A Neural Network Based Soft Sensor For Air Fuel Ratio Dynamics In SI Engines

Yujia Zhai, Ka Lok Man, Sanghyuk Lee, and Fei Xue

***Abstract*—Soft sensors have been widely used in control algorithms of engineering application to enhance the control performance and system robustness. This paper proposes a neural network (NN) based soft sensor scheme for air/fuel ratio sensor in spark-ignition engines. The modeling results show that satisfactory modeling performance can be obtained with moderate computational load.**

***Index Terms*—engine dynamics, soft sensor, neural network, system identification**

I. Introduction

ADVANCED algorithms, 3D mapping, LiDAR (stands for light detection and ranging), and radar and camera sensors have been identified as the key technologies for autonomous vehicles [1][2]. This is because, to make appropriate maneuvers on road, autonomous vehicles should be equipped with control systems that are capable of analyzing sensory data and making correct decisions like a human driver. Consequently, the philosophy of control systems design in AV becomes different. Traditional vehicles work in a passive mode. It means that control systems consider drivers input as disturbance. Each electronic control unit (ECU) has its own objective to achieve. It is human drivers responsibility to make correct controls [3][4]. For autonomous vehicles, ECUs gain full controls on all the actuators in systems. One of the advantages for this change is that the satisfactory engine performance in transient is easily obtained as the actuators for both air and fuel are controlled by ECUs. The speed control and efficient fuel injections could be easier to achieve as the air and fuel dynamics are is highly predictable. However, the challenging question is, without human interference, how an AV can coordinate all the control modules, such as path and speed planning, engine management, body dynamics, and etc., to ensure the maximum performance on effectiveness, efficiency, and stability.

Providing redundancy in both sensor setup and data processing would be a common practice for safety reasons, especially when shifting functionality from a research level to series production level. Duel-sensor systems can be found in some of control application in automobiles, which provide sensor information redundancy on hardware-level. Based on the understanding of engine dynamics, it is also possible to construct soft sensors for some critical application to ensure the robustness of control systems. For example, if any part in sensor systems goes wrong on road, it is highly desirable to have a backup plan on driving control, for the purpose of passengers safety. In this paper, a neural network based soft sensor is realized by using neural network black-box model. Section 2 introduces an bench-mark engine model for engine research; a neural network model adopted in this research is explained in Section 3; simulation result of soft sensor is shown in Section 4; the conclusion is drawn in Section 5.

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II. Mean Value Engine Model

In both industrial practice and scientific research, it has been more popular to use engine simulation models to make engine system analysis and design because it is much more economical than using a real engine test bed. The engine model adopted in this paper is referred to as the mean value engine model (MVEM) developed by Hendricks [5], which is a widely used benchmark for engine modeling and control. The three distinct subsystems of this model are the fuel injection, manifold filling and engine speed dynamics and those systems are modeled independently.

A. Manifold Filling Dynamics

The intake manifold filling dynamics are analysed from the viewpoint of the air mass conservation inside the intake 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 re-circulation (EGR) mass flow, the EGR temperature and the manifold temperature. It is described as

$$\begin{aligned}\dot{p}_i &= \frac{\kappa R}{V_i}(-\dot{m}_{ap}T_i + \dot{m}_{at}T_a + \dot{m}_{EGR}T_{EGR}) \\ &= f_p(\alpha, p_i, T_aT_i, n, m_{EGR}, T_{EGR})\end{aligned} \tag{1}$$

The manifold temperature dynamics are described by the following differential equation

$$\begin{aligned}\dot{T}_i &= \frac{RT_i}{p_iV_i}[-\dot{m}_{ap}(\kappa-1)T_i \\ &+ \dot{m}_{at}(\kappa T_a - T_i) + \dot{m}_{EGR}(\kappa T_{EGR} - T_i)] \\ &= f_T(\alpha, p_i, T_a, T_i, n, m_{EGR}, T_{EGR})\end{aligned} \tag{2}$$

The air mass flow past throttle plate $\dot{m}_{at}$ is related with the throttle position and the manifold pressure. The air mass flow into the intake port $\dot{m}_{ap}$ is represented by a well-known

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speed-density equation:

$$\dot{m}_{at}(u, p_i) = m_{at1}\frac{p_a}{\sqrt{T_a}}\beta_1(u)\beta_2(p_r) + m_{at0} \quad (3)$$

$$\dot{m}_{ap}(n, p_i) = \frac{V_d}{120RT_i}(\eta_i \cdot p_i)n \quad (4)$$

where

$$\beta_1(u) = 1 - \cos(u) - \frac{u_0^2}{2!} \quad (5)$$

$$\beta_2(p_r) = \begin{cases} \sqrt{1 - (\frac{p_r - p_c}{1 - p_c})^2} & if \quad p_r \geq p_c \\ 1 & if \quad p_r < p_c \end{cases} \quad (6)$$

$$p_r = \frac{p_i}{p_a} \quad (7)$$

and m_{at0}, m_{at1}, u_0, p_c are constants. Additionally, instead of directly model the volumetric efficiency η_i, it is easier to generate the quantity $\eta_i \cdot p_i$ which is called normalised air charge. The normalised air charge can be obtained by the steady state engine test and is approximated with the polynomial Equation (8)

$$\eta_i \cdot p_i = s_i(n)p_i + y_i(n) \quad (8)$$

where $s_i(n)$ and $y_i(n)$ are positive, weak functions of the crankshaft speed and $y_i \ll s_i$.

B. Crankshaft Speed Dynamics

The crankshaft speed is derived based on the conservation of the rotational energy on the crankshaft. Its state equation can be written as

$$\begin{aligned} \dot{n} &= -\frac{1}{In}(P_f(p_i, n) + P_p(p_i, n) + P_b(n)) \\ &+ \frac{1}{In}H_u\eta_i(p_i, n, \lambda)\dot{m}_f(t - \Delta\tau_d) \\ &= f_n(p_i, n, m_f, \theta, \lambda) \end{aligned} \quad (9)$$

Both the friction power P_f and the pumping power P_p are related with the manifold pressure p_i and the crankshaft speed n. The load power P_b is a function of the crankshaft speed n only. The indicated efficiency η_i is a function of the manifold pressure p_i, the crankshaft speed n and the air fuel ratio λ.

C. Fuel Injection Dynamics

It has been found that the fuel jet from the injector can be characterised into two portions. One portion mixes with the air stream and enters the cylinder directly; the other portion deposits as fuel film on the surfaces of the intake system components, and mixes with the air stream through the reentrainment/evaporation process during subsequent engine cycles. This is known as wall-wetting.

According to Hendrick's identification experiments with SI engine, the fuel flow dynamics could be described as following equations [5]

$$\ddot{m}_{ff} = \frac{1}{\tau_f}(-\dot{m}_{ff} + X_f\dot{m}_{fi}) \quad (10)$$

$$\dot{m}_{fv} = (1 - X_f)\dot{m}_{fi} \quad (11)$$

$$\dot{m}_f = \dot{m}_{fv} + \dot{m}_{ff} \quad (12)$$

where the model is based on keeping track of the fuel mass flow. The parameters in the model are the time constant for fuel evaporation, τ_f, and the proportion of the fuel which is deposited on the intake manifold or close to the intake valves, X_f. These parameters are operating point dependent and thus the model is nonlinear in spite of its linear form. The MVEM provided by Elbert Hendrick has been validated using the real time data acquired from the engine test bed that equipped with Ford 1.6L engine. The parameters for this model could be approximately expressed in the terms of the states of the model as

$$\begin{aligned} \tau_f(p_i, n) &= 1.35(-0.672n + 1.68)(p_i - 0.825)^2 \\ &+ (-0.06n + 0.15) + 0.56 \end{aligned} \quad (13)$$

$$X_f(p_i, n) = -0.277p_i - 0.055n + 0.68 \quad (14)$$

D. MVEM under AFR Measurement Delay

The AFR could be calculated using Equation (15)

$$\lambda = \frac{\dot{m}_{ap}}{\dot{m}_f} \quad (15)$$

Nowadays, in the practical application of automotive industry, oxygen sensors are used in the fuel injection system. They determine if the air fuel ratio exiting a gas-combustion engine is rich (with unburnt fuel vapour) or lean (with excess oxygen), then, a closed-loop feedback controller,usually a PI controller, adjusts fuel injection rate m_{fi} according to real-time sensor data rather than operating with a open-loop fuel map. Therefore, the time delay of injection systems should also be considered. Manzie's research [6] [7] has shown there are three causes of time delay for injection systems: the two engine cycle delay between the injection 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.

$$t_d = 0.045 + \frac{10\pi}{n} \quad (16)$$

The time delay on air fuel ratio measurement has not been considered in original MVEM. A module used for air fuel ratio measurement is added into original MVEM for the research purpose of AFR control, which is based on Equation (16).

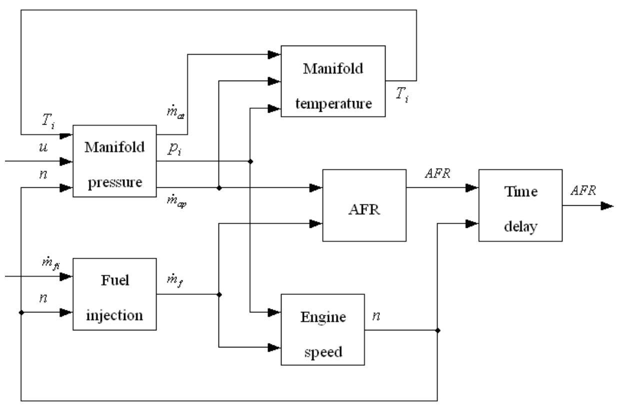

Fig. 1. Mean Value Engine Model with AFR Measurement Delay

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III. NN BASED ENGINE MODELING

The radial basis function neural network (RBFNN) consists of three layers: input layer, hidden layer and output layer, where $x = [x_1, x_2, \cdots, x_n]^T \in \mathcal{R}^n$ is the input

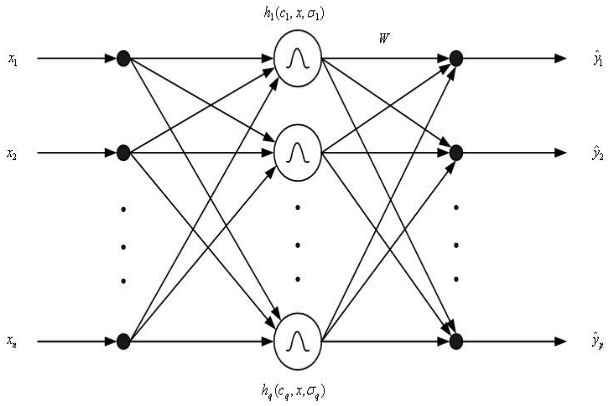

Fig. 2. RBFNN Structure

vector, $h = [h_1, h_2, \cdots, h_q]^T \in \mathcal{R}^q$ is the hidden layer output vector, $W(k) \in \mathcal{R}^{p \times q}$ is the weight matrix with entry w_{ij}, which is the weight linking the jth node in the hidden layer to the ith node in the output layer, and $\hat{y} = [\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_p] \in \mathcal{R}^p$ is the output vector of the RBFNN.

In mathematical terms, we have the following equations to describe the RBFNN.

$$\hat{y}(k) = W \cdot h(k) \tag{17}$$

$$h(k) = f[z(k)] \tag{18}$$

$$z_i(k) = \sqrt{[x(k) - c_i]^T [x(k) - c_i]} = \| x(k) - c_i \| \tag{19}$$

where *i = 1, 2, ..., q*. $c_i \in R^n$ is the i_{th} centre in the input space, and $f[.]$ is the nonlinear activation function in hidden layer. The gaussian basis function given by

$$f[z(k), \sigma] = e^{\frac{-z^2(k)}{\sigma^2}} \tag{20}$$

is chosen in this research, where σ is a positive scalar called width, which is a distance scaling parameter to determine over what distance in the input space the unit will have a significant output.

The RBF neural network models are used in this research to predict system outputs. The procedure of RBFNN modelling and prediction is to determine network inputs according to system dynamics; data collection and scaling; network training and validation; using the network to do prediction. The network training includes determining the number of centres, q, appropriate centres and widths, c_i and σ_i, $i = 1, \cdots, q$ from the training data set; obtaining the weights W by training data, and validating the network by the test data [8].

IV. AIR FUEL RATIO DYNAMICS MODELING

The wideband O2 sensor, also called wide-range air fuel (WRAF) sensor, is widely equiped in modern automotive vehicles to replace the traditional Zirconia oxygen sensor that produces only binary seqence of air fuel ratio. Engine control management system can control the air/fuel mixture at stoichiometric ratio inside the combustion chamber, using the measured signal by WRAF. Since sensors are usually located in exhaust stream, a certain time-delay on the AFR measurement can not be avoided.

Due to the harsh working condition and aging effect, the measured AFR can be biased by control circuits of WRAF sensor. It has been reported in many practical applications that the quality control measures can be obtained by using of soft sensor and the stringent requirements imposed on hardware- based sensors can be reduced significantly. Following this idea, a soft sensor for AFR is constructed by using RBFN model in this research. After studying on SI engine dynamics, the dynamics of AFR can be represented by the following equation:

$$\hat{\lambda} = g(P, T, n, \theta, \dot{m}_{fi}) \tag{21}$$

Here, g is a nonlinear function by RBFN, which is used to mapping the input and output data of SI engines. Therefore, the RBFN based soft sensor for AFR can be realized using the measured variables, such as throttle angle θ , fuel injection rate $\dot{m}_{fi}$, intake manifold pressure P, intake manifold temperature T , engine speed n. Then, the AFR in combustion chamber can be infered as accordingly. Considering the nonlinearity and time-delay in engine dynamics, a second order structure of RBFN is chosen to construct the soft AFR sensor as shown in Equation 22:

$$\begin{aligned} \hat{\lambda} = g[&P(k), T(k), n(k), \theta(k), \dot{m}_{fi}(k), \\ &P(k-1), T(k-1), n(k-1), \theta(k-1), \dot{m}_{fi}(k-1)] \end{aligned} \tag{22}$$

Its structure shown in Fig. 3.

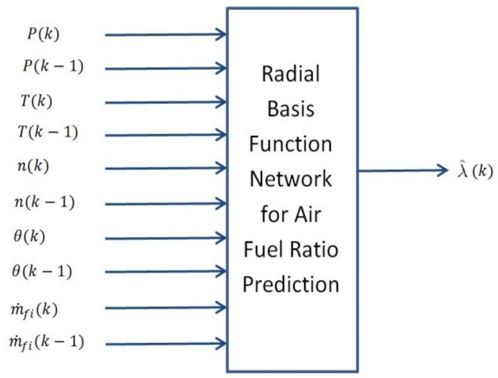

Fig. 3. The Structure of AFR Soft Sensor by RBFN

The soft sensor for AFR can be used as a key component for the fault-tolerant module in engine control system. The performance of the soft sensor is shown in Fig. 4. The mean aboslute error (MAE) of the shown 100 samples is 0.008.

V. CONCLUSION

Redundancy using different principles for sensing and processing is important in modern automotive control systems. The air/fuel ratio soft sensor based on neural network model has been developed in this research.

The modeling performance shows that it could provide reliable information, and such soft sensors can work together with hardware sensors for engine control to achieve the high

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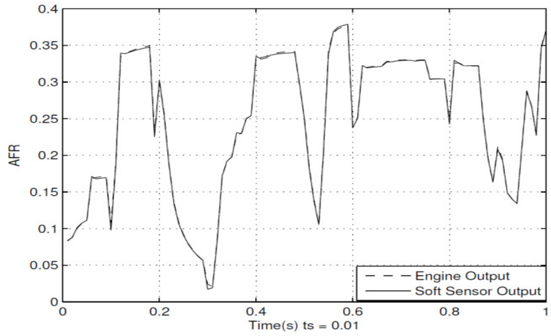

Fig. 4. The Performance of AFR Soft Sensor

robustness that is essential for future autonomous vehicles operations.

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