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Intelligent Robust Automotive Engine Control

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Abstract

In this research, manage the Internal Combustion (IC) engine modeling and a multi-input-multi-output artificial intelligence baseline sliding mode methodology scheme is developed with guaranteed stability to simultaneously control fuel ratios to desired levels under various air flow disturbances by regulating the mass flow rates of engine PFI and DI injection systems. Analytical dynamic nonlinear modeling of internal combustion engine is carried out using elegant Euler-Lagrange method compromising accuracy and complexity. A baseline estimator with varying parameter gain is designed with guaranteed stability to allow implementation of the proposed state feedback sliding mode methodology into a MATLAB simulation environment, where the sliding mode strategy is implemented into a model engine control module ("software"). To estimate the dynamic model of IC engine fuzzy inference engine is applied to baseline sliding mode methodology. The proposed tracking method is designed to optimally track the desired FR by minimizing the error between the trapped in-cylinder mass and the product of the desired FR and fuel mass over a given time interval.

Keyword: *IC engine modeling, nonlinear methodology to control, chattering free baseline sliding mode methodology, artificial intelligence, sliding mode methodology, baseline methodology, fuzzy inference engine*

1. Introduction

Modeling of an entire internal combustion (IC) engine is a very important and complicated process because internal combustion engines are nonlinear, multi inputs-multi outputs (MIMO) and time variant. There have been several engine controller designs over the previous years in which the main goal is to improve the efficiency and exhaust emissions of the automotive engine [1]. Specific applications of air to fuel (A/F) ratio control based on observer measurements in the intake manifold were developed by Benninger in 1991 [2-3]. Another approach was to base the observer on measurements of exhaust gases measured by the oxygen sensor and on the throttle position, which was researched by Onder [4]. These observer ideas used linear observer theory. Hedrick also used the measurements of the oxygen sensor to develop a nonlinear, sliding mode approach to control the A/F ratio [5]. All of the previous control strategies were applied to engines that used only port fuel injections, where fuel was injected in the intake manifold. Current production A/F ratio controllers use closed loop feedback and feed forward control to achieve the desired stoichio metric mixture. These controllers use measurements from the oxygen sensor to control the desired amount of fuel that should be injected over the next engine cycle and have been able to control the A/F very well [6].

In developing a valid engine model, the concept of the combustion process, abnormal combustion, and cylinder pressure must be understood. The combustion process is relatively

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simple and it begins with fuel and air being mixed together in the intake manifold and cylinder. This air-fuel mixture is trapped inside cylinder after the intake valve(s) is closed and then gets compressed [7]. When the air-fuel mixture is compressed it causes the pressure and temperature to increase inside the cylinder. Unlike normal combustion, the cylinder pressure and temperature can rise so rapidly that it can spontaneously ignite the air-fuel mixture causing high frequency cylinder pressure oscillations. These oscillations cause the metal cylinders to produce sharp noises called knock, which it caused to abnormal combustion. The pressure in the cylinder is a very important physical parameter that can be analyzed from the combustion process. After the flame is developed, the cylinder pressure steadily rises, reaches a maximum point after TDC, and finally decreases during the expansion stroke when the cylinder volume increases. Since cylinder pressure is very important to the combustion event and the engine cycle in spark ignition engines, the development of a model that produces the cylinder pressure for each crank angle degree is necessary.

A nonlinear robust controller design is major subject in this work. Controller is a device which can sense information from linear or nonlinear system to improve the systems performance [8-17]. The main targets in designing control systems are stability, good disturbance rejection, and small tracking error [15-17]. Several IC engines are controlled by linear methodologies (*e.g.*, Proportional-Derivative (PD) controller, Proportional- Integral (PI) controller or Proportional-Integral-Derivative (PID) controller), but in uncertain dynamic models this technique has limitations [16-17].

Sliding mode methodology (SMM) is a significant nonlinear optimal control fuel ratio methodology under condition of partly uncertain dynamic parameters of system. This controller is used to control of highly nonlinear systems, because this type of optimal method is a robust and stable [17]. Conversely, pure sliding mode controller is used in many applications; it has two important drawbacks namely; chattering phenomenon, and nonlinear equivalent dynamic formulation in uncertain dynamic parameter. It is possible to solve this problem by combining sliding mode controller and baseline law which this method can helps improve the system's tracking performance by adjusting controller's coefficient [18-19].

In recent years, artificial intelligence theory has been used in nonlinear systems. Neural network, fuzzy logic and neuro-fuzzy are synergically combined with nonlinear methodology and used in nonlinear, time variant and uncertain plant (*e.g.*, IC engine). Fuzzy logic controller (FLC) is one of the most important applications of fuzzy logic theory. This controller can be used to control nonlinear, uncertain, and noisy systems. This method is free of some model techniques as in model-based controllers. As mentioned that fuzzy logic application is not only limited to the modelling of nonlinear systems but also this method can help engineers to design a model-free controller. The main reasons to use fuzzy logic methodology are able to give approximate recommended solution for uncertain and also certain complicated systems to easy understanding and flexible. Fuzzy logic provides a method to design a model-free controller for nonlinear plant with a set of IF-THEN rules. The applications of artificial intelligence such as neural networks and fuzzy logic in modelling and control are significantly growing especially in recent years.

This paper is organized as follows; second part focuses on the modeling dynamic formulation based on Lagrange methodology, fuzzy logic methodology and sliding mode controller to have a robust control. Third part is focused on the methodology which can be used to reduce the error, increase the performance quality and increase the robustness and stability. Simulation result and discussion is illustrated in forth part which based on trajectory following and disturbance rejection. The last part focuses on the conclusion and compare between this method and the other ones.

2. Theorem

Mathematical Modeling of IC Engine Using Euler Lagrange: In developing a valid engine model, the concept of the combustion process, abnormal combustion and cylinder pressure must be understood. The combustion process is relatively simple and it begins with fuel and air being mixed together in the intake manifold and cylinder. This air-fuel mixture is trapped inside cylinder after the intake valve(s) is closed and then gets compressed. When the air-fuel mixture is compressed it causes the pressure and temperature to increase inside the cylinder. In abnormal combustion, the cylinder pressure and temperature can rise so rapidly that it can spontaneously ignite the air-fuel mixture causing high frequency cylinder pressure oscillations. These oscillations cause the metal cylinders to produce sharp noises called knock, which it caused to abnormal combustion. The pressure in the cylinder is a very important physical parameter that can be analyzed from the combustion process. Since cylinder pressure is very important to the combustion event and the engine cycle in spark ignition engines, the development of a model that produces the cylinder pressure for each crank angle degree is necessary.
The dynamic equations of IC engine can be written as:

$$\begin{bmatrix} \boldsymbol{PFI} \\ \boldsymbol{DI} \end{bmatrix} = \begin{bmatrix} \dot{\boldsymbol{M}}_{\boldsymbol{air}_{11}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{12}} \\ \dot{\boldsymbol{M}}_{\boldsymbol{air}_{21}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{22}} \end{bmatrix} \begin{bmatrix} \ddot{\boldsymbol{FR}} \\ \ddot{\boldsymbol{\alpha}}_{\boldsymbol{I}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{P}_{\boldsymbol{motor}_1} \\ \boldsymbol{P}_{\boldsymbol{motor}_2} \end{bmatrix} \begin{bmatrix} \dot{\boldsymbol{FR}} & \dot{\boldsymbol{\alpha}}_{\boldsymbol{I}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{N}_{\boldsymbol{11}} & \boldsymbol{N}_{\boldsymbol{12}} \\ \boldsymbol{N}_{\boldsymbol{21}} & \boldsymbol{N}_{\boldsymbol{22}} \end{bmatrix} \times \begin{bmatrix} \dot{\boldsymbol{FR}} \\ \dot{\boldsymbol{\alpha}}_{\boldsymbol{I}} \end{bmatrix}^2 + \begin{bmatrix} \boldsymbol{M}_{\boldsymbol{a}_1} \\ \boldsymbol{M}_{\boldsymbol{a}_2} \end{bmatrix} \quad \textbf{(1)}$$

There for to calculate the fuel ratio and equivalence ratio we can write:

$$\begin{bmatrix} \ddot{\boldsymbol{FR}}_{\boldsymbol{a}} \\ \ddot{\alpha}_{\boldsymbol{I}_{\boldsymbol{a}}} \end{bmatrix} = \begin{bmatrix} \dot{\boldsymbol{M}}_{\boldsymbol{air}_{11}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{12}} \\ \dot{\boldsymbol{M}}_{\boldsymbol{air}_{21}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{22}} \end{bmatrix}^{-1} \left\{ \begin{bmatrix} \boldsymbol{PFI} \\ \boldsymbol{DI} \end{bmatrix} - \left\{ \begin{bmatrix} \boldsymbol{P}_{\boldsymbol{motor}_1} \\ \boldsymbol{P}_{\boldsymbol{motor}_2} \end{bmatrix} \begin{bmatrix} \dot{\boldsymbol{FR}} & \dot{\alpha}_{\boldsymbol{I}_{\boldsymbol{a}}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{N}_{\boldsymbol{11}} & \boldsymbol{N}_{\boldsymbol{12}} \\ \boldsymbol{N}_{\boldsymbol{21}} & \boldsymbol{N}_{\boldsymbol{22}} \end{bmatrix} \times \begin{bmatrix} \dot{\boldsymbol{FR}}_{\boldsymbol{a}} \\ \dot{\alpha}_{\boldsymbol{I}_{\boldsymbol{a}}} \end{bmatrix}^{\boldsymbol{2}} + \begin{bmatrix} \boldsymbol{M}_{\boldsymbol{a}_1} \\ \boldsymbol{M}_{\boldsymbol{a}_2} \end{bmatrix} \right\} \right\} \quad \textbf{(2)}$$

To solve $\dot{\boldsymbol{M}}_{\boldsymbol{air}}$ **,** we can write**;**

$$\dot{\boldsymbol{M}}_{\boldsymbol{air}} = \begin{bmatrix} \dot{\boldsymbol{M}}_{\boldsymbol{air}_{11}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{12}} \\ \dot{\boldsymbol{M}}_{\boldsymbol{air}_{21}} & \dot{\boldsymbol{M}}_{\boldsymbol{air}_{22}} \end{bmatrix} \qquad \text{Where } \dot{\boldsymbol{M}}_{\boldsymbol{air}_{12}} = \dot{\boldsymbol{M}}_{\boldsymbol{air}_{21}} \quad \textbf{(3)}$$

Where $\dot{\boldsymbol{M}}_{\boldsymbol{air}}$ is the ratio of the mass of air.

Matrix P_{motor} is a 1×2 matrix:

$$P_{motor} = \begin{bmatrix} \boldsymbol{P_1} \\ \boldsymbol{P_2} \end{bmatrix} \quad \textbf{(4)}$$

Matrix engine angular speed matrix(N) is a 2×2 matrix

$$N = \begin{bmatrix} \boldsymbol{N}_{\boldsymbol{11}} & \boldsymbol{N}_{\boldsymbol{12}} \\ \boldsymbol{N}_{\boldsymbol{21}} & \boldsymbol{N}_{\boldsymbol{22}} \end{bmatrix} \quad \textbf{(5)}$$

Where,
Matrix mass of air in cylinder for combustion matrix (M_a) is a 1×2 matrix.

$$M_a = \begin{bmatrix} \boldsymbol{M_{a_1}} \\ \boldsymbol{M_{a_2}} \end{bmatrix} \tag{6}$$

The above target equivalence ratio calculation will be combined with fuel ratio calculation that will be used for controller design purpose.

Sliding Mode methodology: Consider a nonlinear single input dynamic system is defined by:

$$\boldsymbol{x^{(n)} = f(\vec{x}) + b(\vec{x})u} \tag{7}$$

Where u is the vector of control input, $\boldsymbol{x^{(n)}}$ is the $\boldsymbol{n^{th}}$ derivation of $\boldsymbol{x}$, $\boldsymbol{x = [x, \dot{x}, \ddot{x}, \dots, x^{(n-1)}]^T}$ is the state vector, $\boldsymbol{f(x)}$ is unknown or uncertainty, and $\boldsymbol{b(x)}$ is of known *sign* function. The main goal to design this controller is train to the desired state; $\boldsymbol{x_d = [x_d, \dot{x}_d, \ddot{x}_d, \dots, x_d{}^{(n-1)}]^T}$, and trucking error vector is defined by:

$$\boldsymbol{\tilde{x} = x - x_d = [\tilde{x}, \dots, \tilde{x}^{(n-1)}]^T} \tag{8}$$

A time-varying sliding surface $\boldsymbol{s(x,t)}$ in the state space $\boldsymbol{R^n}$ is given by:

$$\boldsymbol{s(x,t) = (\frac{d}{dt} + \lambda)^{n-1}\, \tilde{x} = 0} \tag{9}$$

where λ is the positive constant. To further penalize tracking error, integral part can be used in sliding surface part as follows:

$$\boldsymbol{s(x,t)} = (\frac{d}{dt} + \boldsymbol{\lambda})^{\boldsymbol{n-1}} \left(\int_{\boldsymbol{0}}^{\boldsymbol{t}} \boldsymbol{\tilde{x}\, dt} \right) = \boldsymbol{0} \tag{10}$$

The main target in this methodology is kept the sliding surface slope $\boldsymbol{s(x,t)}$ near to the zero. Therefore, one of the common strategies is to find input $\boldsymbol{U}$ outside of $\boldsymbol{s(x,t)}$.

$$\boldsymbol{\frac{1}{2}\frac{d}{dt} s^2(x,t) \le -\zeta |s(x,t)|} \tag{11}$$

where ζ is positive constant.

$$\text{If } \mathbf{S(0)>0} \rightarrow \mathbf{\frac{d}{dt} S(t) \le -\zeta} \tag{12}$$

To eliminate the derivative term, it is used an integral term from t=0 to t=$\boldsymbol{t_{reach}}$

$$\boldsymbol{\int_{t=0}^{t=t_{reach}} \frac{d}{dt} S(t) \le -\int_{t=0}^{t=t_{reach}} \eta \rightarrow S\,(t_{reach}) - S(0) \le -\zeta(t_{reach} - 0)} \tag{13}$$

Where t_{reach} is the time that trajectories reach to the sliding surface so, suppose S ($t_{reach} =$ 0) defined as

$$\mathbf{0} - \boldsymbol{S}(\mathbf{0}) \leq -\boldsymbol{\eta}(\boldsymbol{t}_{\boldsymbol{reach}}) \rightarrow \boldsymbol{t}_{\boldsymbol{reach}} \leq \frac{\boldsymbol{S}(\mathbf{0})}{\boldsymbol{\zeta}} \tag{14}$$

And

$$\boldsymbol{if}\ \boldsymbol{S}(\mathbf{0}) < 0 \rightarrow 0 - S(\mathbf{0}) \leq -\boldsymbol{\eta}(\boldsymbol{t}_{\boldsymbol{reach}}) \rightarrow \boldsymbol{S}(\mathbf{0}) \leq -\boldsymbol{\zeta}(\boldsymbol{t}_{\boldsymbol{reach}}) \rightarrow \boldsymbol{t}_{\boldsymbol{reach}} \leq \frac{|\boldsymbol{S}(\mathbf{0})|}{\boldsymbol{\eta}} \tag{15}$$

Equation (15) guarantees time to reach the sliding surface is smaller than $\frac{|\boldsymbol{S}(\mathbf{0})|}{\boldsymbol{\zeta}}$ since the trajectories are outside of $S(t)$.

$$\boldsymbol{if}\ \boldsymbol{S}_{\boldsymbol{t}_{\boldsymbol{reach}}} = \boldsymbol{S}(\mathbf{0}) \rightarrow \boldsymbol{error}(\boldsymbol{x} - \boldsymbol{x}_{\boldsymbol{d}}) = \mathbf{0} \tag{16}$$

suppose S is defined as

$$\boldsymbol{s}(\boldsymbol{x}, \boldsymbol{t}) = (\frac{\boldsymbol{d}}{\boldsymbol{dt}} + \boldsymbol{\lambda}) \quad \widetilde{\boldsymbol{x}} = (\dot{\mathbf{x}} - \dot{\mathbf{x}}_{\mathbf{d}}) + \boldsymbol{\lambda}(\mathbf{x} - \mathbf{x}_{\mathbf{d}}) \tag{17}$$

The derivation of S, namely, $\dot{S}$ can be calculated as the following;

$$\dot{\boldsymbol{S}} = (\ddot{\mathbf{x}} - \ddot{\mathbf{x}}_{\mathbf{d}}) + \boldsymbol{\lambda}(\dot{\mathbf{x}} - \dot{\mathbf{x}}_{\mathbf{d}}) \tag{18}$$

suppose the second order system is defined as;

$$\ddot{\boldsymbol{x}} = \boldsymbol{f} + \boldsymbol{u} \ \rightarrow \dot{\boldsymbol{S}} = \boldsymbol{f} + \boldsymbol{U} - \ddot{\boldsymbol{x}}_{\boldsymbol{d}} + \boldsymbol{\lambda}(\dot{\mathbf{x}} - \dot{\mathbf{x}}_{\mathbf{d}}) \tag{19}$$

Where $\boldsymbol{f}$ is the dynamic uncertain, and also since $S = 0\ and\ \dot{S} = 0$, to have the best approximation ,$\widehat{\boldsymbol{U}}$ is defined as

$$\widehat{\boldsymbol{U}} = -\widehat{\boldsymbol{f}} + \ddot{\boldsymbol{x}}_{\boldsymbol{d}} - \boldsymbol{\lambda}(\dot{\mathbf{x}} - \dot{\mathbf{x}}_{\mathbf{d}}) \tag{20}$$

A simple solution to get the sliding condition when the dynamic parameters have uncertainty is the switching control law:

$$\boldsymbol{U}_{\boldsymbol{dis}} = \widehat{\boldsymbol{U}} - \boldsymbol{K}(\vec{\boldsymbol{x}}, \boldsymbol{t}) \cdot \mathbf{sgn}(\boldsymbol{s}) \tag{21}$$

where the switching function $\mathbf{sgn}(\mathbf{S})$ is defined as

$$\boldsymbol{sgn}(\boldsymbol{s}) = \begin{cases} \mathbf{1} & \boldsymbol{s} > 0 \\ -\mathbf{1} & \boldsymbol{s} < 0 \\ \mathbf{0} & \boldsymbol{s} = \mathbf{0} \end{cases} \tag{22}$$

and the $\boldsymbol{K}(\vec{\boldsymbol{x}}, \boldsymbol{t})$ is the positive constant. Suppose by (11) the following equation can be written as,

$$\frac{\mathbf{1}}{\mathbf{2}}\frac{\boldsymbol{d}}{\boldsymbol{dt}}\boldsymbol{s}^{\mathbf{2}}(\boldsymbol{x}, \boldsymbol{t}) = \dot{\mathbf{S}} \cdot \mathbf{S} = \left[\boldsymbol{f} - \widehat{\boldsymbol{f}} - \boldsymbol{K}\mathbf{sgn}(\boldsymbol{s})\right] \cdot \boldsymbol{S} = \left(\boldsymbol{f} - \widehat{\boldsymbol{f}}\right) \cdot \boldsymbol{S} - \boldsymbol{K}|\boldsymbol{S}| \tag{23}$$

and if the equation (15) instead of (14) the sliding surface can be calculated as

$$s(x,t) = (\frac{d}{dt} + \lambda)^2 \left(\int_0^t \tilde{x}\, dt\right) = (\dot{x} - \dot{x}_d) + 2\lambda(\dot{x} - \dot{x}_d) - \lambda^2(x - x_d) \tag{24}$$

in this method the approximation of $\boldsymbol{U}$ is computed as

$$\hat{U} = -\hat{f} + \ddot{x}_d - 2\lambda(\dot{x} - \dot{x}_d) + \lambda^2(x - x_d) \tag{25}$$

Baseline methodology: The design of a baseline controller to control the fuel ratio was very straight forward. Since there was an output from the fuel ratio model, this means that there would be two inputs into the baseline controller. Similarly, the output of the controller result from the two control inputs of the port fuel injector signal and direct injector signal. In a typical PID controller, the controller corrects the error between the desired output value and the measured value. Since the equivalence ratio and fuel ratio are the two measured signals, two controllers were cascaded together to control the PFI and DI inputs. The first was a PID controller that corrected the error between the desired equivalence ratio and the measured equivalence ratio; while the second was only a proportional integral (PI) controller that corrected the fuel ratio error.

$$e_1(t) = \alpha_{target}(t) - \alpha_d(t) \tag{26}$$

$$e_2(t) = Fuel\, ratio_a(t) - Fuel\, Ratio_d(t) \tag{27}$$

$$PFI_\alpha = K_{p_a} e_1 + K_{V_a} \dot{e_1} + K_{I_a} \sum e_1 \tag{28}$$

$$DI_\alpha = K_{p_b} e_1 + K_{V_b} \dot{e_1} + K_{I_b} \sum e_1 \tag{29}$$

$$PFI_F = (K_{p_c} e_2 + K_{I_c} \sum e_2) \times PFI_\alpha \tag{30}$$

$$DI_F = DI_\alpha \tag{31}$$

3. Methodology

This part is focused on design SISO fuzzy estimation baseline sliding mode methodology for system's management based on Lyapunov formulation. The firs type of fuzzy systems is given by

$$f(x) = \sum_{l=1}^{M} \theta^l \mathcal{E}^l(x) = \theta^T \mathcal{E}(x) \tag{32}$$

Where
$\theta = (\theta^1, \dots, \theta^M)^T, \mathcal{E}(x) = (\mathcal{E}^1(x), \dots, \mathcal{E}^M(x))^T, and\ \mathcal{E}^l(x) =$
$: \prod_{i=1}^{n} \frac{\mu_{A_i^l}(x_i)}{} \sum_{l=1}^{M}(\prod_{i=1}^{n} \mu_{A_i^l}(x_i))$. $\theta^1, \dots, \theta^M$ are adjustable parameters in (23) . $\mu_{A_1^1}(x_1), \dots, \mu_{A_n^m}(x_n)$ are given membership functions whose parameters will not change over time.

The second type of fuzzy systems is given by

$$\boldsymbol{f(x)} = \frac{\sum_{l=1}^{M} \theta^{l}\left[\prod_{i=1}^{n} \exp\left(-\left(\frac{x_i-\alpha_i^l}{\delta_i^l}\right)^2\right)\right]}{\sum_{l=1}^{M}\left[\prod_{i=1}^{n} \exp\left(-\left(\frac{x_i-\alpha_i^l}{\delta_i^l}\right)^2\right)\right]} \quad \textbf{(33)}$$

Where θ^l , α_i^l and δ_i^l are all adjustable parameters. From the universal approximation theorem, we know that we can find a fuzzy system to estimate any continuous function. For the first type of fuzzy systems, we can only adjust θ^l in (23). We define $f^{\wedge}(x|\theta)$ as the approximator of the real function$f(x)$.

$$\boldsymbol{f^{\wedge}(x|\theta) = \theta^T \varepsilon(x)} \quad \textbf{(34)}$$

We define θ^* as the values for the minimum error:

$$\boldsymbol{\theta^* = \arg\min_{\theta\in\Omega}\left[\sup_{x\in U} | f^{\wedge}(x|\theta) - g(x)|\right]} \quad \textbf{(35)}$$

Where Ω is a constraint set for θ. For specific x , $sup_{x\in U}|f^{\wedge}(x|\theta^*) - f(x)|$ is the minimum approximation error we can get.

We used the first type of fuzzy systems (23) to estimate the nonlinear system (11) the fuzzy formulation can be write as below;

$$\boldsymbol{f(x|\theta) = \theta^T \varepsilon(x) = \frac{\sum_{l=1}^{n} \theta^l\left[\mu_{A^l}(x)\right]}{\sum_{l=1}^{n}[\mu_{A^l}(x)]}} \quad \textbf{(36)}$$

Where $\theta^1, \dots, \theta^n$ are adjusted by an adaptation law. The adaptation law is designed to minimize the parameter errors of $\theta - \theta^*$. A MIMO (multi-input multi-output) fuzzy system is designed to compensate the uncertainties of the nonlinear system. The parameters of the fuzzy system are adjusted by adaptation laws. The tracking error and the sliding surface state are defined as:

$$\boldsymbol{e = q - q_d} \quad \textbf{(37)}$$

$$\boldsymbol{s = \dot{e} + \lambda_e} \quad \textbf{(38)}$$

We define the reference state as

$$\boldsymbol{\dot{q}_r = \dot{q} - s = \dot{q}_d - \lambda e} \quad \textbf{(39)}$$

$$\boldsymbol{\ddot{q}_r = \ddot{q} - \dot{s} = \ddot{q}_d - \lambda \dot{e}} \quad \textbf{(40)}$$

The general MIMO if-then rules are given by

$$\boldsymbol{R^l: if\ x_1\ is\ A_1^l\ , x_2\ is\ A_2^l\ , \dots, x_n\ is\ A_n^l\ ,} \quad \textbf{(41)}$$
$$\boldsymbol{then\ y_1 is\ B_1^l\ , \dots, y_m\ is\ B_m^l}$$

Where $l = 1,2,\dots,M$ are fuzzy if-then rules; $x = (x_1,\dots,x_n)^T$ and $y = (y_1,\dots,y_n)^T$ are the input and output vectors of the fuzzy system. The MIMO fuzzy system is define as

$$\boldsymbol{f(x)} = \ominus^{\boldsymbol{T}}\, \boldsymbol{\varepsilon(x)} \tag{42}$$

Where

$$\ominus^{\boldsymbol{T}} = (\boldsymbol{\theta_1},\dots,\boldsymbol{\theta_m})^{\boldsymbol{T}} = \begin{bmatrix} \boldsymbol{\theta_1^1}, \boldsymbol{\theta_1^2}, \dots, \boldsymbol{\theta_1^M} \\ \boldsymbol{\theta_2^1}, \boldsymbol{\theta_2^2}, \dots, \boldsymbol{\theta_2^M} \\ \vdots \\ \boldsymbol{\theta_m^1}, \boldsymbol{\theta_m^2}, \dots, \boldsymbol{\theta_m^M} \end{bmatrix} \tag{43}$$

4. Results and Discussion

This section is focused on compare between baseline methodology to FR optimization (BLO) and artificial intelligence (fuzzy) baseline Sliding Mode methodology (FBSMM). These controllers were tested by MATLAB/SIMULINK environment.

FR tracking: Based on equations in sliding mode methodology; this method performance is depended on the gain updating factor (K) and sliding surface slope coefficient (λ). These two coefficients are computed by gradient descent optimization in pure SMM. After this process the main important challenge is, optimizer is depending on sliding surface slope coefficients so baseline method is apply. Figure 1 shows FR tracking performance in BLO and FBSMM without torque load disturbance.

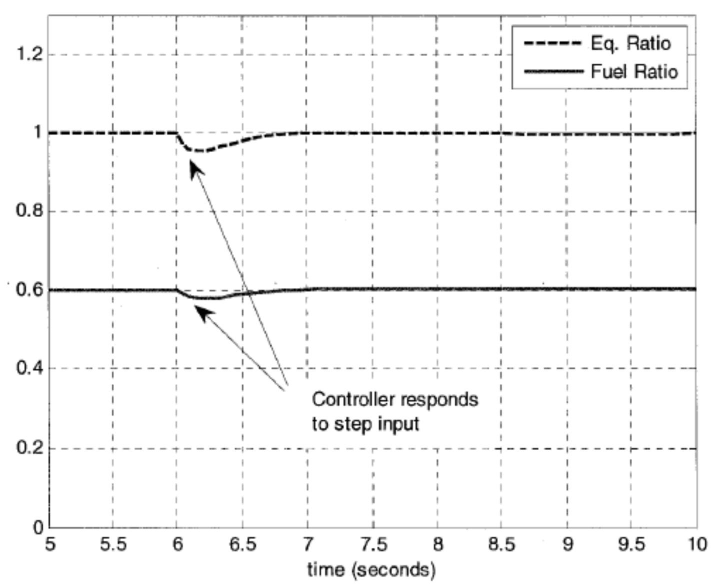

Figure 1. FBSMM and BLO for Adjust FR without Torque Load Disturbance

Based on Figure 1 it is observed that, BLO has oscillation in this nonlinear system, caused to instability in tuning the FR but FBSMM has steady in response. BLO's overshoot is 1.3% but BSMM's overshoot is 0%.

PFI and DI control: Figures 2 shows the PFI and DI control. This simulates a situation where the throttle (air) initially remains open at a constant angle and then quickly (almost instantaneously) opens or closes to a larger or smaller angle. The constant value was chosen to be

0.1 and the step input value is chosen to be 0.15. The time at which the step input would be added to the constant value was chosen to be at 6 seconds. The controller quickly adjusted the control inputs to maintain the desired equivalence ratio and fuel ratio.

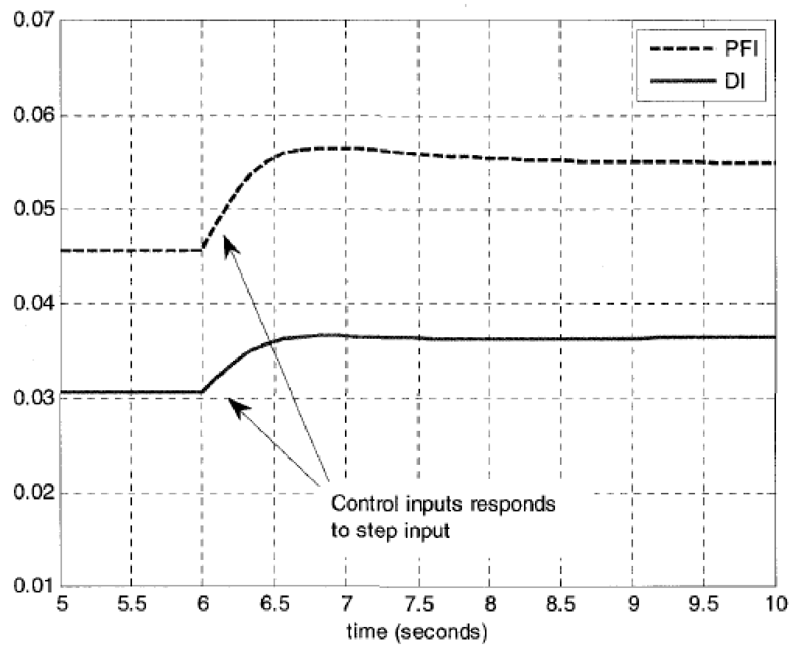

Figure 2. PFI and DI Control Inputs

Based on Figure 2; by comparing PFI and DI trajectory with 10% torque load disturbance of relative to the input signal amplitude in BSMM and BLO, BSMM's overshoot about (0%) is lower than BLO's **(2.3%)** . Based on Figure 2, it is observed that FBSMM's performance is better than BLO and it also can eliminate the chattering in presence of 10% disturbance.

5. Conclusion

Refer to this research, IC engine modeling based on Lagrange and an artificial intelligence based sliding mode methodology is proposed for tuning the FR in internal combustion engine. Control the stability and convergence of the fuzzy sliding mode controller based on discontinuous function is guarantee and proved by the LYAPUNOV method. The simulation results exhibit that the fuzzy baseline sliding mode methodology tuning the IC engine variable very well in various situations. The FBSMM gives significant steady state error managing performance when compared to BLO.

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