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Neuro-Fuzzy-based Improved IMC for Speed Control of Nonlinear Heavy Duty Vehicles

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ABSTRACT

A neuro-fuzzy based improved internal model control (I-IMC) is proposed for speed control of uncertain nonlinear heavy duty vehicle (HDV) as the standard IMC (S-IMC) can't tackle the nonlinear systems effectively and degrades the performance of HDV system. Adaptive neuro-fuzzy inference system and artificial neural network with adaptive control are used for the design of I-IMC. The proposed control techniques are developed to achieve the better speed tracking performance and robustness of HDV system under the influence of road grade disturbance.

Keywords: Adaptive neuro-fuzzy inference system, improved internal model control, heavy duty vehicle

1. INTRODUCTION

The design of controller for nonlinear systems is difficult and useful for real applications. It has always remained a challenging task for the researchers. Heavy duty vehicle (HDV) is a practical nonlinear system and play an important role in the field of transportation. The objective of automated speed control of nonlinear HDV through the throttle valve is to enhance better speed tracking performance with improved fuel efficiency and reduced pollution under uncertain environment[1]. In recent years intelligent soft computing techniques such as fuzzy inference system (FIS), artificial neural network (ANN), and Adaptive neuro-fuzzy inference system (ANFIS) are widely used in various scientific domains as a powerful tool of identification, modeling and control of highly nonlinear and complex systems. Among these techniques ANFIS is one of the best tradeoff between neural and fuzzy systems; it provides smoothness and knowledge representation due to the fuzzy logic and adaptability capability due to the ANN[2-5].

Standard improved internal model control (S-IMC) is a effective strategy in process control and it was introduced by Garcia and Morari[6]. The extension of S-IMC for nonlinear system is proposed by Economou[7], *et al.* and is called nonlinear IMC. The structure of ANN based nonlinear IMC i.e. IMC for nonlinear system is presented by researchers[1,2,8]. For nonlinear IMC, it is not easy to design the ANN and ANFIS based internal model (IM) and its inverse, i.e. inverse controller (IC) because of the following reasons.

(i) The system to be controlled must be stable in open-loop.
(ii) The system to be controlled is required to have stable zero dynamics because the use of inverse system.

One of the solutions to minimise these problems is to train an IM and IC with the help of the identified ANN from stabilised nonlinear system using linear IMC. Large number of engineering applications of ANN and ANFIS are presented in literature review such as voltage and frequency regulation in micro-grids[9], thermal control[5], control of a grid connected hybrid system[10] and autonomous flight control of an unmanned air vehicles[11], etc. The applications of IMCs for different systems are presented in[12-16]. A conventional first order low pass filter is considered for S-IMC[12]. A modified second order filter is designed in this study.

Based on the S-IMC structure, a new IMC structure with enhanced robustness was developed and named as enhanced IMC by Zhu[17], *et al.* In enhanced IMC structure, an additional path is incorporated to the plant through a compensator $C_2(s)$ and the application of enhanced IMC is presented[18,19]. In this study, an adaptive control is used for design of $C_2(s)$ that can further reduce the effects of parametric uncertainties and external disturbances as compared to the S-IMC. A modified IMC is proposed by Li & Gu[14] and applied to PMSM. In modified IMC, a feedback control term $C_3(s)$ is designed. Based an enhanced, modified and nonlinear IMC, a novel structure of IMC is proposed and called I-IMC. In this study I-IMC is designed for nonlinear HDV via the linearised HDV system. For nonlinear HDV system, I-IMC is designed using ANN and ANFIS i.e. IM and IC are designed using ANN and ANFIS. A comparative performance analysis of ANN and ANFIS based I-IMC for nonlinear HDV is presented in order to identify the better one. The performance specifications such as integral of the absolute error (IAE), integral of the square of error (ISE), overshoot (OS), rise time (RT) and settling time (ST) are considered for performance analysis of HDV with designed controllers.

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2. NONLINEAR HDV SYSTEM

The complete block diagram of HDV system with electronic throttle control (ETC) for speed control application is given in Fig. 1. The desired throttle angular position θ^* is achieved by the IMC techniques based on the desired and actual speed of vehicle.

The detailed modelling of HDV system is presented by Yadav & Gaur[12]. The dynamics of BLDC servo motor for design of ETC system is as follows[12]:

$$L_s \frac{di_s}{dt} = -R_s i_s - K_b N \frac{d\theta}{dt} + E_a \tag{1a}$$

$$J\frac{d^2\theta}{dt^2} = -B\left(\frac{d\theta}{dt}\right) + NT_m - T_a \tag{1b}$$

where i_s is stator current (A), E_a applied motor voltage, K_b is back EMF constant, R_s and L_s are stator resistance and inductance of motor, respectively. The gear ratio N is defined as $N = \frac{\theta_m}{\theta} = \frac{T_g}{T_L}$, where is motor shaft angular position in radians θ is the throttle plate angular position in radians, T_g is the torque transmitted from gear to throttle, T_L is the load torque (Nm) and T_a is torque due to air mass flow (Nm). Neglecting the airflow torque T_a because it is very small as compared to the other torques present. The motor torque T_m is defined as $T_m = K_t i_s$ where K_t is motor torque constant. In Eqn (1); J and B are described as: $J=N^2J_m+J_{th}$ and $B=N^2B_m+B_{th}$, where J_m and J_{th} are the inertia of the motor and throttle respectively, and B_m and B_{th} are damping coefficient of the motor and throttle, respectively.

The nonlinear dynamics of HDV is given by Yadav & Gaur[12] and it is as follows:

$$m\frac{dV}{dt} = F_i + \gamma\sqrt{\theta} - \tau_e \frac{dF_e(\theta)}{dt} - \mu mg\cos\beta - mg\sin\beta - b_w V / r_{tire} - \alpha V^2 \tag{2}$$

where F_i is engine idle force caused by mechanical friction and pumping losses in the engine and varies with different engine power ratings and increases with engine size, whereas γ approximately reflects the combustion efficiency. It is almost the same for different size of engines. F_e is an engine force that is the function of the throttle position θ, μ is rolling resistance coefficient and τ_e is engine time constant. In Eqn. (2), α is defined as $\alpha = 0.5\times\rho\times A_{fr}\times c_d$, where ρ, A_{fr} and c_d represent the density of air (kg/m^3), the vehicle effective frontal area (m^2), and aerodynamic drag coefficient (Ns^2/Kgm) respectively. The symbols b_w, r_{tire}, m, V, g and β represent the bearing damping coefficient, effective radius of tire, mass of vehicle, speed, gravity acceleration and road slope, respectively. The road slope β is taken as a random value with variance of $\frac{\pi}{20}$ radians that gives non-deterministic slope of road. If m is total mass of the vehicle, it is defined as $m_{vehicle}+m_{fuel}$, where m_{fuel} is assumed to decrease linearly at the rate of 0.6 kg/km.

3. I-IMC FOR HDV SYSTEM

The structure of I-IMC is given in Fig. 2, here $C_1(s)$ is a S-IMC, $C_2(s)$ is an adaptive control, $C_3(s)$ is a proportional controller i.e. $C_3(s) = k_p$ IM $G_m(s)$ and the uncertain real HDV system $G(s)$ which is influenced by external disturbance as road grade and a noise.

The condition for perfect speed tracking, rejection of external disturbances and minimising the effective noise is achieved if $G_m(s) = G(s)$, and it is factorised as given below:

$$G_m(s) = G_m^-(s)\times G_m^+(s) \tag{3}$$

where $G_m^-(s)$ is minimum phase part and $G_m^+(s)$ is non-minimum phase part of system, and for stable IM only $G_m^-(s)$ is considered. The closed loop system is stable only if $G(s)$ and $C_1(s)$ are stable. The controller $C_1(s)$ is defined as follows:

$$C_1(s) = F(s)/G_m^-(s) \tag{4}$$

where $F(s)$ is a low pass filter that is considered by Yadav & Gaur[12] which is described as $F(s) = (\mu s+1)^{-n}$, where μ is tuning parameter, which maintains the speed tracking performance and robustness of the system, and also minimises the matching error $\tilde{e} = V - \hat{V}$ as shown in Fig. 2, $\tilde{e}$ is high at large disturbance and noise. is an integer and chosen such that $C_1(s)$ becomes proper or semi-proper for physical realisation. In this study $F(s)$ is replaced by filter $F'(s)$ which is as follows[15]:

$$F'(s) = \frac{\lambda s^2 + \varphi s + 1}{(\mu s+1)^n} \tag{5}$$

where λ and φ should satisfy the condition as shown in Eqn. (6) for poles p_1 and p_2 of second order system. N = 3 or 4 depending upon the requirement to make controller proper.

$$\lim\left(1 - T(s)\right) = 0\ ,\ i \tag{6}$$

$$\text{where: } T(s) = C_1(s)\times G_m(s) \tag{7}$$

From Eqns. (3) - (5) and (7), we get

$$T(s) = G_m^+(s)\times\frac{\lambda s^2 + \varphi s + 1}{(\mu s+1)^n} \tag{8}$$

For the determination of modified filter parameter λ and φ, a generalised from of $G_m^+(s)$ is considered whereas Saxena & Hote[15] considered it separately i.e. three different cases, which has both all-pass and delay terms and defined as below:

$$G_m^+(s) = \frac{(1-as)}{(1+as)}\times e^{-T_d s} \tag{9}$$

From Eqns. (6), (8) and (9), we obtained Eqns. (10) and (11) which is given below:

$$\lambda = \left[\frac{(\mu p_1+1)^n}{p_1(p_1-p_2)}\times\frac{(1+ap_1)}{(1-ap_1)}\times e^{T_d * p_1}\right] - \left[\frac{(\mu p_2+1)^n}{p_2(p_1-p_2)}\times\frac{(1+ap_2)}{(1-ap_2)}\times e^{T_d * p_2}\right] + \frac{1}{p_1 p_2} \tag{10}$$

$$\varphi = \left[\frac{p_2(\mu p_1+1)^n}{p_1(p_2-p_1)}\times\frac{(1+ap_1)}{(1-ap_1)}\times e^{T_d * p_1}\right] - \left[\frac{p_1(\mu p_2+1)^n}{p_2(p_2-p_1)}\times\frac{(1+ap_2)}{(1-ap_2)}\times e^{T_d * p_2}\right] - \frac{(p_1+p_2)}{p_1 p_2} \tag{11}$$

where p_1 and p_2 are poles of the second order IM and satisfy the condition $|p_1| > |p_2|$. Equations (10) and (11) are modified according to type of $G_m^+(s)$ For example, if $G_m^+(s)$=1, i.e. neither contains all-pass term nor delay term then put a=0 and Td=0 in Eqns. (10) and (11). From Fig. 2 the controlled input to the HDV system has the form as follows:

$$u = \theta^* = u^* - u^{**} \Rightarrow u' + u'' - C_2(s) \times \tilde{e} \tag{12}$$

where u' and u'' are the outputs of $C_1(s)$ and $C_3(s)$ of S-IMC respectively. The gain $k_p > 0$ is designed such that $\int_0^\infty k_p dt < \infty$, then speed tracking error $e(t)$ will asymptotically converge to zero. $C_2(s)$, is an adaptive control which is defined as $\dot{k} = u^* \times \tilde{e} \times \Gamma$, where Γ is an adaptation gain.

3.1 Design of of S-IMC via IM

For the design of S-IMC, initially it is required to design the original nonlinear HDV system in s domain, and then stable and reduced second order IM is obtained from the linearised system. The complete linear HDV system $G(s)$ is defined as

$$G(s) = G_{ETC}(s) \times G_{vehicle}(s) \tag{13}$$

where $G_{ETC}(s)$ and $G_{vehicle}(s)$ are the transfer functions of ETC and vehicle systems. The two conventional PI controllers namely speed and position controllers are used for $G_{ETC}(s)$ which is seen in Fig. 1. The numerical values of HDV system parameters in SI unit are given in Table 1[12]. The gains of these PI controllers are determined using Ziegler Nichols tuning method. The gains such as k_p = 15.75, k_i = 3150 and k_p = 7, k_i = 105 for speed and position controllers, respectively for system parameters as given in Table 1 are obtained. The closed loop transfer function of ETC system is as follows:

$$G_{ETC}(s) = \frac{\theta(s)}{\theta^*(s)} = \frac{3.56\times10^6 s^2 + 7.66\times10^8 s + 1.1\times10^{10}}{s^5 + 450.8s^4 + 5.1\times10^5 s^3 + 1.05\times10^8 s^2 + 7.66\times10^8 s + 1.1\times10^{10}} \tag{14}$$

For the design of $G_{vehicle}(s)$ the nonlinear vehicle model is linearised at speed 25m/s and throttle position 0.1649 radian or 9.54^0, and the transfer function of linearised HDV is obtained and is given by: $v(s)/\theta(s) = 0.278/(s^2 + 2s + 0.0062)$. The actual linearised complete vehicle system with ETC system and dead time is represented as:

$$G(s) = \frac{V(s)}{\theta^*(s)} = \frac{9.897*10^5 s^2 + 2.127*10^8 s + 3.058*10^9}{s^7 + 452.8s^6 + 5.1*10^5 s^5 + 1.1*10^8 s^4 + 9.8*10^8 s^3 + 1.3*10^{10} s^2 + 2.2*10^{10} s + 6.82*10^7} \times e^{-T_d s} \tag{15}$$

Equation (15) is to be reduced to second order for the design of IM and IC controller to avoid further complications as IMC order also depends on the order of IM. Hankel approximation was performed using the MATLAB command '*hankelmr*'. It gives reduced second order IM, and given below:

$$G_m(s) = \frac{-0.015s + 0.32}{s^2 + 2.27s + 0.007} \times e^{-T_d s} \tag{16}$$

From Eqns. (3), (16) is factorised as

$$G_m^-(s) = \frac{0.015s + 0.32}{s^2 + 2.27s + 0.007} \text{ and } G_m^+(s) = \frac{0.32 - 0.015s}{0.32 + 0.015s} \times e^{-T_d s} \tag{17}$$

The value of ISE of IM using Hankel is 2.12×10^{-4}, which is calculated using $ISE = \sum_{i=0}^{n}\left[g(t) - g_r(t)\right]^2$, where $g(t)$ and $g_r(t)$ are the step responses of original and reduced order systems, respectively.

Taking $\mu = 1.2, T_d = 0.1, n = 3$ and using Eqns. (10) and (11), $\lambda and \varphi$ are determined. The S-IMC with modified filter using Hankel approach is given by Eqn. (18).

$$C_1(s) = \frac{0.832 + 3.7805s + 1}{(1.2*s+1)^3} \times \frac{s^2 + 2.27s + 0.007}{0.015s + 0.32} \tag{18}$$

where $\lambda and \varphi$ are 0.832 and 3.7805, respectively.

Table 1. Numerical values of single phase BLDC motor and vehicle used in simulation[12].

Single Phase BLDC motor for design of ETC system											
R_s	L_s	K_b	N	K_t	B_m	B_{th}	J_m	J_{th}			
0.27	0.6	0.01	10	0.01	$1.3*10^{-6}$	0.004	$1.6*10^{-6}$	0.005			
Ω	mH	Vs/rad	-	Nm/A	Nms/rad	Nms/rad	Kg m^2	Kg m^2			
Vehicle											
m	ρ	F_i	c_r	A_{fr}	c_d	γ	g	B_w	r_{tire}	τ_e	T_d
31000	1.27	2000	0.012	7.5	0.4	7000	9.8	0.052	210	0.5	0.1
kg	Kg/m^3	N	-	m^2	Ns^2/Kg m	N	m/s^2	Nms/rad	mm	s	s

3.2 Simulation Results and Discussion

Simulation results of linearised and nonlinear HDV system with S-IMC and I-IMC structures are presented here. Figures 3 and 4 show the simulation results of linear and nonlinear HDV with S-IMC and I-IMC, respectively to verify the supremacy of I-IMC

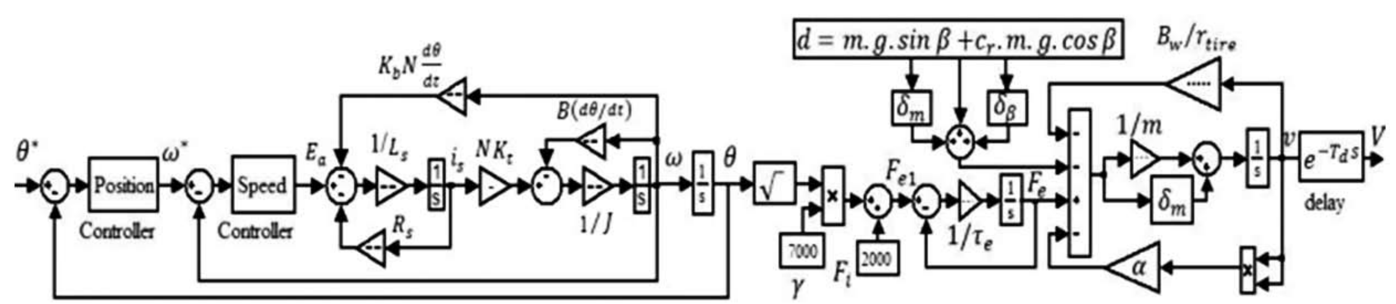


Figure 1. Block diagram of nonlinear HDV with ETC system.

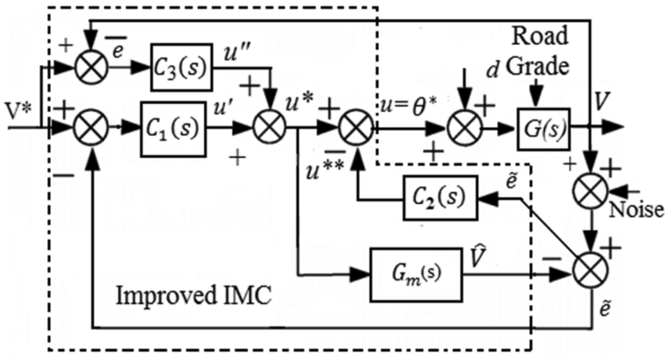


Figure 2. Structure of I-IMC.

over S-IMC. Figure 5 represents the matching error with these controllers for linear and nonlinear systems. For S-IMC only $C_1(s)$ as in Eqn. (18) is considered, and for I-IMC $C_1(s)$, $C_2(s)$, and $C_3(s)$ all are considered as given in Fig. 2. The gain of C_3 is optimised using genetic algorithm with fitness function $J = w_{iae} \times \int_0^\infty |e(t)|\,dt + w_{ise} \times \int_0^\infty e^2(t)dt$, where w_{iae} and w_{ise} are weights to performance specifications such as IAE and ISE respectively. The adaptation gain Γ for C_2 is 0.001 and the gain k_p of C_3 is 0.0004. The nonlinear HDV with S-IMC does not give the desirable performance such as 84.87 per cent OS, 6.2s RT, and 37.6s ST whereas S-IMC for linear HDV system gives desirable performance i.e. nearly 30 per cent OS and 5 s ST for the selected vehicle speed (SVS) of 15 m/s as shown in Fig. 3. The speed response of nonlinear HDV using I-IMC significantly improves the performances in terms of OS, RT and ST by 8 per cent, 39.52 per cent, and 51.86 per cent respectively. The percentage improvement using I-IMC is achieved by reducing the matching error $\tilde{e} = V - \hat{V}$ between original nonlinear HDV system and reduced linear model as shown in Fig. 5.

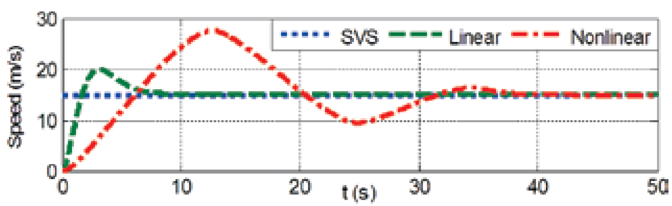


Figure 3. Speed response of HDV system with S-IMC.

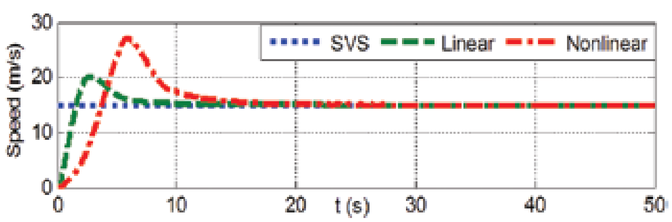


Figure 4. Speed response of HDV system with I-IMC.

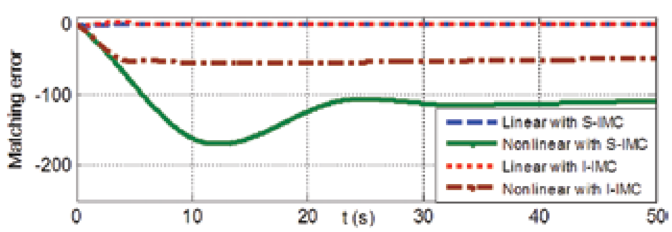


Figure 5. Matching error in speed of HDV system with S-IMC and I-IMC.

From response Figs. 3 to 5, it can be concluded that I-IMC gives improved tracking performance as compared to the S-IMC for nonlinear HDV model.

4. ANN AND ANFIS BASED I-IMC FOR NONLINEAR HDV

ANN and ANFIS based I-IMCs are developed for actual nonlinear HDV system. For I-IMC, ANFIS and ANN are used to design IM and IC as shown in Fig. 6. In this figure, $C_2(s)$, $C_3(s)$ and the filter part of $C_I(S)$ are same as previous section, and only IM and IC are designed using ANN and ANFIS.

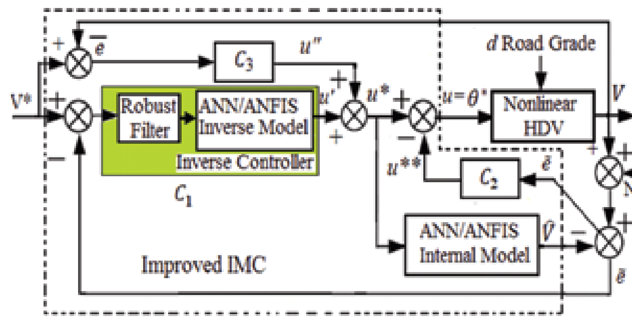


Figure 6. Basic structure of ANN/ANFIS based I-IMC.

4.1 Design of an ANN based IM and IC

The ANN based I-IMC strategy has advantages over mathematical strategies i.e. S-IMC in terms of accurate speed control with reduced road grade disturbances and mass uncertainty. Using neural network toolbox of MATLAB, an ANN model is developed. ANN utilises connectivity between input, hidden and output neurons for calculating the optimal output in absence of mathematical model. The input layer consists of two neurons namely desired throttle position θ^* and its derivative $d\theta^*/dt$. The hidden layer has 20 neurons and output of the output layer is speed V for the IM. For the design of IC, input neurons are V and dv/dt, 20 neurons are used by hidden layer and θ^* is taken as output of the output neuron. The training data sets of 64042 in numbers are acquired from the nonlinear HDV system that is controlled by C_1 of S-IMC for that response is shown in Fig. 3. In training goal mean square error is set to 0.0001 with a maximum 500 epochs, 0.06 learning rate, and the Levenberge Marquardt algorithm is used as a training algorithm.

4.2 Design of an ANFIS-based IM and IC

Inherently, fuzzy logic controller is difficult in developing optimal fuzzy rules and membership functions, so, in many cases, rules are organised intuitively. To overcome this difficulty, a new approach ANFIS has been introduced for developing a globally-applicable control model. It is one of the most successful neuro-fuzzy systems developed by Jang, which applies neural learning rules to identify and tune the parameters and structure of a fuzzy inference system, based only on the available data. Its main characteristics are:

- the implementation is easy
- the learning is fast and accurate
- it has strong generalisation skills
- the fuzzy rules make its understanding easier, and
- it is easy to incorporate both linguistic and numeric knowledge for problem solving.

In ANFIS, the FIS is designed a five-layer adaptive network[4] as shown in Fig. 7 in which a circle indicates a fixed node, and a square indicates an adaptive node. The hybrid learning rule, which combines a back propagation type gradient descent and the least-square estimate, is used to optimize the parameters of FIS on an adaptive network. ANFIS can approximate all nonlinear systems using less training data, a speedy learning process, and superior precision.

To design the ANFIS based IM and IC of the I-IMC for nonlinear HDV; the following basic steps are used:

1) data generation
2) rule extraction and membership functions
3) training and testing, and
4) results.

The structure of the proposed ANFIS is the Sugeno-type, and the general form of a fuzzy rule for a 2-input and 1-output first-order Sugeno fuzzy system is given as follows:

$$If\,(x = A_i)\,and\,\left(y = B_j\right)then\left(f_k = p_k x + q_k y + r_k\right) \qquad (19)$$

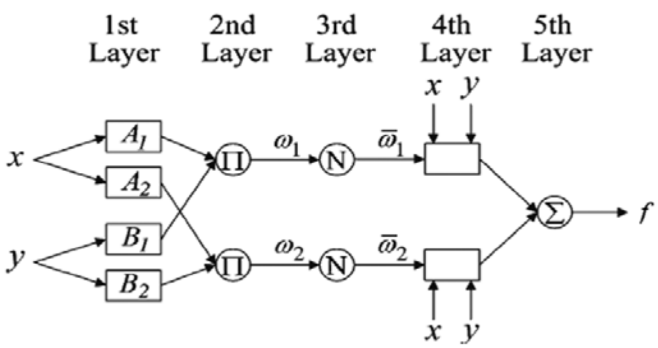
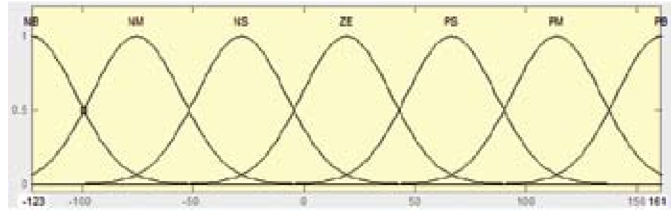


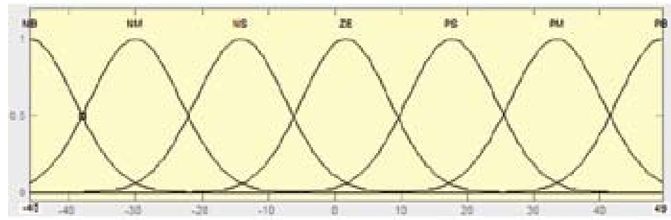
Figure 7. Structure of ANFIS.

For $i = 1,...L; j = 1,...M; k = 1,...N; N = L \times M$, where x and y are the inputs, and L is the size of fuzzy set A and M is the size of fuzzy set B and N is the size of fuzzy rule. f_k is the output within the fuzzy region specified by the fuzzy rule; p_k, q_k and r_k are the designed parameters that are determined during the training process; and i and j are the number of membership functions of each inputs.

In ANFIS based IM and IC, developed inputs and outputs are same as in ANN. The membership functions for input variables θ^* and $\dot{\theta}^*$ for IM are shown in Fig. 8(a) and 8(b), respectively, and the membership functions for input variables V and $\dot{V}$ for IC are presented in Figs. 9(a) and 9(b), respectively. The ANFIS based IM and IC is designed by using the ANFIS editor toolbox in MATLAB. Gaussian and linear type of membership functions for input and output variables respectively are selected for IM and IC. The number of epochs is selected as 25. A hybrid learning algorithm, i.e., a mixed least-square and back-propagation scheme is used for training the ANFIS. The detailed parameters of the proposed ANFIS

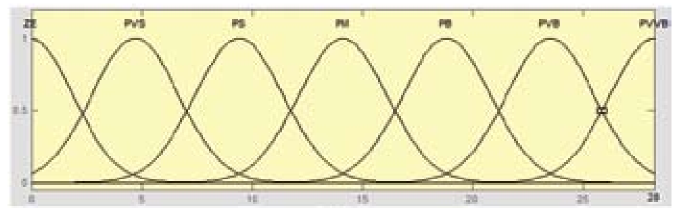


(a)

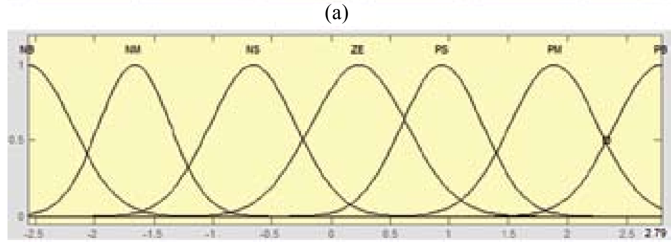


(b)

Figure 8. Membership functions of input variables for IM (a) θ^* and (b) $\dot{\theta}^*$



(a)



(b)

Figure 9 Membership functions of input variables for IC (a) V and (b) $\dot{V}$.

are: number of nodes = 131, number of linear parameters = 147, number of nonlinear parameters = 28, total number of parameters = 175 and number of training data pairs = 64042. The numbers of Sugeno fuzzy rules are 49 for both IM and IC. The training errors as 0.617471 for IM and 0.019821 for IC are observed.

The linguistic variables of the inputs are negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM), positive big (PB), positive very small (PVS), positive very big (PVB) and positive very very big (PVVB). The Sugeno fuzzy rules for IM are observed as: if θ^* is *negative big* and $\dot{\theta}^*$ is also *negative big* then vehicle speed $V = -173.3\theta^* + 92.27\dot{\theta}^* - 1.817$. Similarly, the Sugeno fuzzy rules for IC are observed as: if V is *zero* and $\dot{V}$ is *negative big* then desired throttle position $\theta^* = 12.2V - 2.77\dot{V} + 0.26$.

5. SIMULATION RESULTS AND DISCUSSION

Simulation results of nonlinear HDV with I-IMC, designed using ANN and ANFIS are presented here. The closed loop nonlinear model of HDV is run and response is studied for a SVS in acceleration, deceleration and cruise control modes. Figure 10 shows the speed response of nonlinear HDV with ANN and ANFIS based I-IMC. The road grade $\beta = \pi/20$ as disturbance and a random noise signal is considered.

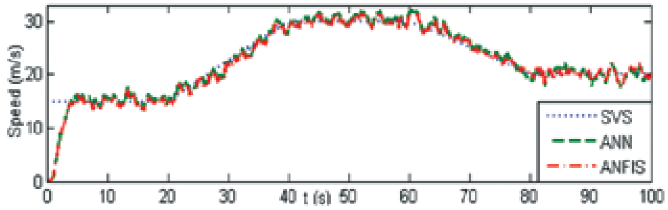


Figure 10. Speed response of ANN and ANFIS based I-IMC.

The ANFIS based I-IMC gives the value of IAE and ISE as 101.1 and 462.8, respectively which are less as compared to values obtained from ANN based I-IMC as 107.7 and 475.3. Hence ANFIS based I-IMC is better for nonlinear HDV under non-deterministic road grade disturbance and noise. Figure 11 shows the comparison in speed response for the ANFIS based I-IMC with and without adaptive control i.e. C_2 as shown in Fig. 6 in servo and regulatory modes of nonlinear HDV system.

The speed response without adaptive control gives 1.85 per cent servo OS and 6.1 s servo ST and the speed response with adaptive control gives servo OS of 4.16 per cent and comparatively small servo ST of 5.6 s. Hence I-IMC with adaptive control gives desirable high servo OS and improves the servo ST by 8.9 per cent. To test the regulatory behavior, i.e. road grade disturbance rejection and effect of mass uncertainty on speed performance of HDV using ANFIS based I-IMC with and without adaptive control, $\delta_\beta = pi/4$ radian road slope and $\delta_m = 20000$ kg mass at t = 10 s for 1 s are applied simultaneously. From the enlarged view of Fig. 11, since δ_m and δ_β are considered simultaneously, the large dip in speed i.e. 5.52 m/s and 5.9 m/s with and without adaptive control respectively is seen. The speed recovery time i.e. regulatory ST is 2.5 s and 3 s using with and without adaptive control of I-IMC. When adaptive control is used, regulatory dip in speed is improved by 6.5 per cent and regulatory ST is about 17 per cent less as compared to without adaptive control. From Fig. 11, it is clearly seen that the servo and regulatory performance specifications such as servo OS and ST are improved using I-IMC with adaptive control over I-IMC without adaptive control. The more OS and ST in the HDV system have some implication with more fuel consumption.

Figures 12(a) to 12(d) show the speed response of uncertain vehicle under non-deterministic road grade varying within $\pm pi/20$ radian and vehicle under 50 per cent uncertainty

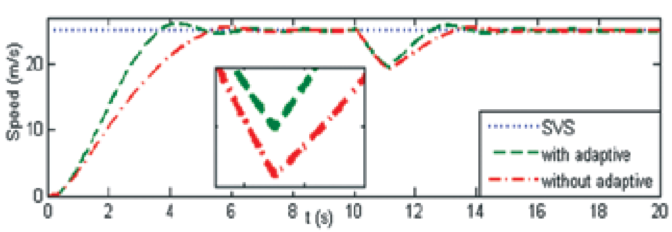
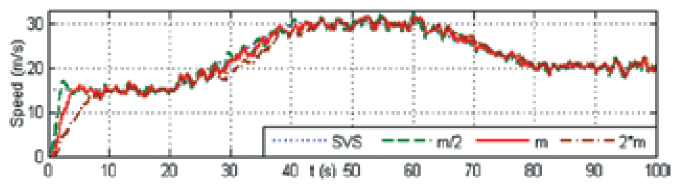


Figure 11. Response of nonlinear HDV with ANFIS based I-IMC.

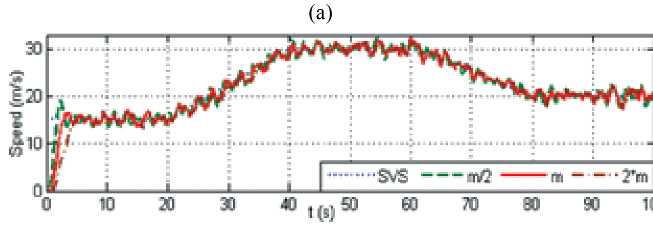
in mass i.e. vehicle with partially loading and overloading conditions without and with adaptive control of ANN and ANFIS based I-IMC, respectiviely. In Figs. 12(a) to 12(d); the SVS is represented by dotted line which are in acceleration, deceleration and constant speed modes. These results are used to verify the robustness of the uncertain and nonlinear HDV system with and without adaptive control of ANN and ANFIS based I-IMC.

The IAE $(=\int_0^T |e(t)| dt)$ and ISE $(=\int_0^T e^2(t) dt)$ are determined using response plots as given in Figs. 12 (a) to 12(d) with $T = 100s$ and $e = V^* - V$. The values of IAE and ISE for nominal and 50% uncertainty in mass are given in Table 2. The main goal of designing of I-IMC with adaptive control is its ability to work well under uncertain environment. The IAE and ISE are used for robustness performance of ANN and ANFIS based I-IMC with and without adaptive control for the nonlinear and uncertain HDV. It is clearly seen from Figs. 12(a) to 12(d) that the HDV speed tracks the SVS. It also shows the robust performance because it gives nearly the same response for a large range of uncertainties.

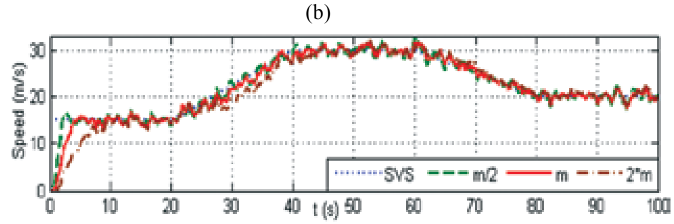
Form Table 2, the ANFIS based I-IMC with adaptive control gives a smaller value of IAE and ISE for nominal and uncertain system. Hence the ANFIS based I-IMC with adaptive



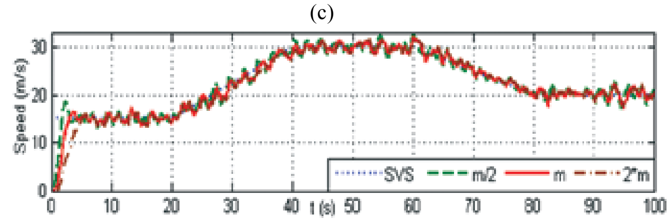
(a)



(b)



(c)



(d)

Figure 12. Response of speed under non-deterministic road grade, noise and uncertainty in mass ; (a) ANN based I-IMC without adaptive control, (b) ANN based I-IMC with adaptive control, (c) ANFIS based I-IMC without adaptive control, (d) ANFIS based I-IMC with adaptive control.

Table 2. Performance index for nominal and uncertain HDV system

I-IMC		Nominal mass (*m*)		±50% uncertainty in mass			
				Lower (*m*/2)		Upper (2 x *m*)	
		IAE	ISE	IAE	ISE	IAE	ISE
ANN based	without adaptive	102.2	467.2	90.3	323.8	161.6	864
	with adaptive	94.9	407.5	96.36	327.4	110.7	591.9
ANFIS based	without adaptive	101.1	463.2	89.76	322	160.9	859.1
	with adaptive	94.1	403.9	93.95	318.5	111.3	585.4

control gives more robustness to the system i.e. disturbance and noise rejection as compared to the other designed controllers. Apart from robustness a steady state error is observed when vehicle runs in accelerating mode as seen in Figs. 12(a) and 12(c) at 30s - 40s. The presence of steady state error is due to the uncertainties, the effect of which cannot be eliminated using I-IMC without adaptive control. Therefore, vehicle consumes more fuel when the system has oscillations without reach to the desired speed hence this way ANFIS based I-IMC with fuzzy adaptive control removes steady state error, and improves overall performance by less energy consumption.

6. CONCLUSION

In this study, the ANN and ANFIS based I-IMC with an adaptive control is designed and its performance is compared with ANN and ANFIS based I-IMC without adaptive control for the nonlinear and uncertain HDV system. A detailed comparative analysis of ANN and ANFIS based I-IMC with and without adaptive control for speed control of nonlinear HDV vividly shows that the ANFIS based I-IMC with adaptive control gives better transient, steady state and robust performance as compared to ANN and ANFIS based I-IMC without adaptive control. The least values of OS, ST, IAE and ISE are achieved using the ANFIS based I-IMC with adaptive control. Fast response with negligible steady state error in desired speed, requires minimal change in the current and torque for the desired throttle position which ensures better fuel economy and efficiency of HDV. The proposed ANFIS based I-IMC with adaptive control for nonlinear HDV is more suitable for variable speed under uncertain environment and long drives. This usually results in better fuel economy with reduced pollution. This technique may also be used for other complex and nonlinear systems.

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In the current study, she provided initial idea for ANN based improved IMC, writing of introduction and improving the overall manuscript.