A NEW METHOD OF ROBUST FUZZY CONTROL: CASE STUDY OF ENGINE TORQUE CONTROL OF SPARK IGNITION ENGINE

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ABSTRACT

The problem of designing a robust state feedback control that provides global stability for an uncertain nonlinear system has been the subject of considerable research over the last decade. To resolve these problems, a new design method of robust fuzzy control proposed in this paper. The solution offered is by creating multiple soft-switching with Takagi-Sugeno fuzzy model for optimal solution control at all operating points that generate uncertainties. Optimal solution control at each operating point was designed using linear quadratic integral tracking problem optimal control. A case study of engine torque control of spark ignition engine is used to prove this method, since spark ignition engine is a non-linear system with wide uncertainty.

Key words: robust state feedback control, robust fuzzy control, engine torque control, spark ignition engine.

1. INTRODUCTION

It is known that the exact mathematical model of the controlled plant is not always available in the real world. That is, the mathematical plant model includes uncertainties. The structured (parametric) uncertainties may arise from the major variations in the parameters due to mass series production, to different operating environment, and to aging problem. The unstructured uncertainties appear when a parameterized mathematical model fails to specify the system with dynamic models.

The problem of designing a robust state feedback control that provides global stability for an uncertain nonlinear system has been the subject of considerable research over the last decade. Most results addressing this problem are available in the control literature, for example, in [1] and references therein. Applications of these approaches are quite limited because they rely on the exact knowledge of the plant nonlinearities. To relax some of the exact model-matching restrictions, several adaptive schemes have recently been introduced to solve the problem of linearly parameterized uncertainties, which are referred to as *structured uncertainties*. Unfortunately, in the industrial control environment, there are some controlled systems that are characterized not only by the unstructured uncertainties, but are also represented by all the terms that cannot be modeled or are not repeatable. A solution to those problems was first presented in [2]; the fuzzy systems were proposed to uniformly approximate the uncertain nonlinear functions in the designed system by use of the universal approximation properties of certain classes of fuzzy systems presented in [3]-[6], and a Lyapunov based learning law was used. Then several stable adaptive fuzzy controllers that ensure the stability of the overall system were developed in [7]-[10]. The more application-motivated problem of adaptive fuzzy control for the uncertain nonlinear systems has gradually gained much attention [11], [12]. However, there is a substantial restriction in the aforementioned works: Many parameters need to be tuned in the learning laws when there are many state variables in the designed system and many rule bases have to be used in the fuzzy system for approximating the nonlinear uncertain functions, so that the learning times tend to become unacceptably long for the systems of higher order, and a time-consuming process is unavoidable when the fuzzy logic controllers are implemented. This problem has been pointed out in [10] and first researched in [13].

In this research, a new design method of robust fuzzy control proposed to provide global stability for an uncertain nonlinear system. The solution offered is by creating multiple soft-switching with Takagi-Sugeno (T-S) fuzzy model for optimal solution control at all operating points that generate uncertainties. Optimal solution control at each operating point was designed using linear quadratic integral tracking (LQIT) problem optimal control. A case study of engine torque control of spark ignition engine is used to prove this method, since spark ignition engine is a non-linear system with wide uncertainty.

2. TAKAGI-SUGENO FUZZY MODEL

A dynamic T-S fuzzy model is described by a set of fuzzy "IF … THEN" rules with fuzzy sets in the antecedents and dynamic linear time-invariant systems in the consequents [14]. A generic T-S plant rule can be written as follows [15]:

i^{th} Plant Rule:

IF $x_1(t)$ *is* M_{i1} *and...* $x_n(t)$ *is* M_{in} THEN $\dot{x} = A_i x + B_i u$

where $x \in R^{nx1}$ is the state vector, *r* is the number of rules, M_{ij} are input fuzzy sets, $u \in R^{mx1}$ is the input and $A \in R^{nxn}$, $B \in R^{nxm}$ are state matrix and input matrix respectively.

Using singleton fuzzifier, max-product inference and center average defuzzifier, the aggregated fuzzy model can be written as:

$$\dot{x} = \frac{\sum_{i=1}^{r} \omega_i(x)(A_i x + B_i u)}{\sum_{i=1}^{r} \omega_i(x)} \tag{1}$$

with the term ω_i is defined by:

$$\omega_i(x) = \prod_{j=1}^{n} \mu_{ij(x_j)} \tag{2}$$

Where μ_{ij} is the membership function of the j^{th} fuzzy set in the i^{th} rule. Defining the coefficients α_i as:

$$\alpha_i = \frac{\omega_i}{\sum_{i=1}^{r} \omega_i} \tag{3}$$

then (1) can be modified as:

$$\dot{x} = \sum_{i=1}^{r} \alpha_i(x)(A_i x + B_i u)\ i = 1, \dots, r \tag{4}$$

where $\alpha_i > 0$ and $\sum_{i=1}^{r} \alpha_i = 1$.

Using the same method for generating T-S fuzzy rules for the controller, the controller rules defined in [16] as:

i^{th} *Controller Rule*:

IF $x_1(t)$ *is* M_{i1} *and...* $x_n(t)$ *is* M_{in} THEN $u = -K_i x$

The overall controller would be:

$$u = -\sum_{i=1}^{r} \alpha_i(x) K_i x \tag{5}$$

3. ROBUST FUZZY CONTROLLER DESIGN

The basic idea of the controller design is by creating multiple soft-switching with fuzzy reasoning as T-S inference system in (5) for the optimal solution control at every operating point. Optimal solution control at each operating point was designed using LQIT problem optimal control.

The design concept steps can be explained as follows:

1st Step: Creating linear models by piece-wise linearization of the origin nonlinear uncertain plant.

Piece-wise linearization basically used to create linear model under its operating point that generate plant uncertainties. A fuzzy model that has similar characteristic to the origin plant constructed using the T-S fuzzy model described in (1). Every rule describes one linear model characteristic of the plant under its operating point.

2nd Step: Optimizing every linear model described in 1st step using Linear Quadratic Integral Tracking (LQIT) *problem optimal control.*

Every linear model under piece-wise linearization controlled by solving LQIT problem optimal control described in [17], and T-S control action as (5) in section II can be modified as:

$$\begin{gathered} R^i: IF\ x_1\ is\ F_1^i\ AND\ x_2\ is\ F_2^i \dots\dots\dots AND\ x_n\ is\ F_n^i \\ AND\ w_1\ is\ G_1^i\ AND\ w_2\ is\ G_2^i \dots\dots\dots AND\ w_m\ is\ G_m^i \\ AND\ r_1\ is\ H_1^i\ AND\ r_2\ is\ H_2^i \dots\dots\dots AND\ r_k\ is\ H_k^i \end{gathered}$$

$$THEN \begin{cases} \dot{x} &= A_i x + B_i u \\ u &= -K_x x - K_w w + K_r r \end{cases} \quad i = 1, \dots, L \tag{6}$$

where

R^i = rule associated with i^{th} model
L = number of operating points
F^i_j= fuzzy sets of state variables (x)
G^i_j= fuzzy sets of integral error between references and outputs (w)
H^i_j= fuzzy sets of tracking references (r)
n = number of state variables
m= number of integral error variables
k = number of tracking references
K_x= optimal gains for state feedback

K_w= optimal gains for integral error
K_r= optimal gains for reference input

3rd Step: Adding associate operating points as condition signals to change T-S fuzzy inference system as multiple soft-switching.

As multiple soft-switching, the T-S fuzzy inference system modified by LQIT optimal control described in (6) should be added by additional inputs as condition signals i.e. the signals that associated with operating point of each partial linear model described in *1st* step. By adding some new inputs, T-S inference system in (6) can be modified as:

$$K_c c - K_x x - K_w w + K_r r \tag{7}$$

Where

O^i_j= fuzzy sets of condition signals
q = number of condition signals
K_c= condition signal gain (as triggering signal, defined K_c is zero vector)

4th Step: Construct fuzzy sets of condition signal inputs based on operating point spreading data under all operating point bound, and single fuzzy set for other inputs.

Condition signal inputs are used for rule selection associate with model and controller design under detected operating point. Combination of all fuzzy sets of these inputs must equal to number of fuzzy rules.

Due to its function as controller input and needs to be crisp input, the other inputs such as state variables, integral error variables, and references, designed to be only have one fuzzy set.

5th Step: Rules design.

Fuzzy rules designed to achieve soft-switching system to select appropriate model and controller based on condition signal inputs. Number of rules is equal to number of linear model generated by piece-wise linearization in *1st* step design.

A case study of engine torque control of spark ignition engine is used to prove this method, since spark ignition engine is a non-linear system with wide uncertainty.

4. SPARK IGNITION ENGINE WITH ENGINE TORQUE MANAGEMENT STRATEGY

Spark ignition engines or gasoline engines are highly uncertain nonlinear systems. Their operation is affected by many factors ranging from statistical perturbations in the combustion process itself to variations in properties of key parameters in their dynamics to external perturbations of many kinds. In this research, we use spark ignition engine model proposed before by A. Stefanopoulou [18].

Engine Torque Management Strategy

Basically, the engine torque management strategy use throttle opening control function, air to fuel ratio (AFR), and ignition timing simultaneously to produce desired engine torque [19]. In practical reality, desired engine torque does not exist, because the input given by the driver on the system is the pedal position (throttle degree). For that reason, the engine torque control strategy known as the mapping between pedal position and engine speed with engine torque command [20]. Figure 1 shows the mapping for the sporty vehicle feel and Figure 2 shows the mapping for economical vehicle feel.

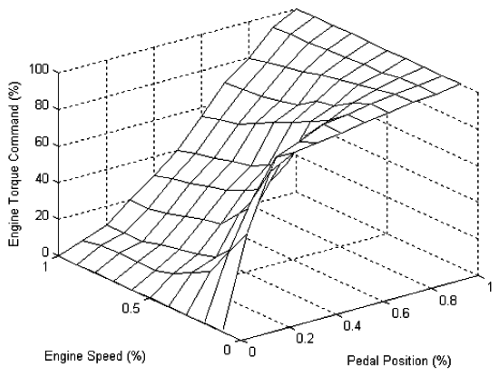

Fig. 1. *Engine Torque Mapping for Sporty Vehicle Feel [20]*

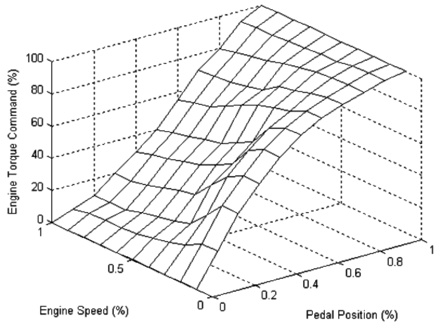

Fig. 2. *Engine Torque Mapping for Economical Vehicle Feel [20]*

In this research, engine torque control regulation conducted only by controlling throttle degree with secondary throttle [18]. AFR and ignition time is left on the standard setting that ideally yield maximum engine torque, i.e. at 14.7 AFR and the spark advance to 15 degree MBT.

5. DESIGN IMPLEMENTATION AND ANALYSIS

The nonlinear uncertain spark ignition engine described in section 4 will be linearized using piece-wise linearization on every operating point. In this case, we choose variation of throttle degree and gear position similar to variation of operating point as shown in Table I.

Table 1. Variation of si engine operating point

Model		Throttle Degree				
		Th_1	Th_2	Th_3	Th_4	Th_5
Gear Position	G_1	M_1	M_2	M_3	M_4	M_5
	G_2	M_6	M_7	M_8	M_9	M_{10}
	G_3	M_{11}	M_{12}	M_{13}	M_{14}	M_{15}
	G_4	M_{16}	M_{17}	M_{18}	M_{19}	M_{20}

G_i represents gear position on i^{th} stage, while Th_i represents throttle degree in limit range (with overall limit is between 0 – 100 degree) as:

(8)

M_i represent linear model generated by input-output identification on its appropriate operating point.

Every linear model analyzed using LQIT problem optimal control to calculate optimal gains described in (6), and then distribute all of those gains on the fuzzy rules as in (7). Note that K_c should be zero vectors as condition signals cannot be involved to the calculation of output in (7).

As a switching mechanism, the rules of the fuzzy inference system are redesigned as one of example as follows:

Rule-i:

If (*Cond1 is Th1*) and (*Cond2 is G1*) and (*Ref is EngDes*) and (*IntErr is dotw*) and (*State1 is x1*) and (*State2 is x2*)

Then

$$u_i = K_c^i[Cond1 \quad Cond2]^T - K_x^i[x1 \quad x2]^T - K_w^i.IntErr + K_r^i.Ref \tag{9}$$

Robust fuzzy controller is designed using Matlab Fuzzy Toolbox as Figure 3 shows input-output global design, and Figure 4 and Figure 5 show example of fuzzy sets of input and output. The structure of controller is shown in Figure 6.

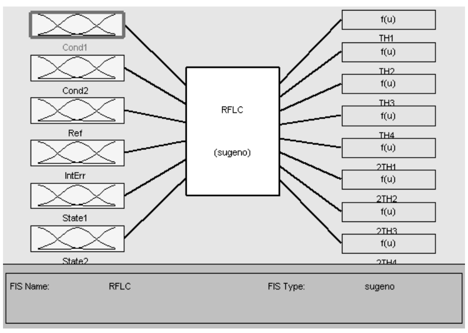

Fig. 3. *Input-output design*

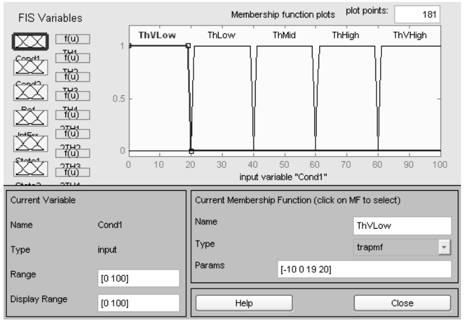

Fig. 4. *Fuzzy sets of first condition signal (Cond1)*

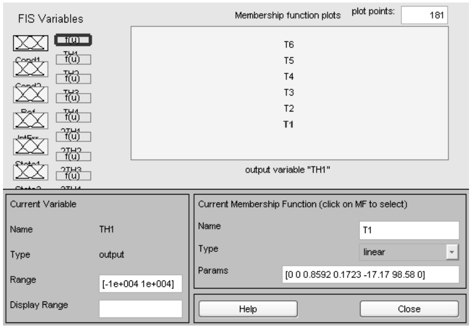

Fig. 5. *Fuzzy sets of the optimal control gain TH1*

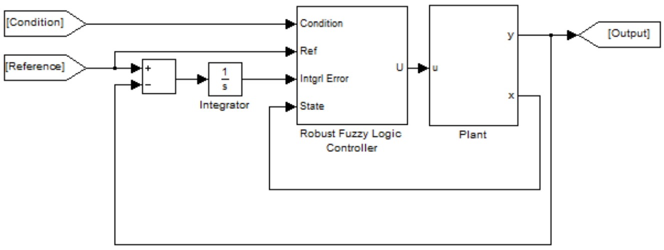

Fig. 6. *The structure of robust fuzzy controller*

6. SIMULATION AND ANALYSIS

Simulations performed with Matlab Simulink. The simulation results with some operating point are shown in Figure 7-10. Figure 7 simulated using operating condition throttle opening about 10 degrees and first gear application. Figure 8 simulated using throttle opening about 10 degrees and second gear application. It can be shown that there are different characteristics of the system with the addition of gear position. By providing such a robust fuzzy controller applications that have been designed previously, we see that the system works better by performing tracking the desired engine torque based on throttle input opening.

Similarly, by changing the throttle opening wide enough, with the same gear position, as shown in Figure 9 and Figure 10, where Figure 9 shows the simulation with the input throttle opening of about 30 degrees and the third gear position, and Figure 10 shows the simulation with the input throttle opening amounting to about 50 degrees and the third gear position, we see that the system will work better too by performing tracking the desired engine torque based on throttle input opening.

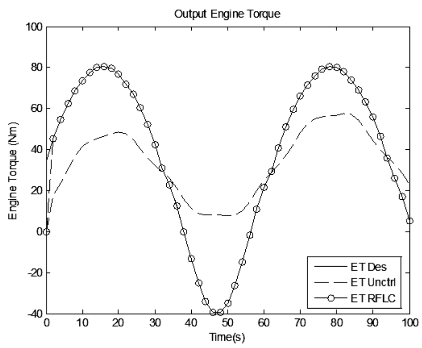

Fig.7. *Simulation result with engine operating condition: throttle opening about 10 degrees and first gear application*

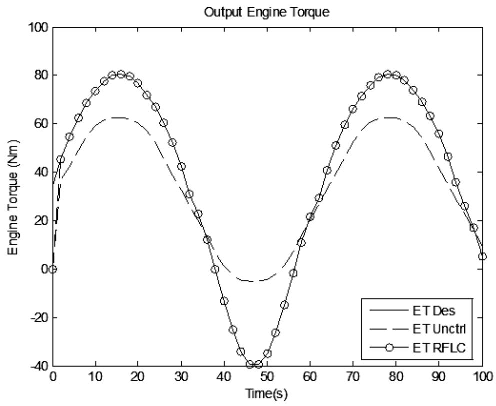

Fig. 8. *Simulation result with engine operating condition: throttle opening about 10 degrees and second gear application*

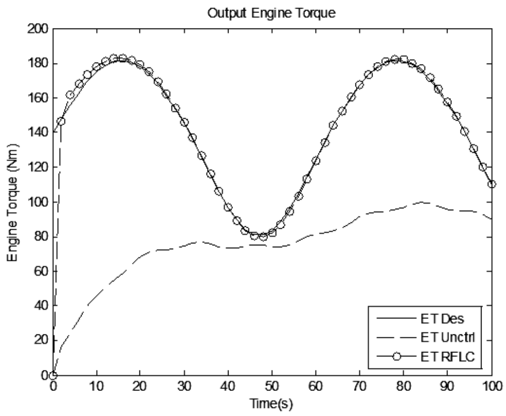

Fig. 9. *Simulation result with engine operating condition: throttle opening about 30 degrees and third gear application*

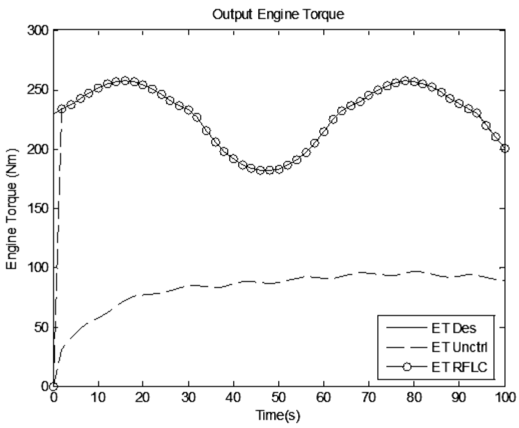

Fig. 10. *Simulation result with engine operating condition: throttle opening about 50 degrees and third gear application*

7. CONCLUSION

As introduce in design concepts, this new robust controller design has some benefit that fuzzy parameters not need to be tuned in the learning laws, need only a view rules to make an inference system, and more simple in implementation.

From the simulation results, it can be summarized that by using robust fuzzy controller design as above, the controller operates very well for a wide operating point with the character differences are quite striking. This will give a controller design effectiveness and impact indirectly plays an important role in improving engine performance.

It can be concluded too that the use of knowledge-based control system applications will be very beneficial to overcome control problems with performance index contradictory as torque settings on spark ignition engines.

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