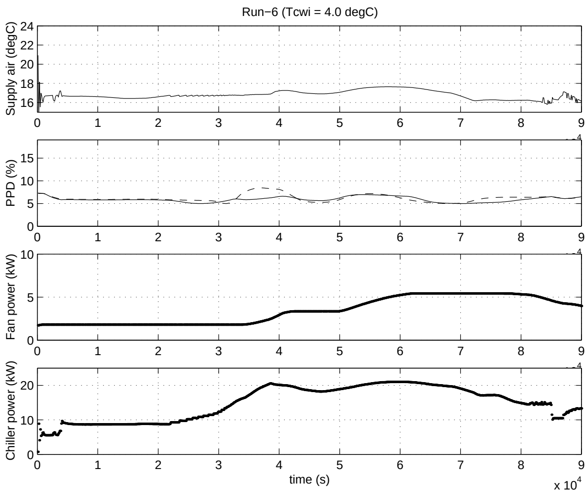

Figure 10: Operation with 1 mm of water-side fouling ($T_{cws} = 4.0^oC$)

only three fuzzy sets to describe each of the input variables is now being examined. A full implementation of the fuzzy model-based fault tolerant supervisor is also being developed so that it can be tested on-line on the simulated air-conditioning system.

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