Adaptive Fuzzy Control for Air-Fuel Ratio of Automobile Spark Ignition Engine

Ali Ghaffari, A. Hosein Shamekhi, Akbar Saki, and Ehsan Kamrani

Abstract—In order to meet the limits imposed on automotive emissions, engine control systems are required to constrain air/fuel ratio (AFR) in a narrow band around the stoichiometric value, due to the strong decay of catalyst efficiency in case of rich or lean mixture. This paper presents a model of a sample spark ignition engine and demonstrates Simulink's capabilities to model an internal combustion engine from the throttle to the crankshaft output. We used well-defined physical principles supplemented, where appropriate, with empirical relationships that describe the system's dynamic behavior without introducing unnecessary complexity. We also presents a PID tuning method that uses an adaptive fuzzy system to model the relationship between the controller gains and the target output response, with the response specification set by desired percent overshoot and settling time. The adaptive fuzzy based input-output model is then used to tune on-line the PID gains for different response specifications. Experimental results demonstrate that better performance can be achieved with adaptive fuzzy tuning relative to similar alternative control strategies. The actual response specifications with adaptive fuzzy matched the desired response specifications.

Keywords—Modelling, Air–fuel ratio control, SI engine, Adaptive fuzzy Control.

I. INTRODUCTION

GLOBALIZATION and growing new markets, as well as increasing emission and fuel consumption requirements, force the car manufacturers and their suppliers to develop new engine control strategies in shorter time periods. This can mainly be reached by development tools and an integrated hardware and software environment enabling rapid implementation and testing of advanced engine control algorithms. Automotive internal combustion engine control is one of the most complex control problems for control system engineers and researchers [1]. Due to the increasing requirements of governments and customers, car manufacturers always strive to reduce substantially emissions and fuel consumption while maintaining the best engine performance. To satisfy these requirements, a variety of variables need to be controlled, such as engine speed, engine

torque, spark ignition timing, fuel injection timing, air intake, air–fuel ratio (AFR) and so on. These variables are complicatedly related to each other. Moreover, car engines have several different operating modes including start up, idle, running and braking. Engine dynamics are highly non linear and multivariable because of these factors [2-5]. Among all of the engine control variables, AFR is related to fuel efficiency, emission reduction and drivability improvement. Maintaining AFR to be the stoichiometric value (14.7) can obtain the best balance between power output and fuel consumption [6]. AFR can also influence the effect of emission control because its stoichiometric value ensures the maximum efficiency of three-way catalysts (TWC). Variations of greater than 1% below 14.7 can result in significant increase of CO and HC emissions. An increase of more than 1% will produce more NOx up to 50% [7-8] Fig. 1.
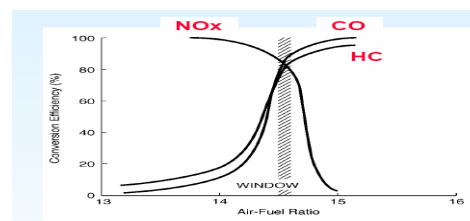

Fig. 1 Replacing Fuel Dynamics with Block of division to 14.7

Some researches on AFR control have been investigated in recent years. Choi and Hedrick developed an observer-based fuel injection control algorithm to improve the AFR control by using sliding mode control method [9]. It solves the problems of fast response and small amplitude chattering of the AFR, but the fuel film dynamics due to ageing or different fuel properties has not been considered. Yoon and Sunwoo use an adaptive dynamic sliding-mode control to deal with the problem caused by engine uncertainties [10]. Manzie proposed a radial basis function (RBF) neural network based approach for the fuel injection control problem and found that this network is suitable for estimating the air mass flow into the cylinder [7]. A follow-up paper [8] implemented a model predictive control (MPC) scheme for maintaining the AFR. In [8] the RBF network was used as an observer of the air system and a linear predictive control algorithm was realized by using the active set method to solve quadratic programs. However, the lean engines currently in production use the fuel consumption advantage only in steady-state operation and not

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during transients [11], [12]. Therefore, it is necessary to develop a new transient control strategy for lean burn engines, so as to benefit from the fuel consumption advantage over a broader operating range. This paper presents a model of a sample spark ignition engine and demonstrates Simulink's capabilities to model an internal combustion engine from the throttle to the crankshaft output. We used well-defined physical principles supplemented, where appropriate, with empirical relationships that describe the system's dynamic behavior without introducing unnecessary complexity. Over the past two decades, the field of fuzzy controller applications has broadened to include many industrial control applications, and significant research work has supported the development of fuzzy controllers. In 1974, Mamdani [13] pioneered the investigation of the feasibility of using compositional rule of inference that has been proposed by Zadeh [14], for controlling a dynamic plant. A year later, Mamdani and Assilian [15] developed the first fuzzy logic controller (FLC), and it successfully implemented to control a laboratory steam engine plant. In a strict sense, the first fuzzy controller shown in [15] was equivalent to two-input fuzzy PI (or PI-like) controllers where error and error change, were used as the inputs for the inference. Mamdani's pioneering work also introduced the most common and robust fuzzy reasoning method, called Zadeh–Mamdani min–max gravity reasoning. Also, a significant number of in-depth theoretical and analytical investigations related to this structure have been reported in [16-19]. Takagi and Sugeno [20] introduced a different linguistic description of the output fuzzy sets, and a numerical optimization approach to design fuzzy controller structures. There are several types of control systems that use FLC as an essential system component. The majority of applications during the past two decades belong to the class of fuzzy PID controllers. These fuzzy controllers can be further classified into three types: the direct action (DA) type, the gain scheduling (GS) type and a combination of DA and GS types. The majority of fuzzy PID applications belong to the DA type; here the fuzzy PID controller is placed within the feedback control loop, and computes the PID actions through fuzzy inference. In GS type controllers, fuzzy inference is used to compute the individual PID gains and the inference is either error driven self-tuning [21] or performance-based supervisory tuning [22]. In addition to the common Mamdani-type PI structure, several other structures using one- or three-input controllers have been reported. In [23], a one-input fuzzy PID structure was used to control several first- and second-order plant models. The one-input FLC with fewer rules has not been commonly used for simultaneously deriving the three fuzzy PID actions. In this paper we also presents a PID tuning method that uses an adaptive fuzzy inference system to model the relationship between the controller gains and the target output response, with the response specification set by desired percent overshoot and settling time. The adaptive fuzzy based input-output model is then used to tune on-line the PID gains for different response specifications. Experimental results demonstrate that better performance can

be achieved with adaptive fuzzy tuning relative to similar alternative control strategies. The actual response specifications with adaptive fuzzy matched the desired response specifications. Furthermore, we need a perfect and comprehensive engine model in order to achieve a suitable control strategy. Several SI engine models have been proposed in literatures. They range from detailed models, mainly oriented to facilitate the design of air/fuel ratio (AFR) control systems, describing the mixture formation phenomena [24] to the gray-box models. This latter approach proposed by Moskwa[6], Aquino[25], Hendricks and Sorenson[26], Gambino, Pianese, and Rizzo[27] among others, are suitable for the on-line AFR control operation. They are indeed based on a mean value scale and allow observing the fuel film dynamics with a good level of accuracy with a limited computational demand. Nevertheless, due to the presence of at least two main parameters, the gray-box models need to be accurately identified in order to guarantee their accuracy over the wide engine operating range. This problem is solved by identifying model parameters for several engine operating condition and by designing look-up tables or polynomial regressions which could match the identification results vs. the main control variables (e.g. engine load and speed) [28]. We have used a model based on these literatures and implement the control algorithm on this model. our model also show a better performance and is more mach with experimental results in compare with similar models proposed before. The rest of this paper is organized as follows. In Section II the SI engine dynamics have been explained. In Section III, we introduce Various AFR Control Strategies. An adaptive fuzzy inference system for AFR Control is discussed in Section IV. In Section V, the simulation results are presented and explained. Section VI contains the results and conclusions.

II. SI ENGINE DYNAMICS

In the Fig. 2 a block diagram of the whole system model is sketched. The figure evidences the main sub models corresponding to the Air-Fuel manifold dynamics, to the engine torque-emissions production and to the driveline module accounting for crankshaft, clutch, transmission and vehicle dynamics. The ECU module accounts for control strategies for fuel metering, spark advance, electronic throttle and transmission actuation. In the following each module will be described in detail.
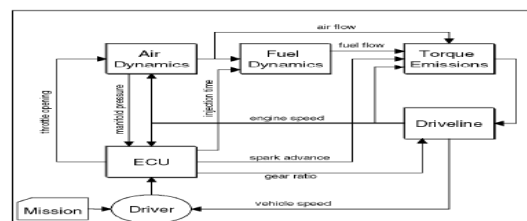

Fig. 2 Block diagram of the simulation Model

In order to investigate the feasibility of model based adaptive fuzzy control for SI engines, engine simulations should be used first instead of using a real engine test bed. The engine simulation model used here is an expanded system based on the generic mean value engine model developed by Hendricks [29], a well-known and widely used benchmark or engine modeling and control. As shown in Fig. 3, it consists of three sub- models that describe the intake manifold dynamics including air mass flow, pressure and temperature, the crankshaft speed and the fuel injection. Then the simulation model has two inputs, the throttle angle u and the injected fuel mass $\frac{dm_{fi}}{dt}$, and one output, AFR value. All the variables in this section are defined in the notation.
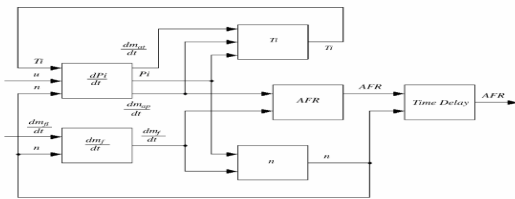
Fig. 3 The engine simulation model

A. Intake Manifold Filling Dynamics

The intake manifold filling dynamics are analyzed from the viewpoint of the air mass conservation inside the ntake manifold. It includes two nonlinear differential equations, one for the manifold pressure and the other for the manifold temperature. The manifold pressure is mainly a function of the air mass flow past throttle plate, the air mass flow into the intake port, the exhaust gas recirculation (EGR) mass flow, the EGR temperature and the manifold temperature. It is described as

$$\dot{p}_m = \frac{kR}{V_m}(-\dot{m}_{ap}T_i + \dot{m}_{at} + \dot{m}_{EGR}T_{EGR})$$
(1)

The manifold temperature dynamics are described by the following differential equation:

$$\dot{T}_m = \frac{RT_m}{P_mV_m}[-\dot{m}_{ap}(k-1)T_m + \dot{m}_{at}(kT_{amb} - T_m) + \dot{m}_{EGR}(kT_{EGR} - T_m)]$$
(2)

Here, the EGR mass flow is not considered and simply set to be zero. In eqs. (1) and (2), the air mass flow dynamics in the intake manifold can be described as follows. The air mass flow past throttle plate _ mat is related with the throttle position and the manifold pressure. The air mass flow into intake port _ map is represented by a well-known speed–density equation:

$$\dot{m}_{at} = \frac{p_{amb}}{\sqrt{RT_{amb}}}\beta_1(\theta) \times \beta_2(p_r)$$
(3)

$$\beta_1(\theta) = b_0 + b_1\cos(\theta) + b_2\cos^2(\theta)$$
(4)

$$\beta_2(p_r) = \begin{cases} \frac{1}{0.74}\sqrt{p_r^{0.4404} - p_r^{2.3086}} & p_r \geq 0.4125 \\ 1 & p_r < 0.4125 \end{cases}$$
(5)

$$p_r = \frac{p_m}{p_{amb}}$$
(6)

$$\dot{m}_{ap}(n, p_m) = \frac{V_d}{2RT_m}(\eta_{vol}, p_m)n$$
(7)

$$\eta_{vol} \ p_m = sp_m - y$$
(8)

s and y are related with n. follow the Fig. 4 .

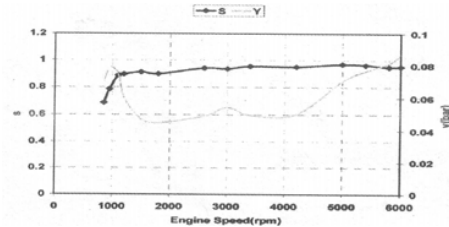Where s and y are positive, weak functions of the crankshaft speed and y<<s.

Fig. 4 s,y versus n

B. Crankshaft Speed Dynamics

The crankshaft speed is derived based on the conservation of the rotational energy on the crankshaft.

$$\dot{n} = -\frac{1}{In}\left(P_f(p_m,n) + P_p(p_m,n) + P_b(n)\right) + \frac{1}{In}H_u\eta \ (p_{mi},n,\lambda)\dot{m}_f(t - \Delta\tau_d)$$
(9)

Both the friction power Pf and the pumping power Pp are related with the manifold pressure pm and the crankshaft speed n. The load power Pb is a function of the crankshaft speed n only. The indicated efficiency η a function of he manifold pressure pm the crankshaft speed nand the air/fuel ratio λ.

C. Fuel Injection Dynamics

In Hendricks's package [30], the engine port fuel mass flow $\dot{m}_f$ is described by the following equation:

$$\dot{m}_f = \frac{\dot{m}_{ap}}{L_{th}}.$$
(10)

This means that the simulation works at the ideal condition, that is the AFR value is always equal to its stoichiometric value. Instead of using this ideal simulation of the injection system, a more practical fuel flow dynamic sub-model must be considered, which is described as follows [29]:

$$\dot{m}_{ff} = \frac{1}{\tau_f}(-\dot{m}_{ff} + X_f\dot{m}_{fi})$$
(11)

$$\dot{m}_{fv} = (1 - X_f)\dot{m}_{fi}$$
(12)

$$\dot{m}_f = \dot{m}_{fv} + \dot{m}_{ff}$$
(13)

This model represents the fuel flow dynamics of manifold injection engine considering the fuel evaporation occurs in the intake manifold. The parameters in the model are the time constant for fuel evaporation τf and the proportion of the fuel that is deposited on the intake manifold or close to the intake

valves Xf. These two parameters are operating point dependent and can be expressed in terms of the states of the model as:

$$\tau_f(p_m, n) = 1.35 \times (-0.672n + 1.68) \times (p_m - 0.825)^2$$
$$+ (-0.06 \times n + 0.15) + 0.56$$
$$\text{(14)}$$

$$X_f(p_m, n) = -0.277\,p_m - 0.055\,n + 0.68 \tag{15}$$

D. Air– Fuel Ratio Measurement

In this simulation model, the AFR is calculated by using (16). The air mass flow into intake port _ map is output of the intake manifold sub-model and the engine port fuel mass flow _ mf is the output of the fuel injection sub-model:

$$\lambda = \frac{\dot{m}_{ap}}{\dot{m}_f} \tag{16}$$

Additionally, time delays of injection systems should also be considered. There are three causes of time delay for injection systems: the two engine cycle delay between the injection of fuel and the expulsion from the exhaust valves, the propagation delay for the exhaust gases to reach the oxygen sensor and the sensor output delay. It has been found that the engine speed has more influence on these delays than the manifold pressure. Therefore the following equation can be used to represent the delays of injection systems [7,8]:

$$t_d = 0.045 + \frac{10\,\Pi}{n} \tag{17}$$

III. AIR-FUEL RATIO CONTROL

There are two kinds of air-fuel ratio control systems fuel control and air control. In a fuel control system, which is the only one used in production today, the fuel flow is regulated to match the air flow commanded by the driver. In contrast, an air control system allows the driver to command the fuel flow while the controller regulates the air flow. Comparisons between these two schemes have been studied by Stivender [31] and Woods [32] in the late 70's. With electronic port fuel injection and the drive-by-wire (DBW) throttle becoming more common in today's automotive applications, it seems desirable in the near future to devise an air-fuel management system which will be able to regulate both the fuel flow and the air flow jointly to achieve the scheduled AFR according to the driver's command and the engine conditions. The AFR control system presented here takes a step toward this goal. If automotive engines always operated at steady state, AFR control would not be a difficult task. However, automotive engines seldom operate at a steady state for prolonged periods during practical driving conditions. Undesirable AFR excursions occur during transient engine operations. To control AFR precisely, we must first identify the physical effects that result in AFR excursions and then design a control strategy to compensate for these effects.

A. Design of a PID Controller

A block diagram of the PID force control system for air-fuel ratio of automobile spark ignition engine is shown in Fig. 5. The PID control law can be written as follows:

$$u(t) = K_p e(t) + K_I \int e(t)dt + K_D \frac{de(t)}{dt} \tag{18}$$

$$e(t) = 14.7 - AFR \tag{19}$$

Where u(t) is the control signal, e(t) is the error in 14.7, and K_P, K_I, and K_D are the proportional, integral, and derivative gains, respectively. In this paper K_P and K_D gains have to be tuned to achieve an acceptance level of performance.
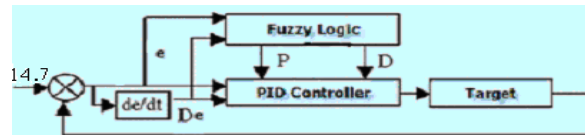

Fig. 5 Control rinciple of self regulation PID

IV. FUZZY CONTROL

Fuzzy logic is a 'soft computing' technique, which mimics the ability of the human mind to learn and make rational decisions in an uncertain and imprecise environment [33]. Fuzzy control has the potential to decrease the time and effort required in the calibration of engine control systems by easily and conveniently replacing the 3-D maps used in conventional ECUs. Fuzzy logic provides a practicable way to understand and manually influence the mapping behavior. In general, a fuzzy system contains three main components, the fuzzification, the rule base and the defuzzification. The fuzzification is used to transform the so-called crisp values of the input variables into fuzzy membership values. Afterwards, these membership values are processed within the rule base using conditional 'if-then' statements. The outputs of the rules are summed and defuzzified into a crisp analogue output value. The effects of variations in the parameters of a Fuzzy Control System (FCS) can be readily understood and this facilitates optimization of the system. The system inputs, which in this case are the engine speed and the throttle angle, are called linguistic variables, whereas 'large' and 'very large' are linguistic values which are characterized by the membership function. Following the evaluation of the rules, the defuzzification transforms the fuzzy membership values into a crisp output value, for example, the fuel pulse width. The complexity of a fuzzy logic system with a fixed input-output structure is determined by the number of membership functions used for the fuzzification and defuzzification and by the number of inference levels. The advantage of fuzzy methods in the application of engine control over conventional 3-D mappings is the relatively small number of parameters needed to describe the equivalent 3-D map using a fuzzy logic representation. The time needed in tuning a FCS compared to the same equivalent level of 3-D map look-up control can be significantly reduced.

A. Implementation of Adaptive Fuzzy for on-line PID Tuning

The most widely used form of industrial controllers is proportional-integral-derivative (PID). This is due in part to its simple structure and robust performance over a wide range of operating conditions. The design of a PID controller requires specification of three gains: proportional K_P, integral K_I and derivative K_D. Numerous researchers have worked to develop methods to reduce the effort to optimize or tune the gains. Ziegler-Nichols (Z/N) is probably the most widely known tuning method. Typically, Z/N is used to obtain the initial estimates. But in actual application, many controlled objects have complex mechanism. They are non-linear, time varying and lagging; we can not establish the math model of these objects easily. But fuzzy control can describe control rules using if-then fuzzy rules and it can incorporate experts' control rules. It has good robust which can defeat the influence of Non-Linear Factor. Therefore, we combine fuzzy control and PID control, which can absorb both advantages, make the adjustment of PID parameters online. It can highly increase the precision, flexibility and practicability of system. In this paper we use PID control principle so considering system stability, response rate, high adjust and stable precision, we sum up the effects of K_P and K_D are: Proportional coefficient K_P is used to quicken system response rate, increase system precision. If the K_P is bigger, the system warp response rate is quicker, and the adjust precision is higher. But at the same time, it also easily produces over adjust, which makes the system unstable. If the K_P is smaller, the system can adjust precision is lower and the response rate is slower. Differential coefficient K_D is used to improve dynamic performance of system and restrain warp changes.

We can take e and Δe as input, and use the method of fuzzy logic to adjust K_P and K_D parameters, in order to satisfy different requirements of warp e and warp ratio Δe in parameter control, and make the controlled objects with good dynamic and static performance. Aiming at different e and Δe, we have summed up a adjust rule of K_P and K_D.

(a) When |e| is relatively big, in order to quicken the system response rate, a bigger K_P is required. In the Meanwhile, at the beginning when e changes quickly, to avoid differential over saturated and control effects greater than permit range, we should use smaller K_P.

(b) When |e| and Δ|e| is at the medium, in order to make the system with a suitable value and insure the natural response rate, K_P should be smaller and K_D should be medium.

(c) When |e| is small and near fixed value, we should increase K_P for a stable performance. At the same time, when Δ|e| is bigger, considering the anti-jamming performance, we can give K_D a smaller value; otherwise, K_D should have a bigger value.

B. Membership Functions and Control Rules

According to the requirement, we have chosen two forms of double-inputs and single-output, in order to adjust the parameters of K_P and K_D. This controller takes the |e| and Δ|e| as input, K_P and K_D as output. The range of |e| and Δ|e| is [-1,1], the range of K_P is [0,3] and the range of K_D is [0,1]. The overall membership functions and PID gain output of adaptive fuzzy, given in Figs. 6-8 and fuzzy rules giving in Table I, II.

NH = Negative High
NL = Negative Low
ZO = Zero
PL = Positive Low
PH = Positive High
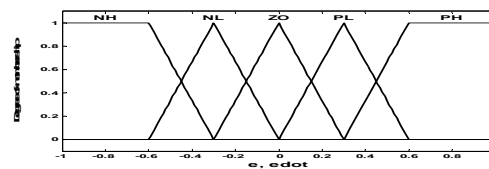ZO = Zero
L = Low
H = High
MH = Much Higher

Fig. 6 Membership function of e and Δe
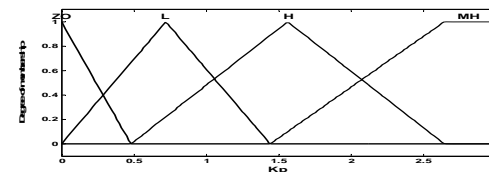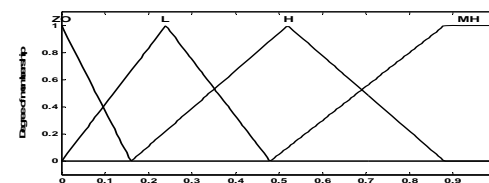

Fig. 7 Membership function of K_P

Fig. 8 Membership function of K_D
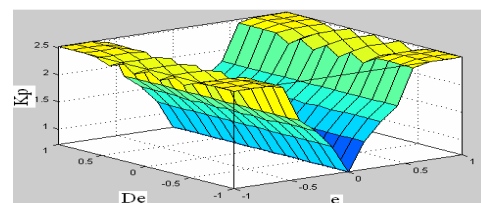

Fig. 9 K_P signal surface variation according to e and De

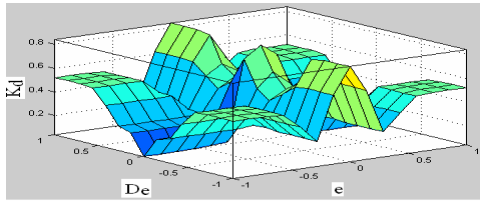Fig. 10 K_D Signal surface variation according to e and De

Table. 1. Fuzzy Rules for of K_P

K_P	e				
		PH	PL	ZO	NL	NH
D_e	PH	H	L	L	L	H
	PL	MH	L	H	L	MH
	ZO	MH	H	MH	H	MH
	NL	MH	L	H	L	MH
	NH	H	L	L	L	H

Table. 2. Fuzzy Rules for of KD

K_D	e				
		PH	PL	ZO	NL	NH
D_e	PH	L	H	L	H	L
	PL	L	H	H	H	L
	ZO	ZO	L	MH	L	ZO
	NL	L	H	H	H	L
	NH	L	H	L	H	L

The on-line adaptive fuzzy tuner continuously adjusts the K_P and K_D gains until the step response meets the desired specifications.

V. SIMULATION RESULTS AND DISCUSSION

We have used MATLAB to Simulation model of Air and Fuel Dynamics and evaluate the behavior of engine dynamics in relation to AFR, based on various control systems applied to it. At the first we assume that the throttle angle change according to (Figs. 11,12).
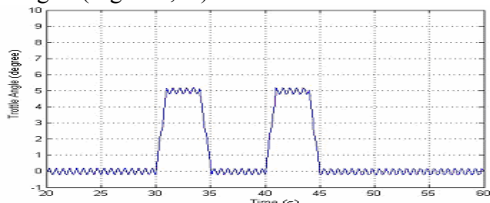

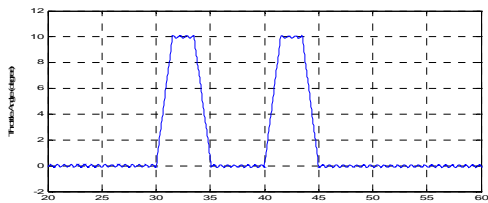Fig. 11 Throttle angle variation paradigm I

Fig. 12 Throttle angle variation paradigm II

Based on these throttle angle variations, cylinder air flow input will be changed. Divide the cylinder air flow input to 14.7 and consider it as fuel input. We consider this state as a time when no control is implemented yet. The AFR in this situation is shown in Fig. (12,13).
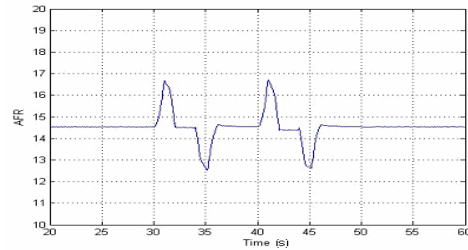

Fig. 12. AFR with variation of throttle angle I
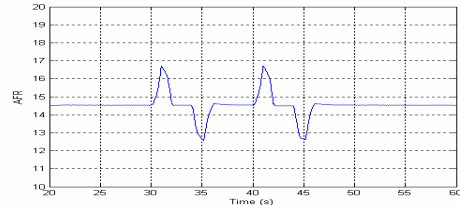

Fig. 13. AFR with variation of throttle angle II

Looking at Fig. 12,13 is clear that in steady states there is a proper reaction in AFR, but when the throttle angle changes abruptly, the AFR considerably will move away from 14.7. so it is necessary to implement a controller in order to survive this ratio in an acceptable region. With design of a PID controller as shown in Fig. 14, the AFR will be better in compare to the time when there is no controller but still there is an considerable different between 14.7 and AFR ratio in engine and this could not be accepted as a satisfactory situation (Figs. 15,16).
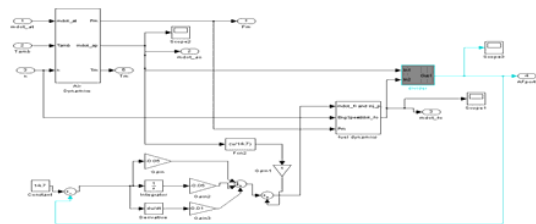

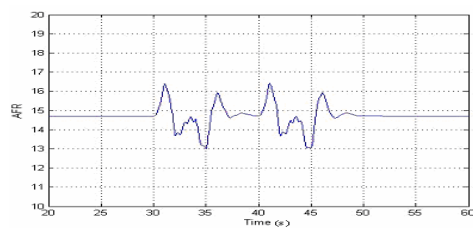Fig. 14 The PID controller in Simulink

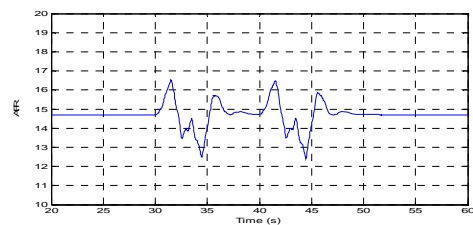

Fig. 15 AFR when applying the PID Controller I

Fig. 16 AFR when applying the PID Controller II

By implementing the fuzzy-PID controller (described in sec. IV) on the simulated engine model, the AFR will show a better adaptive behavior in respect to the parameter variations and this ratio will sustain in an authorized band (Figs. 17,18).
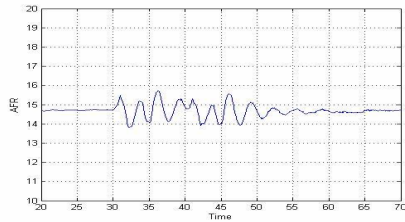

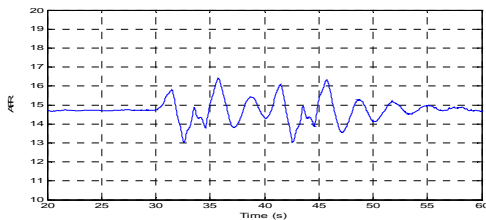Fig. 17 AFR when applying proposed fuzzy-PID Controller I

Fig. 18 AFR when applying proposed fuzzy-PID Controller II

Now we assess system responses based on mathematical parameters shown in below:

a) Difference between maximum of AFR and 14.7 (20<t<60)

b) Difference between minimum of AFR and 14.7 (20<t<60)

c) $\int_{20}^{60} e\,dx$

d) $\int_{20}^{60} e^2\,dx$

TABLE I
AFR MATHEMATICAL PARAMETERS AT VARIANT STATUSES OF THROTTLE ANGLE

statuses	mathematical parameters	AFR_{max}	AFR_{min}	$\int_{20}^{60} e\,dx$	$\int_{20}^{60} e^2\,dx$
variation of throttle angle I	No control	16.68	12.54	14.23	14.82
	PID controller	16.4	13	10.91	11.32
	PID-fuzzy controller	15.72	13.74	9.71	5.03
variation of throttle angle II	No control	16.69	12.54	14.42	14.88
	PID controller	16.53	12.74	12.3	14.49
	PID-fuzzy controller	16.14	13.17	12.53	9.19

From the table above, we can see different values corresponding to different control characters. When controlled objects use the method of fuzzy-PID control, we can easily confirm a better control result. If the throttle angle variation

be considered as a paradigm shown in Fig. 19, we consider this state when no control, PID control and fuzzy-PID control are implemented. The AFR in this period of time is shown in (Figs. 20,21,22).
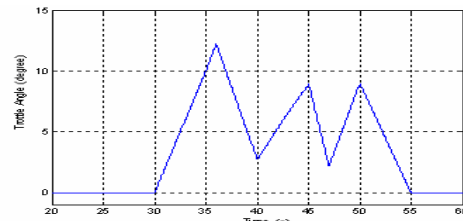

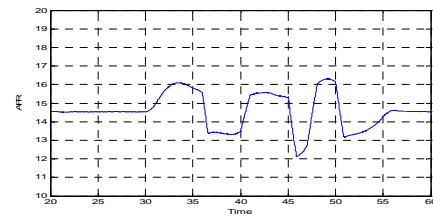Fig. 19 Throttle angle variation paradigm III

Fig. 20 AFR with variation of throttle angle III

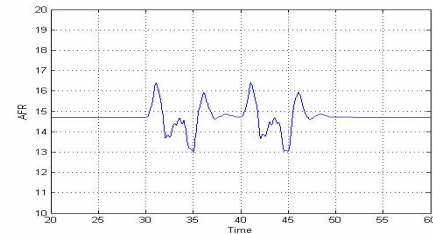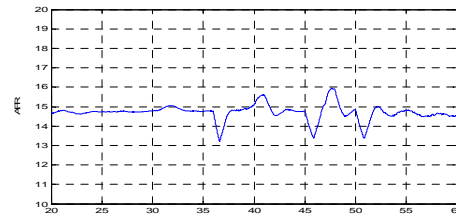Fig. 21 AFR when applying the PID Controller III

Fig. 22 AFR when applying proposed Adaptive Fuzzy Controller III

Comparing the Fig. 22 with Fig. 20 and Fig. 21, show that when we have adaptation in PID controller parameters, the results are better. Now we assess system responses when we have the throttle angle erratic variation describe in Fig. 19 based on mathematical parameters shown in above:

TABLE II
AFR MATHEMATICAL PARAMETERS AT ERRATIC VARIATION OF THROTTLE ANGLE

mathematical parameters / statuses	AFR$_{max}$	AFR$_{min}$	$\int_{20}^{60} e\,dx$	$\int_{20}^{60} e^2 dx$
variation of throttle angle III — No control	16.32	12.11	29.2	35.58
variation of throttle angle III — PID controller	16.15	12.6	15.39	13.49
variation of throttle angle III — Fuzzy-PID controller	15.96	13.37	8.73	5.71

From the Table II., we can see that when controlled objects use the method of fuzzy-PID control, control performance for air–fuel ratio is much better than a conventional PID controller.

VI. CONCLUSION

In this paper a comprehensive model for automobile spark ignition engine have been proposed based on Simulink and MATLAB, and this model have been modified specially for Air-Fuel Ratio control in automobile spark ignition engine. Several proposed controllers for AFR control have been investigated and a fuzzy-PID system is designed in order to model complex, nonlinear, and vague dynamics in SI engine. The fuzzy-PID architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, all yielding remarkable results. Fuzzy-PID controller uses Mamdani-type fuzzy inference system, which is a natural and efficient gain scheduler for the proportional-integral-derivative (PID) gains and is well-suited for modeling nonlinear systems by interpolating between multiple linear models, and this is the key reason for application of fuzzy to PID tuning. So the fuzzy-PID architecture used to schedule the PID gains on-line. The results show that its control performance for air–fuel ratio is much better than that of a conventional PID controller. Thus, the fuzzy-PID model is a potential control scheme to replace the PID control of the production ECU for controlling Air-Fuel Ratio.

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