

A Self-Tuning Fuzzy Controller for Torque and RPM Control of a Vehicle Engine

°Kwon Seok Seon*, Seung You Na*

*Graduate College, Chonnam National University, Puk-ku, Kwangju 500-757, KOREA

*Dept. of Electronics Eng., Chonnam National University, Puk-ku, Kwangju 500-757, KOREA

Tel: +82-62-520-6394, Fax: +82-62-520-6390, E-mail: syna@chonnam.chonnam.ac.kr

Abstracts A practical application of self-tuning fuzzy controller to a multi-input multi-output complex system of a vehicle engine is investigated. The objective is to design a controller to improve the transient performance in torque and RPM mode changes. For the performance improvement in the multivariable complex system, the self-tuning function of internal parameters is essential and practical. The measured output variables using different control schemes are compared. The advantages of the self-tuning fuzzy logic controller are better output performances and the effectiveness in the controller design using many parameters.

Keywords Vehicle Engine Control, Torque, RPM, Self-Tuning Fuzzy Control

1. INTRODUCTION

Due to the severe environmental pollution caused by the increase of automobiles, the regulation of automobile emission gas becomes much stricter than ever. Emission regulation will not only be stricter from 1996, but the test mode will be changed from 6 modes into 13 modes. According to this change, a stable control is necessary in each mode transition to satisfy an exact test.

Since an RPM and a Torque variables have a complementary relation and nonlinear characteristics, it is not easy to control two variables at the same time. The knowledge and experience of an expert can be represented by a fuzzy controller which contains the inference rules with a formula of "If ~ Then ~", when the characteristic of the system is so complex that it is difficult to interpret with conventional

exact methods or when the obtained information is qualitative and in natural expression forms.

So far the fuzzy controller, as the form of simple, neuro, learning, etc., has been applied to many devices including home appliances such as washers and elevators. However, self-tuning of inference rules is necessary for applying the fuzzy controller to the complex nonlinear system. This is because it takes much time for development to establish optimal inference rules through an experiment of trial and error. In case of a controller which has the form of multivariables, there are many tuning parameters, and difficulty increases in tuning by experiments.

The fuzzy controller applied in this paper has a structure of multivariable fuzzy neuro forms to be used in a complex system. The weight values are obtained through performing an adequate learning, and then self-tuning is made

possible by using these values. Applying this scheme to controlling torque and RPM of a vehicle engine demonstrates its validity.

2. SELF-TUNING FUZZY CONTROLLER

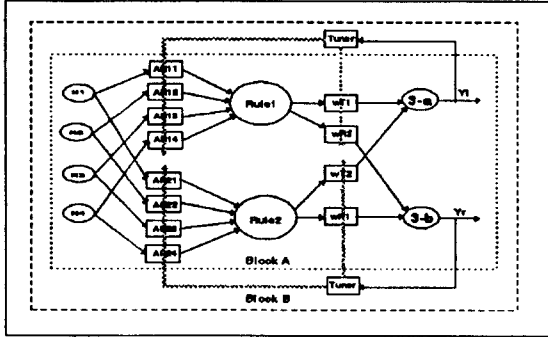


Fig. 1. Multivariable fuzzy neuro controller

The fuzzy controller applies the fuzzy logic rules that are described in a linguistic form. So the values of input variables need a scale mapping which properly transforms the input value ranges into the whole set of fuzzy variables.

In this paper, each rule consists of antecedent variables (errors and error rates) and consequent variables for two parameters. Let the input variables be x_1, x_2, \dots, x_m , and output variables be y_t, y_r , then the rules take the form of eq.(1)

Rule i: If x_1 is AR_{i1} and x_m is AR_{im}
 Then y_t is w_{Ti} and y_r is w_{Ri} -- (1)
 ($i = 1, 2, \dots, n$)

where AR_{ij} is a membership function of antecedent parts, w_{Ti} and w_{Ri} are real values of consequent parts. Output variables are obtained through the fuzzy reasoning of the following equations.

$$u_i = AR_{i1}(x_1) AR_{i2}(x_2) \cdots AR_{im}(x_m) \quad \text{-----(2)}$$

$$y_t = \frac{\sum_{i=1}^n u_i w_{Ti}}{\sum_{i=1}^n u_i} \quad \text{-----(3-a)}$$

$$y_r = \frac{\sum_{i=1}^n u_i w_{Ri}}{\sum_{i=1}^n u_i} \quad \text{-----(3-b)}$$

Block A represents the fuzzy reasoning in Fig. 1. which shows the multivariable fuzzy neuro controller. The membership function AR_{ij} is shown in Fig. 2. which is typical and easy for calculation. The function value is given by

$$AR_{ij}(x_i) = 1 - \frac{2|x_i - a_{ij}|}{b_{ij}} \quad \text{-----(4)}$$

where $b_{ij} > 0$.

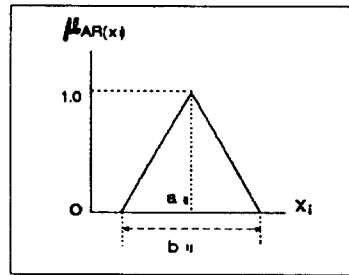


Fig. 2. Membership function of antecedent part

3. ADAPTIVE LEARNING FOR SELF-TUNING

y_{ti} and y_{ri} are obtained through the fuzzy reasoning of an engine torque and RPM errors and error rates. Using these input and output data, AR_{ij}, w_{Ti} and w_{Ri} are tuned. In other words improved solutions are obtained through the learning process using input and output data[4,5].

Let the cost function to be minimized be

$$E = \frac{1}{2} (y_i - y^r)^2 \quad \text{-----(5)}$$

where y^r is the desired response acquired from an expert. Using descent method gradient vector indicates the direction of the adaptive learning process which is given by

$$a_y(t+1) = a_y(t) - K_a \frac{\partial E}{\partial a_y} \quad \text{-----(6)}$$

$$b_y(t+1) = b_y(t) - K_b \frac{\partial E}{\partial b_y} \quad \text{-----(7)}$$

$$w_{(T \text{ or } R)_i}(t+1) = w_{(T \text{ or } R)_i}(t) - K_w \cdot \frac{\partial E}{\partial w_{(T \text{ or } R)_i}} \quad \text{-----(8)}$$

These learning equations for self-tuning are represented as a block B in Fig. 1.

4. VEHICLE ENGINE EXPERIMENT

Fig. 3. shows the block diagram of the experiment applied to a vehicle engine. The output of the controller are throttle angle for air-fuel mixture rate and load magnitude to determine torque and RPM of the engine. Input are errors of torque and RPM. The experiment is to control the throttle angle and load to obtain proper curves of torque and RPM eventually to set points.

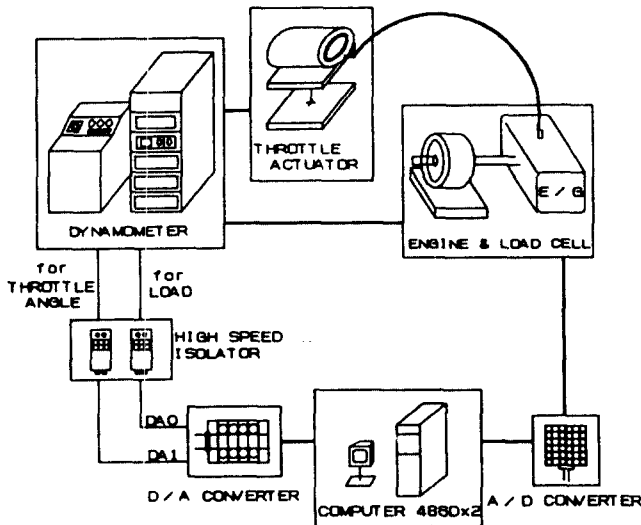


Fig. 3. Block diagram of an engine experiment

Fig. 4. is a curve of torque when RPM is changed at the state of 100% load and maximum throttle angle. Fig. 5. is a curve of RPM with the change of throttle angle at the state of zero load. These curves show the engine characteristics of nonlinearity, and

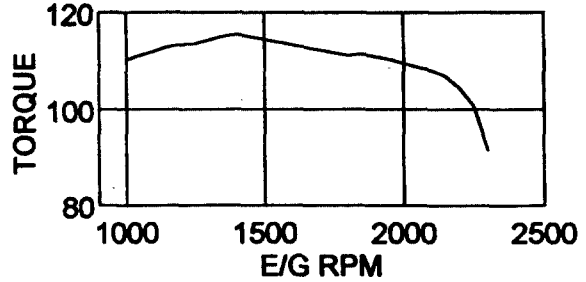


Fig. 4. Engine characteristic of RPM and torque

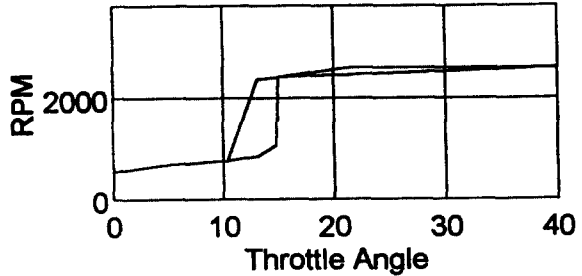


Fig. 5. Engine characteristic of RPM and throttle angle

therefore it is not easy to control torque and RPM simultaneously.

The general fuzzy controller which is used in this system has the structure of Fig. 6.

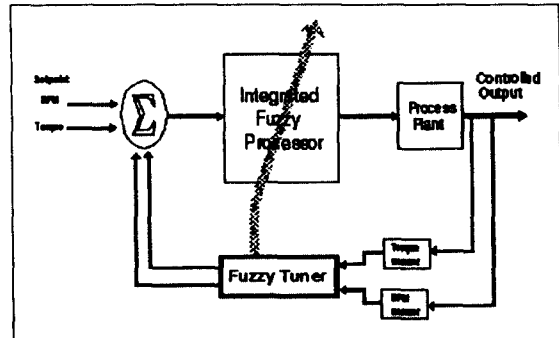


Fig. 6. Structure of a fuzzy-neuro controller

Fig. 7. represents responses of torque and RPM for each learning number. With the increase of learning number the output control responses show some improvement. Fig. 8. indicates the response characteristics of torque and RPM by the PD, FLC and self-tuning FLC which is designed in this paper. As shown in Fig. 8. at first both RPM and torque have little change and then RPM increases before torque. The

reason is that, as illustrated in Fig. 4., though torque is increased and approaches to the reference value, it changes quickly by the change of RPM. Therefore, RPM approaches the reference value first and then torque curve gets to the set value by increasing load. Set point value of RPM is 1800 rev/min. and torque is 50 kg-m.

5. CONCLUSION

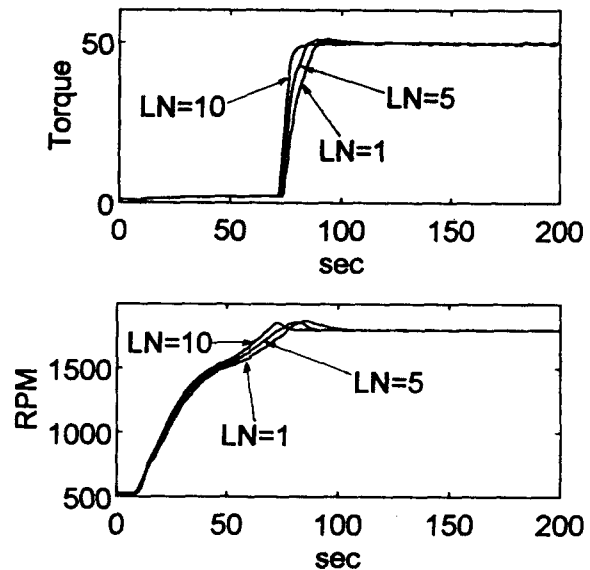
In this paper, a self-tuning fuzzy controller is introduced and applied to a vehicle engine for torque and RPM control problem. The fuzzy controller is implemented in the form of neural network for learning process. Therefore inferring and learning abilities are used for self-tuning control.

The controller in this paper is constructed for the control of torque and RPM which is determined by the throttle angle of air-fuel mixture rate and load by the eddy current of dynamometer. Output responses show that satisfactory curves can be obtained even for a nonlinear engine control system, and the parameter tuning allows improved responses.

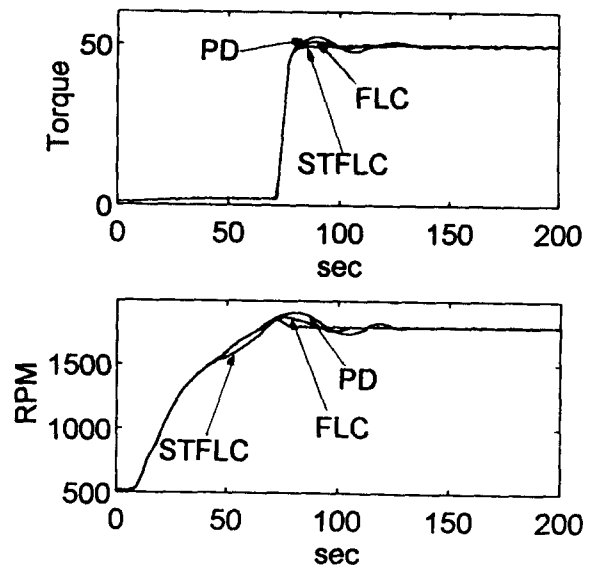
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(a) Torque (b) RPM
 Fig. 7. Responses by learning numbers



(a) Torque (b) RPM
 Fig. 8. Responses by controller types