GENERIC MODELLING OF HVAC PLANT FOR FAULT DIAGNOSIS

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ABSTRACT

A methodology is presented for creating models which are suitable for use in fault detection and diagnosis schemes in applications where it is impossible to obtain data from the actual plant. Generic qualitative models based on fuzzy rules are used to describe the basic features of the behaviour of a class of plants of similar design. The generic models are identified off-line from training data produced by computer simulation of typical plant designs. The method uses a data clustering algorithm to assist in identifying the structure and a fuzzy identification algorithm to estimate the parameters of the model from the training data.- A measure of the degree of similarity between fuzzy models is introduced to determine the extent to which the behaviour of individual plants is similar to that of the generic model.

The method is used to generate generic models of a cooling coil subsystem when it is operating correctly and when the coil has become fouled. Results are presented which show that the generic models can be used to describe a class of plant designs without greatly increasing the ambiguity associated with the fault diagnosis.

INTRODUCTION

Many methods of fault detection and diagnosis use mathematical models to define the behaviour of the system when it is operating correctly and when faults are present [1]. Although schemes based on quantitative models have been proposed for detecting faults in heating, ventilation and air-conditioning (HVAC) systems [2,3,4,5,6], a knowledge-based treatment is usually required for fault diagnosis, since it is very difficult to obtain adequate representations of the complex and often highly non-linear behaviour of faulty plant using quantitative models. Diagnosis schemes based on both classification [7,8,9,10,11,12,13,14,15] and deep knowledge [16,17] qualitative models have been described.

Fuzzy qualitative models have been used to take account of the uncertainties and imprecision associated with describing the behaviour of the HVAC plant [18,19,20,21], Models of this type allow whatever qualitative domain knowledge is available about the system to be combined with information extracted from measured data [22,23,24]. However, in practice, it is unlikely that training data which are representative of faulty behaviour can be collected from the plant itself, since the introduction of physical defects into a real system in an occupied building is usually unacceptable and, in the case of faults like fouling, the defects are themselves very difficult to reproduce in a realistic manner. Generic models, which describe the underlying behaviour of a class of plants of a similar design, must be used where it is impossible to obtain detailed information about or measurement data from a specific plant. Generic fuzzy models can be based on expert knowledge or generated off-line from training data produced by computer simulation of typical plant, with and without the faults [25]. Clearly, models which are too generic must be avoided, since they may not be able to distinguish between the correct and faulty behaviour of the plant, and a trade-off exists between the range of applicability of the models and the sensitivity of the associated diagnosis.

A method of generating generic fuzzy models which can represent a class of plants of similar designs is described in this paper. Training data for each example of the class are obtained and normalised to design parameters. Data clustering is then performed on the data to identify the basic features of the behaviour of the class. A measure of the degree of similarity between fuzzy models is introduced to determine the extent to which the behaviour of individual plants is similar to that of the generic model. The generic modelling approach is applied to the cooling coil sub-system of an air-handling unit.

GENERIC FUZZY MODELS

The term generic fuzzy model is used to describe a fuzzy model which describes those features of the behaviour which are common to a whole class of plants. The development of a suitable generic model involves many difficult issues such as the appropriate choice and normalisation of the input and output variables, the size of the class to be represented, the degree of similarity between the behaviour of the individual plants of the class, and the modelling accuracy demanded by the particular application.

Fuzzy modelling is an approach that provides an approximate and yet effective means of describing the behaviour of systems which are complex and too ill-defined to admit use of precise mathematical analysis [26]. A fuzzy model consists of a set of IF-THEN rules which describe the essential features of the behaviour of a system. A particular model is defined by the fuzzy sets which are used to describe its inputs and outputs, and by the values of the elements of an associated fuzzy relational matrix. Each entry in the matrix is a measure of belief (the credibility) in the associated rule correctly describing the behaviour of the systēm around a particular operating point. The creation of a fuzzy model can be divided into two parts: structure identification and parameter estimation. Structure identification is concerned with selecting the variables, partitioning the input and output space (selecting the number and shape of the fuzzy sets), and choosing the most appropriate form for the relationship between the input and output variables (choosing the number and format of the rules to be used in the model). Parameter estimation is concerned with determining values for the parameters which define the membership functions of the fuzzy sets [27] and the elements of the relational matrix [28]. The partition of the input-output space into fuzzy regions and the form of the rules can be based on expert knowledge or determined automatically using a clustering scheme to extract the information from measured data [29]. A simple fuzzy identification scheme [30] can be used to estimate the elements of the fuzzy relational matrix.

Generic fuzzy model are generated from training data obtained by simulating plants of similar design which belong to the same class. The basic steps in the identification of a generic fuzzy model are:

a) Define the class of plants of similar design

b) Select suitable input and output variables and specify the operating ranges

c) Partition the input space using fuzzy reference sets which have triangular membership functions

d) Use computer simulation to generate training data which covers the whole operating space for each of the plants

e) Normalise the training data for each plant using its design parameters

f) Clustering the normalised output data from all plants to identify the partitions in the output space

g) Approximate the output partitions by fuzzy reference sets which have triangular membership functions

h) Estimate the elements of the fuzzy relational matrix using a fuzzy identification algorithm and the training data from all of the simulated plants

i) Determine the range of applicability of the generic model by calculating the similarity of the generic fuzzy model and individual fuzzy models identified using training data obtained by simulating single plant designs.

DEGREE OF SIMILARITY OF MODELS

A fuzzy measure of the degree of similarity between fuzzy models can be used to check the validity of using a generic model to represent the individual examples of the class of designs, and other designs outside the class.

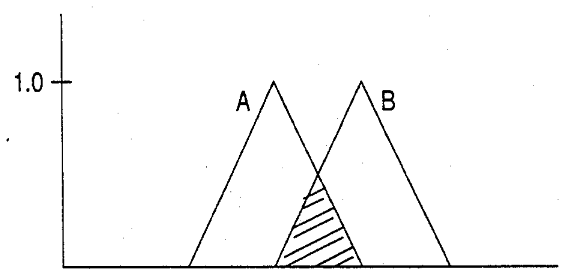

Figure 1: Matching of two fuzzy sets

Consider two fuzzy sets which have discrete membership functions A and B. The degree of matching of the fuzzy sets $S(A,B)$ (see Figure 1) is defined as the proportion of A that is contained in B and is given by

$$S(A,B) = \frac{\sum_{-\infty}^{\infty} \mu_{A\cap B}(x)}{\sum_{-\infty}^{\infty} \mu_A(x)} \qquad (1)$$

where intersection $\cap$ can be represented in fuzzy logic by the min operator.

A measure of the degree of similarity between two fuzzy models can be evaluated using the same method if the fuzzy models are themselves considered as fuzzy sets with discrete membership functions given by the credibilities of the rules [25]. Thus,

$$S(M_i, M_j) = \frac{\sum_{n=1}^{N} min\{c_{M_i}(n),\ c_{M_j}(n)\}}{\sum_{n=1}^{N} c_{M_i}(n)} \quad (2)$$

where $c_{M_i}(n)$ and $c_{M_j}(n)$ are the credibilities of the nth rule in the fuzzy models M_i and M_j respectively (see Figure 2), and N is the number of rules in the models.

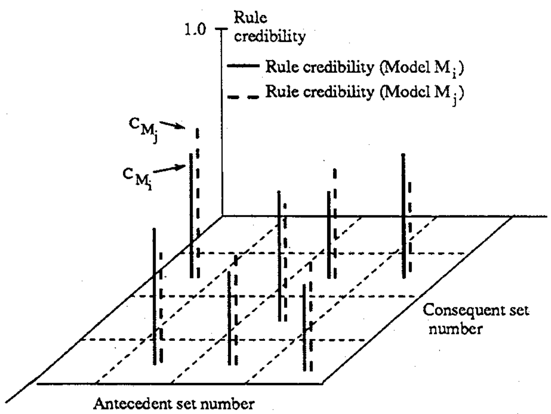

Figure 2: Matching of two fuzzy models

The value of the degree of similarity lies in the range 0 to 1, where $S = 1$ indicates complete similarity between the models and $S = 0$ indicates no similarity.

APPLICATION OF THE GENERIC MODELS

Generic fuzzy models of the cooling coil sub-system (see Figure 3) of an air-handling unit are developed for use in a fuzzy fault diagnosis scheme [25]. Models of both correct and faulty operation (in this case, a build-up of 1mm of scale on the inside of the tubes of the coil) are generated for a class of sub-systems having different designs of cooling coils (Table 1).

Coil designs D1 to D6 have similar cooling duties and face areas, but operate at different chilled water supply temperatures. Design D7 has a higher duty than the other coils. In each case, the valve is sized to achieve a similar valve authority, and the bypass flow resistance is adjusted so that it is equal to that of the coil.

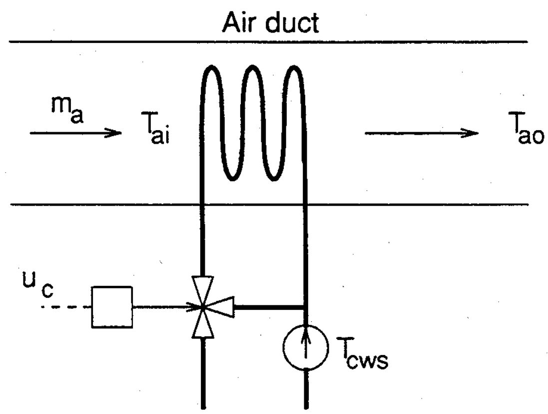

Figure 3: Cooling coil sub-system

Those inputs which can be controlled directly are excited using a staircase waveform so that the training data covers the whole of the operating space. To ensure that the training data nicely fits the structure of the model, the magnitude of the steps is chosen so that the values of the normalised input variables coincide with the values at the apex of the fuzzy reference sets. Output data are collected for all combinations of values of the inputs. The simulations are based on a model of a coil developed for use with the HVACSIM+ simulation package [31].

The input and output variables of the fuzzy models are derived from the inlet temperature T_{ai}, the air mass flow rate m_a, the valve control signal u_c and the outlet temperature T_{ao}.

Coil Design	D1	D2	D3	D4	D5	D6	D7
Coil duty (Kw)	62.2	62.8	74.3	71.2	67.5	63.2	146.6
Air flow (Kg/s)	4.3	4.3	4.3	4.3	4.3	4.3	8.6
Supply temp. (°C)	5	6	7	8	9	10	7
Water flow (Kg/s)	5.0	5.4	6.3	6.8	7.2	7.4	10.0
No. of rows	4	4	6	6	6	6	7
Height of coil (m)	0.9	0.9	1.44	1.5	1.5	1.5	2.0
No. of circuits	30	30	45	50	50	50	75
Valve capacity (m^3/hr)	24.6	26.6	31.0	33.5	35.4	36.4	49.2
Coil resistance (0.001Kg.m)	0.42	0.42	0.30	0.23	0.23	0.23	0.12

Table 1: Design data for cooling coils

The generic fuzzy model has three inputs:

- the valve control signal $X_1 = u_c$
- the normalised air mass flow rate $X_2 = \frac{m_a - m_{a_{min}}}{m_{a_{max}} - m_{a_{min}}}$
- an indicator of whether the coil is dry or wet $X_3 = \frac{(T_{ao} - T_{dew})}{\Delta}$ where T_{dew} is the dew-point temperature and Δ is a user selected parameter whose value reflects the uncertainties associated with this simple method of assessing the wetness of the coil.

and one output:

- the air-side approach of the coil $Y = \frac{(T_{ai} - T_{ao})}{(T_{ai} - T_{cws})}$, where T_{cws} is the design value of the chilled water supply temperature.

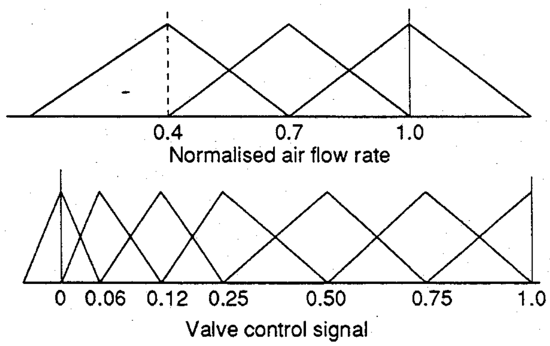

Figure 4: Partitioning of the input space of normalised air flow rate and valve control signal

The partitions of the input space of the normalised control signal and air mass flow rate are shown in Figure 4. Non-uniform partitions are used for the control signal since it is known that higher resolution will be needed when the coil is operating at low duty.

The partitions for the wetness indicator and the air-side approach are obtained by clustering the normalised training data, for both fault-free and faulty operation, from all of the three designs (D3, D4 and D5) which are used to generate the generic models. As can be seen in Figures 5 and 6, the number of clusters are limited to three for the wetness indicator and eight for the approach. The three partitions for the wetness indicator provide a fuzzy indication of whether the coil is operating wet, partially wet, or dry. The larger number of partitions for the air-side approach is necessary to ensure

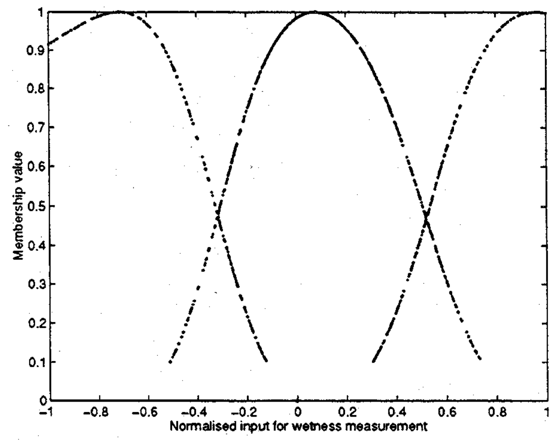

Figure 5: Clustering of the wetness data for fault-free and faulty operation from all examples of the class

sufficient resolution to differentiate between fault-free and faulty behaviour. Fuzzy reference sets are constructed by approximating the partitions of the data by triangular membership functions.

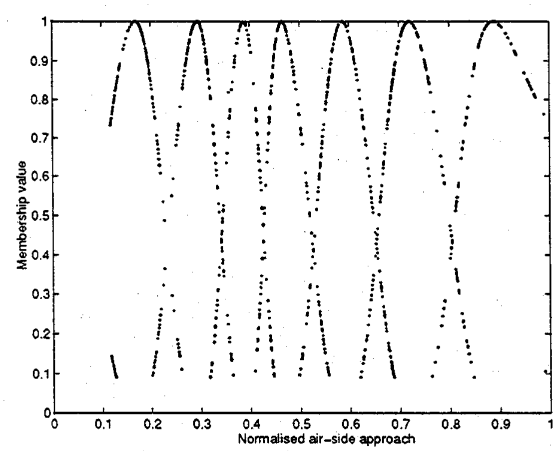

Figure 6: Clustering of the air-side approach data for fault-free and faulty operation from all examples of the class

Individual fuzzy models of both the faulty and fault-free operation of each of the designs are compared to determine whether their behaviour is sufficiently similar for their operation to be described by generic models. The individual models are based on fuzzy partitions obtained by clustering both the faulty and fault-free normalised training data associated with the particular design. The degrees of similarity of each of the designs and the three designs which are used to generate the generic models are given in Tables 2 and 3.

Fault Model	Fault Model						
	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**
D3	33%	34%	100%	90%	84%	81%	82%
D4	31%	32%	89%	100%	92%	88%	73%
D5	27%	29%	84%	93%	100%	95%	67%

Table 2: Similarity of individual models of faulty behaviour

Fault-free model	Fault-free Model						
	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**
D3	32%	39%	100%	88%	82%	77%	76%
D4	29%	34%	89%	100%	90%	80%	68%
D5	27%	31%	82%	89%	100%	84%	65%

Table 3: Similarity of individual models of correct behaviour

ADDITIONAL AMBIGUITY

It is unlikely that the fuzzy models of faulty and fault-free behaviour will be completely different since, in practice, there will be some similarity between the behaviour of the plant with and without fouling at some operating points. In such situations, a model-based fault diagnosis scheme will generate, at least partially, ambiguous results [25]. The levels of ambiguity might be expected to increase as the reference models used in the fault diagnosis scheme become more generic. The degree of similarity of the fault-free and faulty fuzzy models gives some indication of whether the models are suitable for fault diagnosis. The degrees of similarity between the fault-free generic model, the fault-free individual models, and the individual fault models of the three designs within the class, are given in Table 4.

	Individual fault model		
	D3	**D4**	**D5**
Generic fault-free model	60%	65%	69%
Individual fault-free model	57%	56%	56%

Table 4: Similarity of individual fault models and fault-free models for designs within the class

The degrees of similarity between the individual fault models of designs D3, D4 and D5 and the generic model of faulty behaviour are all equal to unity (100%). The results demonstrate that the generic model is representative of each individual example of the class, and suggest that their use will result in a relatively small increase in the levels of ambiguity associated with the diagnosis.

APPLICABILITY TO OTHER DESIGNS

The results of comparing the individual models of the designs D1, D2, D6 and D7 (all with fouling) and the generic models of both faulty and fault-free behaviour are shown in Table 5.

	Individual fault model			
	D1	**D2**	**D6**	**D7**
Generic fault model	33%	35%	96%	82%
Generic fault-free model	26%	27%	71%	52%

Table 5: Similarity of individual fault models and generic models for designs outside of the class

In all cases, the degrees of similarity between the model of the fouled coil and generic model of faulty operation is greater than that of the generic model of correct operation. It is noted that the designs D1 and D2 have similar and markedly lower degrees of similarity than the other designs. The results suggest that, in practice, fault diagnosis based on the generic models could only be used on designs D6 and D7.

CONCLUSIONS

A methodology has been developed for constructing qualitative generic models which can capture the underlying characteristics of the behaviour of a class of plants of similar design. The method has been successfully applied to the modelling of cooling coil sub-systems in air-handling units. The results suggest that the generic models are applicable over a range of coil sub-systems when the designs are based on the same design criteria, that they should be suitable for use in model-based fault diagnosis schemes, and that their use should only result in a relatively small increase in the level of ambiguity, in comparison with plant specific fuzzy models.

ACKNOWLEDGEMENTS

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