Design of Neural Network Based Fuzzy Inference System for Speed Control of Heavy Duty Vehicles with Electronic Throttle Control System

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Abstract: - The objective of this study is to apply various control approaches to control the speed of a heavy duty vehicle (HDV) using an electronic throttle control system. However, the dc servo motor is used for controlling the angular position of electronic throotle valve. Moreover, two control techniquies are used to control prescribed two different random inputs of the heavy duty vehicle speed. These control structures are named as standard PID controller, Adaptive neural network based fuzzy inference (ANFIS) controller. The results of the simulation for two approaches showed that the proposed ANFIS controller has better performance rather than other standard control systems under varying speed conditions. Finally, the proposed control structure will be implemented for speed control of dc servo motor.

Key-Words: - Neural network, anfis controller, heavy duty vehicle, dc servo motor, electronic throttle valve

1 Introduction

Some studies, a few of which are presented below, have been published in the area of the vehicle speed control; several of these researches are given below.

A speed control problem of heavy duty vehicle trough angular position of throttle valve has been researched by Yadav et al. [1]. Modified internal model control with fuzzy supervisor is used to control the speed of heavy duty vehicle. An intelligent evolutionary least learning machine tool investigated to forecast the vehicle speed sequence [2]. Mozaffari et al. were used the driving data collected on the San Francisco urban roads by a private Honda insight vehicle. As results, in their proposed method by Mozaffari et al. was a powerful tool for predicting the vehicle speeds. Tagne et al. [3] have been investigated to lateral displacement control of autonomous vehicle with respect to a given reference path. In the proposed control law was validated a driving simulation engine according to several real driving scenarios. Simulations were also performed using experimental data acquired by a Peugeot 308.

Alam et al. [4] have been investigated the problem of finding a safety criteria between neigh boring heavy duty vehicle platooning and real life experimental results were presented in an attempt to validate the theoretical results in practice. Adaptive intelligent cruise control of heavy duty vehicle was investigated by Alam et al. [5]. In their study, a linear quadratic control framework used for the controller design. The proposed controller performance was evaluated through numerical and experimental studies. The experimental and simulation results showed that heavy duty vehicle platooning could be conducted at close spacing with standardized sensors and control units. Rödönyi et al. [6] researched novel numerical methods for analyzing robust peak-to-peak performance of heterogeneous platoons. The proposed method was indicated on three platoon controllers. A new speed controller for internal combustion engine was designed by Tibola et al. [7]. The proposed controller was used two approaches for the internal combustion engine speed control. Also, the stability analysis for the developed controller was presented.

A lateral control law problem for autonomous vehicles presented [8] and developed a strategy to determine the given speed of autonomous vehicles. Fuzzy logic controller in used to control the steering of autonomous vehicle. From their work, simulation and experimental results have been presented from different reference paths. Marino et al. [9] has been designed a fault-tolerant controller for the cruise control of electric vehicle. CarSim simulations demonstrated the effectiveness of the control approach. A road grade estimation algorithm for heavy duty vehicles was developed by Sahlholm et al. [10]. Measurement data from three test vehicles and six experiments have been used to evaluate the quality of the proposed road grade estimate compared to a known reference. Onivea et al. [11] developed a cruise control system for vehicle low speeds. A method was proposed to allow the on-line evolution of a zero-order fuzzy controller to adapt its behaviour to uncertain road or vehicle dynamics. Extensive experimentation in both simulated and real vehicles showed the method to be both fast and precise, even when compared with a human driver. An Adaptive Neuro-Fuzzy Inference System based on control systems have been designed to reduce the energy consumption of vehicle and to improve the efficiency of vehicle [12]. The vehicle was tested using the adaptive cruise control look-ahead energy management system, the results compared with the vehicle running the same test but without the adaptive cruise control look-ahead energy management system. The evaluation outcome show that the vehicle speeds was efficiently controlled through the look-ahead methodology based upon the driving cycle, and that the average fuel consumption was reduced by 3%.

A robust shift control strategy of a heavy duty vehicle power train system for enhancing shift quality has been researched by Meng et al [13]. Three different robust adaptive control laws were proposed for reducing the output torque during the gear shifts. The developed control structure was tested on a heavy-duty vehicle equipped with automatic transmission. Results from the experimental works indicate that the proposed control strategy could effectively reduce shift shock and smooth the gear shift. A hybrid predictive controller has been designed for automated low speed driving [14]. The developed controller was applied in a gas propelled vehicle to experimentally validate the adopted solution. A Citroen C3 vehicle has been modified to automatically act over its throttle and brake pedals. Numerical and experimental investigation on stochastic dynamic load of a heavy duty vehicle has been presented by Lu et al. [15]. The dynamic model of heavy duty vehicle was validated by testing the data, including vertical acceleration of driver seat, front wheel, intermediate wheel and rear wheel axle head. Using the reliable model, the effects of vehicle speed, load, road surface roughness and tire stiffness on tire dynamic load and dynamic load coefficient were discussed. An advanced error troubleshooting in intelligent manufacturing systems has been researched by Csokmai et al. [16].

2 Mathematical model of electronic throttle control system

In this section, a HDV engine system with electronic throttle control system is represented in Fig.1. [1,17]. The electronic throttle control system used a single phase brushless dc servo motor to controls the angular position of throttle. The electronic throttle control system for HDV has many advantages such as it has large range of speed and it increases the overall efficiency. In Fig.1, the brushless dc servo motor is controlled by the applied motor voltage E_a;

$$L_a \frac{di_a}{dt} = -R_a i_a - E_{m+} E_a \qquad (1)$$

where is the i_a; is armature current. The back electro motive force E_m due to the motor rotation is $K_m(\frac{d\theta_m}{dt})$. The K_m constant is function of rotor magnetic flux ψ and Θ_m is motor shaft angular position. R_a is stator resistance and L_a is inductance. The throttle and motor dynamics is given below:

$$J_m \frac{d^2\theta_m}{dt^2} = -B_m \left(\frac{d\theta_m}{dt}\right) - T_{l+} T_m \qquad (2)$$

$$J_g \frac{d^2\theta}{dt^2} = -B_g \left(\frac{d\theta}{dt}\right) - T_{a+} T_g \qquad (3)$$

where N is gear ratio, T_a is torque due to airflow, T_g is the torque transmitted from gear to throttle, T_l is the load torque and Θ is the throttle angular position. Where;

$$N = \frac{\theta_m}{\theta} = \frac{T_g}{T_l} \qquad (4)$$

$$T_m = K_t\, i_a \qquad (5)$$

where K_t is the motor torque constant. $J = N^2 J_m + J_g$ and $B = N^2 B_m + B_g$; hence Eq.(1)-(3) can be written as;

$$L_a \frac{di_a}{dt} = -R_a i_a - K_m N \frac{d\theta}{dt} + E_a \qquad (6)$$

$$J \frac{d^2\theta}{dt^2} = -B\left(\frac{d\theta}{dt}\right) - T_a + N T_m \qquad (7)$$

Neglecting T_a as it is very small as compared to other torques. For the representation of the system, taking the Laplace transform of Eqs.(6), (7);

$$L_a s I_a(s) = -R_a I_a(s) - K_m N s\theta(s) + E_a(s) \qquad (8)$$

$$J s^2 \theta(s) = -B s\theta_m(s) + N K_t\, I_a(s) \qquad (9)$$

$$w(s) = s\theta(s) \qquad (10)$$

Then

$$\frac{w(s)}{E_a(s)} = \frac{{}^{NK_t}/_{L_a J}}{S^2 + \frac{R_a J + B L_a}{L_a J} S + \frac{R_a B + N^2 K_t K_m}{L_a J}} \qquad (11)$$

Eq.(11) presents the transfer function for angular speed w of throttle valve to apply on brushless dc servo motor.

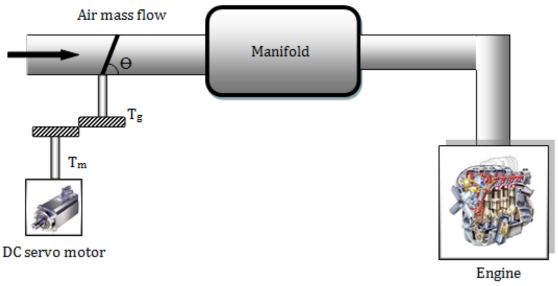

Fig.1. Schematic representation of electronic throttle valve system

3 Description of Controllers

In this study, two different control techniques are used for controlling the speed of the heavy duty vehicle. These control structures are as PID Controller and ANFIS controller. The gain parameters of PID controller was initially tuned using the Ziegler-Nichols method, and the PID parameters are found as K_p=4, K_i= 0.3667 and K_d= 0.1467. ANFIS integrates neural network with Fuzzy Interface System (FIS). The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output. Among many FIS models, the Takagi Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency and adaptive techniques.

For simplicity, it is used two inputs as x_1 and x_2 and one output as z to explain the structure of the fuzzy inference system. If the rule base contains two fuzzy if-then rules such as:

Rule 1: *If* x_1 *is* A_1 *and* x_2 *is* B_1

then $z_1 = p_1 x_1 + q_1 x_2 + r_1$. (12)

Rule 2: *If* x_1 *is* A_2 *and* x_2 *is* B_2

then $z_2 = p_2 x_1 + q_2 x_2 + r_2$. (13)

where A_i and B_i are fuzzy membership sets, q_i is the number of membership functions; r_i is the design parameter that is determined during the train process. The ANFIS consist of six layers:

Layer 1: This is the input layer, which defines dc servo motor speed and desired dc servo motor speed.

Layer 2: Every node in this layer is an adaptive node with a particular fuzzy membership function. For two inputs, the node outputs are:

$$L_i^1 = \mu A_i(x),\ i=1,2 \tag{14}$$

$$L_i^1 = \mu B_i(x),\ i=1,2 \tag{15}$$

where μA_i and μB_i are membership functions. Generally; $\mu A(x)$ and $\mu B(x)$ are selected to be bell shaped with a maximum equal to and minimum equal to 0 such as the generalize 1 bell function;

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right] b_i} \tag{16}$$

where $\{a_i, b_i, c_i\}$ is the parameter set.

Layer 3: Every node in the third layer is a circle node labelled “Π”, which multiples the all incoming signals and send the product out.

$$w_i = \mu A_i(x)\ \mu B_i(x)(i=1,2..) \tag{17}$$

Each of the second layer’s node output represents the firing strength of the associated rule.

Layer 4: Every node in the fourth layer is a circle node labelled “$\mathcal{N}$”. The output of the i^{th} node is the ratio of the firing strength of the i^{th} rule of the sum firing strength of all the rules.

$$\bar{w}_i = \frac{w_i}{w_{1+w_2}}(i=1,2..) \tag{18}$$

This output gives a normalized firing strength.

Layer 5: In this layer, every node i has the following function:

$$L_i^5 = \bar{w}_i f_i = \bar{w}_i(p_i x_1 + q_i x_2 + r_i) \tag{19}$$

with $\bar{w}_i$ being the normalized firing strength form from Layer 3.

Layer 6: The single node in the sixth layer is a circle node labelled “Σ”. It computes overall outputs as summation of all incoming signal.

$$L_i^6 = \sum \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{20}$$

The ANFIS distinguishes itself from normal fuzzy logic systems by the adaptive parameters, i.e., both the premise and consequent parameters are adjustable. The most remarkable feature of the

ANFIS is its hybrid learning algorithm that combines the back propagation gradient descent and least squares methods to create a fuzzy interference system.

4 Simulation Results

This section describes the simulation results of HDV for two different random inputs signal using the conventional PID controller, the ANFIS controller. The PID controller results and the values of error obtained two different input signals have been presented in Fig. 2 (a-b). As seen in the figure, the PID controller exhibits oscillatory response and it is unable to adapt itself to input1 signal. Fig. 2 (c-d) is presented the simulation results and the values of error obtained from the second input signal of the PID controller. In figure 2, the dc servo motor speed is 7 m/s for the first 3 s, then dc servo motor runs at a constant speed of 10 m/s for 3-6 s, for 6-9 s the speed 9.2 m/s and finally from dc servo motor runs at a constant speed of 8.36 m/s. As seen in the figure 2, the PID controller is not able to track the set speed correctly.

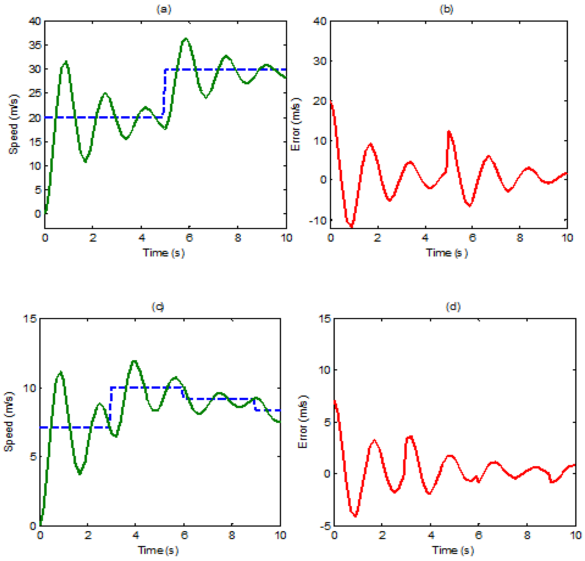

Fig.2. Speed response of dc servo motor for input1 signal a) Random1 input signal b) Error of the PID Controller c) Random2 input signal d) Error of the PID Controller

The second structure used in the control of dc servo motor speed is the ANFIS controller (Fig.3). The analysis of the figure has indicated that the ANFIS structure has yielded far more favourable results compared to other PID controllers. Also it has been observed that there have been considerable reductions in steady state errors.

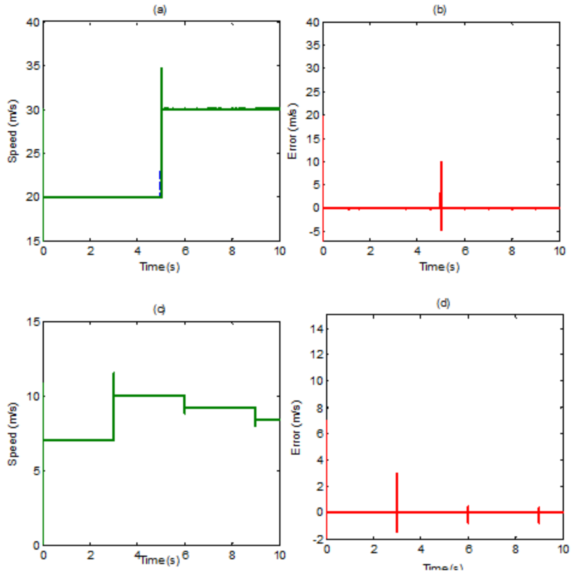

Fig.3. Speed response of dc servo motor for input1 signal a) Random1 input signal b) Error of the ANFIS Controller c) Random2 input signal d) Error of the ANFIS Controller

5 Conclusions and Discussion

In this paper, the ANFIS controller designed and it is performance is compared with the other well known PID controller for speed of heavy duty vehicle under varying set speed conditions. Performance under sudden speed variations is not satisfactory for the PID controller. The reason for preferring the neural network techniques for controlling the system is its ability to learn, their fast performance due to their parallel structure, their capability to generalise, their simple structure and design procedure and fault tolerance. Within used neural network based controller has given the best result. The efficiency of proposed control structure relies on fuzzy membership, function selection, fuzzy rules, neuron numbers of hidden layer, learning algorithm selection and iteration number. From the evaluation of obtained simulation results, the proposed ANFIS control system is suitable for the control of such systems.

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