Engine Idle Speed Control Using ANFIS Controller

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Abstract: - The presented control scheme utilizes Adaptive Neuro Fuzzy Inference System (ANFIS) controller to track a reference engine rotational speed and disturbance rejection during engine idling. To evaluate the performance of the controller a model of the engine is simulated and simulation results presented.
ANFIS implements a first order Sugeno-style fuzzy system. It is a method for tuning an existing rule with a learning algorithm based on a collection of training data.

Key-Words:-Idle speed, Subtractive clustering, ANFIS controller

1 Introduction

The engine idle speed control (ISC) problem represents a typical challenge to automotive control researchers and practitioners. The ISC performance has significant impact on many important vehicle design attributes such as fuel economy, emissions, combustion stability, and NVH (noise, vibration, and harshness) quality. It is truly a multi objective control problem involving signal tracking, disturbance rejection, The engine idle speed refers to engine operation under closed throttle conditions on average, vehicles consume about 30 per cent of their fuel in city driving during idling [1].

It is therefore important to try to optimize vehicle and It comes as no surprise that this control problem has been studied in many different frameworks. The ISC problem is formulated as a tracking and disturbance rejection problem in its simplest form. The tracking requirement is to ensure that the engine speed follows the set point in the presence of load torque disturbances. The reference engine speed is scheduled at the minimum value that yields acceptable combustion quality, accessory performance, and NVH characteristics in order to achieve the best fuel economy. At lower speeds, however, the engine is more susceptible to disturbances which may lead to engine stall or induce NVH problems. A typical ISC system actively controls both the inlet air and spark timing to maintain a desired engine speed and reject disturbances. The idle air bypass valve (ABV) an electronically controlled solenoid valve that acts in parallel to the main throttle as Fig.2, is the primary actuator which controls the amount of air inducted into the cylinders when the main throttle is closed. It has a wide range of control authority the effect of changing the ABV actuator setting on the engine torque is not immediate due to the intake manifold dynamics and intake-to-power stroke delay.

2 ANFIS STRUCTURE

ANFIS has proven to be excellent function approximation tool and implements a first order Sugeno-style fuzzy system [2, 3].

ANFIS structure is shown in Fig.1.Layer 1 consists of membership functions described by generalized bell function as:

$$\mu(X) = 1 + \left(\left({(X-c)}/{a} \right)^{2b} \right)^{-1} \qquad (1)$$

Where *a*, *b* and *c* are adaptable parameters. Layer 2 implemented the fuzzy AND operator while layer 3 acts to scale the firing strengths. The output of the layer 4 is comprised of a linear combination of the inputs multiplied by the normalized firing strength *w*.

$$Y = w(pX + r) \qquad (2)$$

Where *p* and *r* are adaptable parameters. Layer 5 is simple summation of the outputs of layer 4.

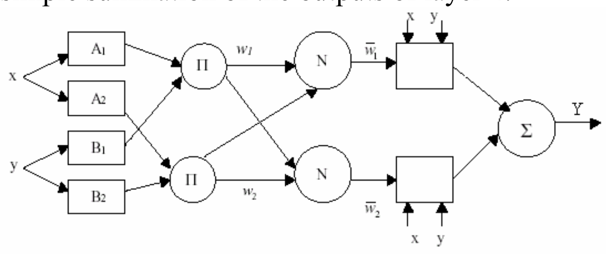

Fig.1. ANFIS structure

The adjustment of modifiable parameters is a two step process. First, information is propagated forward in the network until layer 4, where the parameters are identified by a least squares estimator. Then the parameters in layer 2 are modified using gradient descent.

The indirect method for adjusting the tunable parameters in the ANFIS network is used with the training data. The optimal fuzzy system uses one rule for one input-output pair, thus If number of input-output pairs is large, various clustering can be used to group the input-output pairs so that a group can be represented by one rule.

Clustering means partitioning of a collection of data into disjoint subset or clusters, with the data in a cluster having some properties them distinguish from the data in other clusters.

2.1 Subtractive Clustering

Subtractive Clustering is based on a measure of the density of data points in the feature space [4, 7].

The idea is to find regions in the feature space with high densities of data points. The point with the highest number of neighbors is selected as centre for a cluster. The data points within a prespecified, fuzzy radius are then removed (subtracted), and the algorithm looks for a new point with the highest number of neighbors. This continues until all data points are examined. Consider a collection of K data points specified by m-dimensional vectors u_k, k=1, 2, …, K. Without loss of generality, the data points are assumed normalized. Since each data point is a candidate for a cluster centre, a density measure at data point u_k is defined as

$$D_k = \sum_{j=1}^{k} \exp\left(-\frac{\left\|u_k - u_j\right\|}{\left(\frac{r_a}{2}\right)^2}\right) \qquad (3)$$

Where r_a is a positive constant. Hence, a data point will have a high density value if it has many neighboring data points. Only the fuzzy neighborhood within the radius r_a contributes to the density measure.

After calculating the density measure for each data point, the point with the highest density is selected as the first cluster centre. Let u_{C1} be the point selected and D_{C1} its density measure. Next, the density measure for each data point u_k is revised by the formula

$$D_k^1 = D_k - D_{C1} \exp\left(-\frac{\left\|u_k - u_{C1}\right\|}{\left(\frac{r_b}{2}\right)^2}\right) \qquad (4)$$

Where r_b is a positive constant. Therefore, the data points near the first cluster center u_{C1} will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster centre. The constant r_b defines a neighborhood to be reduced in density measure. It is normally larger than r_a to prevent closely spaced cluster centers; typically $r_b = 1.5 * r_a$.

After the density measure for each point is revised, the next cluster u_{C2} is selected and all the density measures are revised again. The process is repeated until a sufficient number of cluster centers are generated.

3 The Idle Speed Model

At idle the engine throttle is closed and the airflow into the engine is typically controlled by the opening of a simple electromechanical valve sitting on top of the throttle plate and actuated by the engine management system. This provides the principal means to control the engine speed. It is commonly supplemented by control of the spark advance to modulate engine torque production. This input acts quickly but is limited in authority. The idling engine can therefore be modeled as a two inputs, namely the duty cycle of the idle speed air valve DS and the spark advance angle θ If the fuelling strategy is ideal [5, 6].

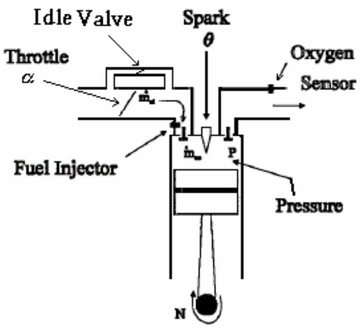

Fig.2. Throttle and air bypass valve in SI engine

The engine has three basic subsystems, describing respectively the dynamics of the fuel vapor and vapor film, the crankshaft speed and the filling-emptying of the manifold,
The corresponding equations are the following

$$\dot{p} = \frac{RT}{V}(\dot{m}_{at}(\alpha) - \dot{m}_{ap}) = -\frac{p}{\tau_m(n,p)} + \frac{RT}{V}\dot{m}_{at}(\alpha) \quad (6)$$

Expressing respectively the fuel film mass flow, the speed and the manifold pressure derivatives. Where $\dot{m}_{at}$ is air mass flow rate past idle speed valve and $\dot{m}_f$ is fuel mass flow rate into intake port.
Engine has three main inputs: the throttle angle α , the injected fuel flow film $\dot{m}_{fi}$ and the ignition timing angle θ. There are three state variables: the fuel film mass flow $\dot{m}_{ff}$, the crankshaft speed n and the intake manifold pressure p. The engine load power Pb is viewed as a disturbance. That is, it is an input which disturbs the engine away from its nominal operating condition. Therefore

$$\dot{m}_f = \frac{\dot{m}_{at} + \dot{m}_{is}}{L_{th}} \quad (7)$$

Where L_{th} =14.67 is stoichiometric air/fuel mass ratio for commercial gasoline
and the idle speed mass flow is $\dot{m}_{is}$ is defined by the Input-Output air by-pass valve characteristic as equation (8).

$$\dot{m}_{is} = -0.0317\,DS^4 + 0.0355\,DS^3 + 0.0082\,DS^2 + 0.0002\,DS \quad (8)$$

$$\dot{n} = \frac{H_u}{nI}\eta_i(n,p,\theta)\frac{\dot{m}_{at} + \dot{m}_{is}(DS)(t-\tau)}{L_{th}} - \frac{p_f(n) + p_p(n,p) + p_b}{nI} \quad (9)$$

$$\dot{p} = -\frac{p}{\tau_m(n,p)} + \frac{RT}{V}(\dot{m}_{at}(\alpha_{min}) + \dot{m}_{is}(DS)) \quad (10)$$

Note that the indicated efficiency $\eta_i(n,p,\theta)$ is a significant component of the system, being the only functional element of the model affected by the spark timing. It is expressed by the following three contributions:

$$\eta_i(n,p,\theta) = \eta_n(n)\,\eta_p(p)\,\eta_\theta(n,p,\theta) \quad (11)$$

Where, in particular

$$\eta_\theta(n,p,\theta) = 0.7117 + .01562(\theta - \theta_{mbt}) + 0.0001(\theta - \theta_{mbt})^2 + .000013(\theta - \theta_{mbt})^3 \quad (12)$$

Where θ_{mbt} is maximum brake torque.

4 Design process

Firstly, sliding controller in order to idle speed control with use of reference [8], is designed. Inputs of sliding controller are idle speed and manifold pressure, and outputs are duty cycle and Spark advance signal. In the next step 575 input-output pairs of the sliding controller are got and ANFIS controller is designed with above data. Then training data with use of subtractive clustering method is classified.
Clustering parameters are selected as:
I. The range of influence (The cluster radius indicates the range of influence of a cluster) of 0.5 has been specified.
II. The squash Factor is set to 1.5, indicating that we only want to find clusters that are far from each.
III. The accept Ratio and reject Ratio are set to 0.8 and 0.7, respectively.
Therefore 2 cluster centers with coordinates:

$$C_1 \begin{vmatrix} 967 \\ 0.66 \\ 0.5 \end{vmatrix}, \quad C_2 \begin{vmatrix} 1002 \\ 0.44 \\ 0.7 \end{vmatrix} \quad (13)$$

are obtained.
Each of the cluster centers represents a rule. To generate rules, the cluster centers are used as the centers for the premise sets in a singleton type of rule base.
ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation. After 30 iterations, error value is 0.0425.
Therefore fuzzy inference system with rules 1 and 2 and membership functions shown in Figs. 3 and 4 obtained.

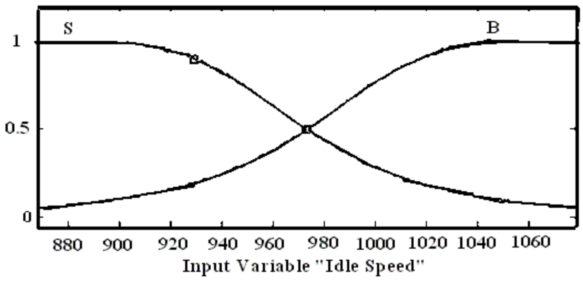

Fig.3. Input membership functions for idle speed

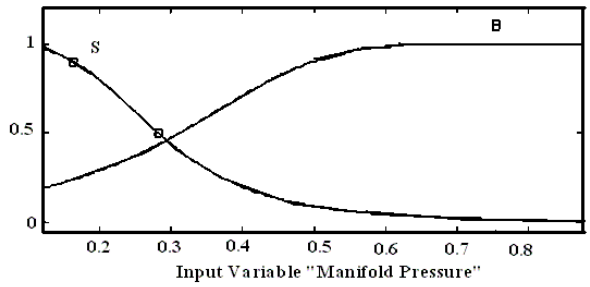

Fig.4. Input membership functions for manifold pressure

Rule base 1. Created rules for the idle speed controller.

If idle speed is S and manifold pressure is S then duty cycle is $0.01683X_1 + 23.7X_2 - 17.52$

If idle speed is S and manifold pressure is B then duty cycle is

$0.0054X_1 + 2.054X_2 - 6$

If idle speed is B and manifold pressure is S then duty cycle is

$0.174X_1 + 2.054X_2 - 20.07$

If idle speed is B and manifold pressure is B then duty cycle is

$0.0032X_1 + 2X_2 - 4.23$

The antecedent part of the rules refers to the input membership functions shown in Fig.3 and Fig.4.

Rule base 2. Created rules for the spark advance controller.

If idle speed is S and manifold pressure is S then spark advance is

$-0.2X_1 - 0.00042X_2 + 220$

If idle speed is S and manifold pressure is B then spark advance is

$-0.198X_1 - 0.015X_2 + 219.5$

If idle speed is B and manifold pressure is S then spark advance is

$-0.2X_1 - 0.00442X_2 + 220$

If idle speed is B and manifold pressure is B then spark advance is

$-0.198X_1 + 0.015X_2 + 219.5$

The antecedent part of the rules refers to the input membership functions shown in Fig.3 and Fig.4.

4-1 Results

At first, load shown in Fig.5, to system is applied.

As shown maximum value of load is approximately 7 kW and at 25 second, a constant load with value of 5kW is applied.

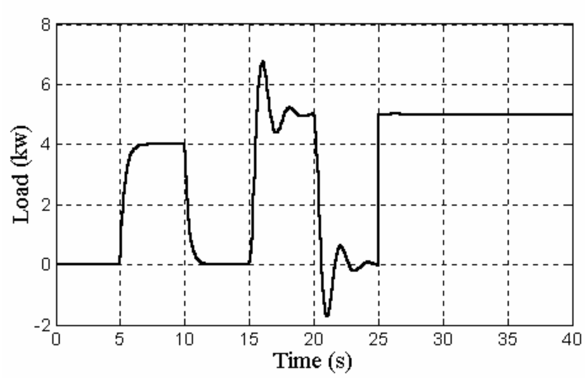

Fig.5. Applied load to SI motor

This load results in high oscillations in the idle speed and speed decreases to approximately 500 rpm according to Fig.6.

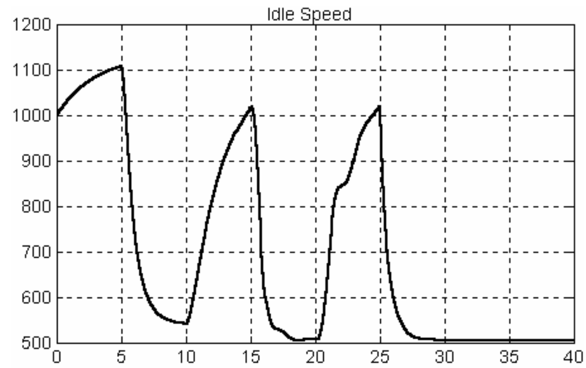

Fig.6. Idle speed without controller

Fig.6. depicts idle speed without use of controller.

By applying designed ANFIS controller to the system Figs.7, 8 and 9, obtained.

According to Fig.7, The controllers nicely regulate the speed to its nominal value (1000 r.p.m) and maximum flare and dip of speed are 90 and 50 r.p.m, respectively. Furthermore effect of disturbance on the idle speed clearly is reduced.

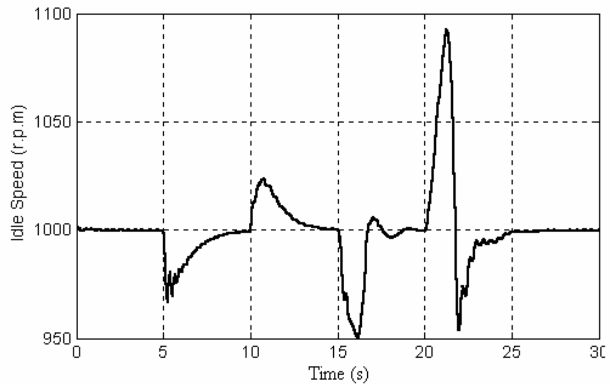

Fig.7. Idle speed variations after applying ANFIS controller

Spark advance control signal shown in the Fig.8, mainly acts to counteract the dips and flares.

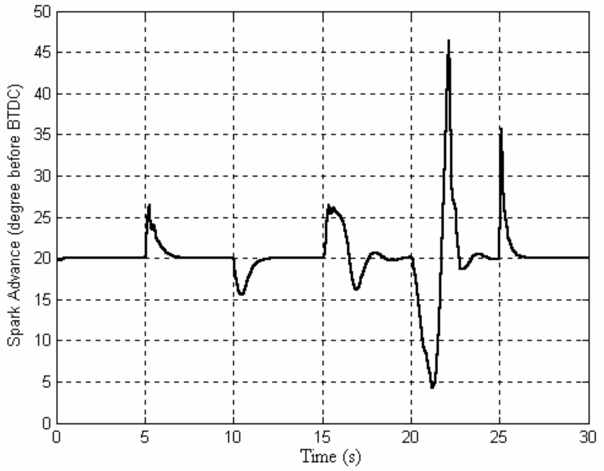

Fig.8. Spark advance control signal

Changes in spark timing have an immediate effect on engine torque and thus are very effective in rejecting disturbances during a transient.
Duty cycle of the idle speed valve shown in Fig.9, Final value of duty cycle is 0.8 and with use of a hard limiter, control signal is limited between 0 and 1.

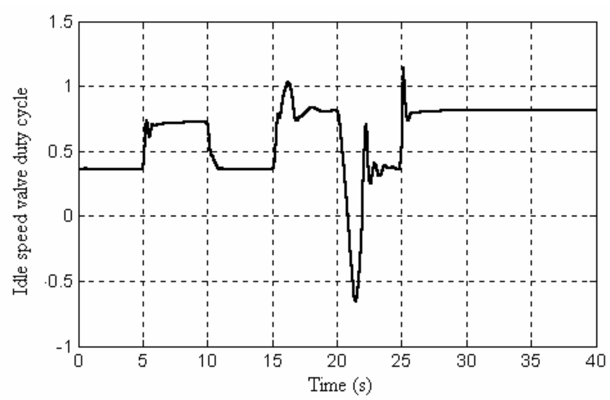

Fig.9. Idle speed valve duty cycle control signal

5 Conclusion

In this study, the ANFIS design methodology is demonstrated to achieve enhanced regulating performance of SI engine.
This structure allows taking into account large dynamic variations of the processes. Using the methodology, a controller is designed to regulate the idle speed of a SI engine subject to a torque disturbance.

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