AERO-ENGINE ADAPTIVE FUZZY DECOUPLING CONTROL

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Abstract: A new kind of multivariable adaptive fuzzy decoupling controller is present for Aero-engine, which consists of multivariable fuzzy decoupling control and fuzzy model reference learning control. A fuzzy inverse model is used to produce and adjust fuzzy rules online. The simulation results show that this controller is effective.

Key words: Aero-engine, fuzzy decouple, Adaptive Fuzzy Control

1. INTRODUCTION

Fuzzy control has emerged in recent years as a promising way to approach nonlinear control problems. An engine system is a non-linear distributed system with complex interactions between sensors and actuators, the dynamics of the system and the dynamics of the environment. Many researchers have investigated control of engines with a motivation towards applying fuzzy control techniques for improve engine performance.

Conventionally, fuzzy rules are established by a combination of knowledge, experience and observation and may thus not be optimal. However, a synthesis of fuzzy logic controllers to a large extent does not rely on sound mathematical principles. It is entirely based on the nature of problem in hand and the ability of the engineer to translate his experience into meaningful rules and fuzzy sets. Although this approach works well for simple problems, or problems with single input and single output, it is almost impossible to manually arrive at fuzzy controllers for more complex problems. Multivariable fuzzy decoupling control can be used to model the multivariable fuzzy controller using the decomposition of the control rule base into a set of simple rule bases. But there are some limitations to such a method including: the difficulties in developing an accurate intuition about how to best compensate for the unpredictable and significant system parameter variations that can occur while the engine flight environment changed and a lack of basic expertise in the decoupling rule–base.

In this paper, we investigate the possibility of consisting the multivariable fuzzy decoupling control and fuzzy model reference learning control for automatically synthesizing and tuning a fuzzy decoupling controller.

2 ADAPTIVE FUZZY DECOUPLING CONTROLLER

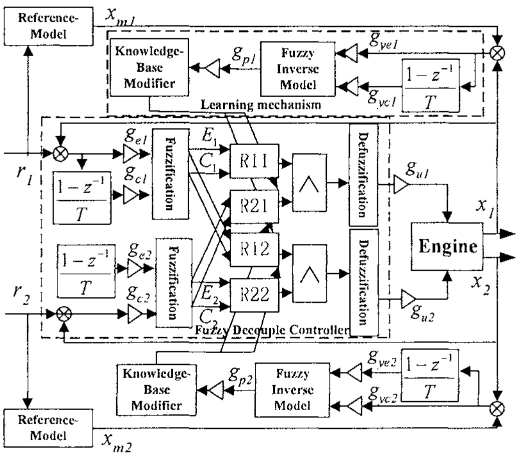

Figure 1. .Architecture for adaptive fuzzy decouple control

Figure 1 shows Architecture for multivariable adaptive fuzzy decoupling control, which consists of fuzzy decoupling controller, reference model and learning mechanism. where the $g_e, g_c, g_{ye}, g_y, g_u, g_p$ is the normalize gains, r_1, r_2 is the reference input, x_{m1}, x_{m2} the reference model output, x_1, x_2 is the plant output.

2.1 The Fuzzy Decoupling Controller

The inputs to the fuzzy controller are the error of the plant output and the reference input and change in error. In this paper, we have 11 fuzzy sets on the input universes of discourse, which is {-1,-0.8,-0.6,-0.4,-0.2,0,0.2,0.4, 0.6,0.8,1}.The knowledge-base for the fuzzy controller associated with the n process inputs is generated from **IF-THEN** control rules of the form:

$$\text{If } E_1^j \text{ and} \ldots \text{and } E_s^k \text{ and } C_1^l \text{ and} \ldots \text{and } C_s^m \text{ then } U_n^{j,\ldots,k,l,\ldots,m} \tag{1}$$

This fuzzy implication can be represented by a fuzzy relation:

$$R_n^{j,\ldots,k,l,\ldots,m} = (E_1^j \times C_1^l) \times \ldots \times (E_s^k \times C_s^m) \times U_n^{j,\ldots,k,l,\ldots,m} \tag{2}$$

The fuzzy controller decision mechanism for this control rule may be expressed by

$$U_n^{j,\ldots,k,l,\ldots,m} = (E_1^j \times C_1^l) \times \ldots \times (E_s^k \times C_s^m) \circ R_n^{j,\ldots,k,l,\ldots,m} \tag{3}$$

The number of rule base can become quite large (in the case of n variables in the premise of the m fuzzy set, the number of cross-products is m^n), multivariable control rules can be approximately decomposed into several sets of two-dimensional rules for each input. The decomposed multivariable control rules is as follows:

$$U_n^{j,\ldots,k,l,\ldots,m} = (E_1^j \times C_1^l) \circ R_{n1}^{jl} \wedge \ldots \wedge (E_s^k \times C_s^m) \circ R_{ns}^{k,m} \tag{4}$$

In this way, multivariable fuzzy controller can be divided into the aggregation of several simple fuzzy controllers, and the rule base number reduces to $(mn)^2$. Let $\mu_{E_iC_i}(e_i, c_i)$ denote the membership of the ith input variable of the subset, then the membership of formula (4) is as follows:

$$\mu_n^{j,\ldots k,l,\ldots,m} = \mu_{E_1C_1}(e_1, c_1) \wedge \ldots \wedge \mu_{EsCs}(e_s, c_s) \tag{5}$$

The "Center of gravity" method calculates the crisp output by:

$$u_n = \frac{\sum_{j,\ldots,k,l,\ldots,m} U_n^{j,\ldots,k,l,\ldots,m} \times \mu_n^{j,\ldots k,l,\ldots,m}}{\sum \mu_n^{j,\ldots k,l,\ldots m}} \tag{6}$$

2.2 The Reference Model

The reference model provides a capability for quantifying the desired performance of the process. The reference model may be any type of dynamical system either linear or nonlinear. It is use to characterize closed-loop specifications such as stability, rise time, overshoot and settling time. The performance of the overall system is computed with respect the error of the plant output and the reference model output. The desired performance of the controlled process is met if the learning mechanism forces the error to remain very small for all time. It is very important to make proper choice for a reference model so that the desired respond does not to dictate unreasonable performance requirements for plant to be control.

$U^{j,k}$						C^j					
	−5	−4	−3	−2	−1	0	+1	+2	+3	+4	+5
−5	−1.0	−1.0	−1.0	−1.0	−1.0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0
−4	−1.0	−1.0	−1.0	−1.0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0	+0.2
−3	−1.0	−1.0	−1.0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0	+0.2	+0.4
−2	−1.0	−1.0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0	+0.2	+0.4	+0.6
−1	−1.0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0	+0.2	+0.4	+0.6	+0.8
E^k 0	−1.0	−0.8	−0.6	−0.4	−0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0
+1	−0.8	−0.6	−0.4	−0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0
+2	−0.6	−0.4	−0.2	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0
+3	−0.4	−0.1	+0.1	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0
+4	−0.2	+0.1	+0.3	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0
+5	0.0	+0.2	+0.4	+0.6	+0.8	+1.0	+1.0	+1.0	+1.0	+1.0	+1.0

Figure 2. Rule base array table

2.3 The Learning Mechanism

As previously mentioned, the learning mechanism performs the function of modifying the knowledgebase of a direct fuzzy controller so that the closed-loop system behaves like the reference model. The learning mechanism consists of two parts: a fuzzy inverse model and a knowledge-base modifier. The fuzzy inverse model performs the function of mapping necessary changes in the process output, and decides how to change the plant command inputs so that this deviation goes to zero. The knowledge-base modifier performs the function of modifying the fuzzy controller's knowledge-base to affect the needed changes in the process inputs. The output of the fuzzy inverse model is represented by $p(kT)$. Then the output, $p(kT)$, is used to modify the controllers rule-base. The controller output that would have been desired is expressed by

$$\overline{u}(kT-T)=u(kT-T)+p(kT)$$

Assume that only symmetric membership functions are defined for the fuzzy controller's output so that $c_{ns}^{p,q}$ denotes the center value of the membership function associated with the rule-base $R_{n1}^{jl}\ldots R_{ns}^{k,m}$. Consider the effect that the above knowledge-base modification in Equation 6. Notice that only those fuzzy relations whose $\mu_n^{j,\ldots k,l,\ldots,m}>0$ contribute to the previous control. For all active rules the modification of the output membership function centers will be

$$\overline{c}_{ns}^{p,q}(kT-T)=c_{ns}^{pq}(kT-T)+p_n(kT)\,,$$

while all other rules stay unchanged. The intersection of the subset should be shifted $p_n(kT)$:

$$\overline{U}_n^{j,\ldots k,l,\ldots m}(kT-T)=U_n^{j,\ldots k,l,\ldots,m}(kT-T)+p_n(kT)$$

Substituting this new fuzzy set into Equation 5 we obtain

$$\overline{u}_n(kT-T)=u_n(kT-T)+p_n(kT)\text{。}$$

It is worth mentioning that the entire rule base does not need to be modified every time step, but the rules that apply to the current situations are changed and stored. Therefore, when the plant returns to a familiar operating point, it does not need to re-adapt or re-tune. The controller will already know how to handle the process. This kind of controller is great for systems in which robustness issues are extremely relevant. Table 2 shows a knowledge-base array table. For our example, assume that $p_n(kT)$=0.1,only four items whose certainty is greater than zero are modified.

The selection of controller gains is an important step in the design progress, as the ability of the controller to track the reference model will heavily depend on particular choices of gains. Due to physical constraints for a given system, the range of values for the process inputs and outputs is generally known from a qualitative analysis of the process. As a result, we can select the controller gains g_e, g_{ye}, g_u, g_p so that each universe of discourse is mapped to the interval [-1,1]. Using standard fuzzy control design techniques or simple experiments choose g_c to map the universes of discourse of c (kT) to [1, 1]. A suitable selection of g_{yc} may be obtained by monitoring the response of the overall process with respect to the reference model response.

3. ENGINE CONTROL APPLICATIONS RESULTS

The verification of the effectiveness of this approach was carry out using a linear turbofan engine model, the dynamical behavior of the engine system can be described by using the state space model

$$\begin{bmatrix} \dot{n}_h \\ \dot{n}_l \end{bmatrix} = \begin{pmatrix} -1.1789 & -0.2119 \\ 2.4610 & -3.6797 \end{pmatrix} \begin{bmatrix} n_h \\ n_l \end{bmatrix} + \begin{pmatrix} 0.4642 & 0.0896 \\ 0.6888 & 0.4324 \end{pmatrix} \begin{bmatrix} m_f \\ A_e \end{bmatrix}$$

where the n_h is compressor rotor speed, n_l is fan rotor speed, m_f is core fuel flow and A_e is nozzle throat area. The system matrices are determined by linearization of non-linear physical model around design condition of Mach 0 and 0-km altitude.

For this application, the controller includes four fuzzy decoupling controllers and two fuzzy inverse models. Usually, the knowledge-base array shown in fig.2 can be employed for both fuzzy inverse models and fuzzy decoupling controllers. The normalizing controller gains are chosen to be g_e=[300,300], g_c=[13.,13.] and g_u=[0.012,0.012], and the normalizing learning mechanism gains are chosen to be g_{ye},=[400,400],g_{yc}=[7.4,7.4] and g_p=[0.012,0.012].

The design condition simulation results for the adaptive fuzzy decoupling controller of the aero-engine are shown in Figure 3 for n_h, and Figure 4 for n_l. Once again the FMRLC provided good system tracking with respect to the reference model. As a result, the system exhibits good steady state and transient response. The main attribute of the adaptive controller is its ability to accommodate system changes. We demonstrate this aspect of the adaptive fuzzy decoupling controller by changing the engine flight environment. Figure 5-Figure 8 shows the step response at Mach 1.3 and 12 km altitude and Mach 1.5 and 18km altitude. It is observed the system exhibits good tracking with the reference model even after engine flight environment changes significantly.

4 CONCLUDING REMARKS

The key advantages of the adaptive fuzzy decoupling controller are:

1. Providing an automatic method to synthesize a portion of the knowledge-base for the direct fuzzy controller while at the same time it ensures that the system will behave in a desirable fashion
2. Updating the knowledge-base in the fuzzy decoupling controller dynamically and continually in response to process parameter variations or disturbances. In this way if engine flight environment changes, the controller can make on-line adjustments to fuzzy decoupling controllers to maintain adequate performance levels
3. Decomposition of multivariable control rules into several sets of two-dimensional rules for each input, simplified the evolution of the rule base.

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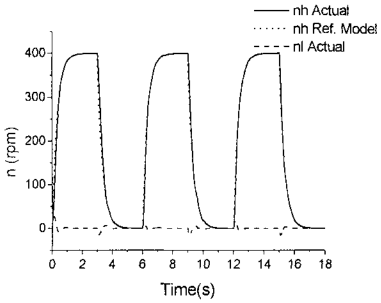

Figure. 3 Step response of n_h at Mach 0 and 0 km altitude

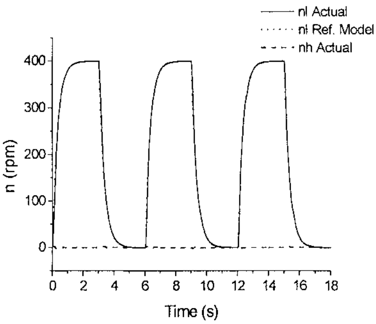

Figure. 4 Step response of n_l at Mach 0 and 0 km altitude

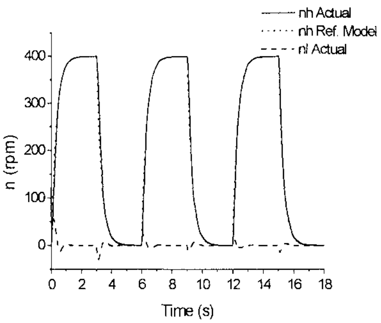

Figure. 5 Step response of n_h at Mach 1.3 and 12 km altitude

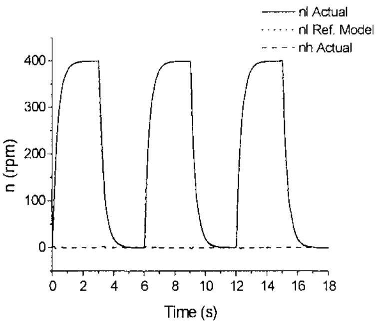

Figure. 6 Step response of n_l at Mach 1.3 and 12 km altitude

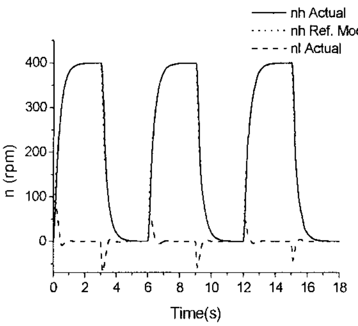

Figure. 7 Step response of n_h at Mach 1.5 and 18km altitude

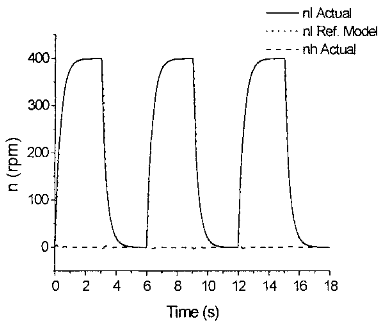

Figure. 8 Step response of n_l at Mach 1.5 and 18 km altitude