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Research paper

Effects of engine parameters on ionization current and modeling of excess air coefficient by artificial neural network

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HIGHLIGHTS

- The effects of engine parameters on the ionization current were investigated.
- An artificial neural network for modeling of excess air factor was developed.
- The coefficient of determination of the developed network is 0.99508.
- Prediction results of the ANN model were compared with the experimental results.

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ABSTRACT

This study investigates the effects of engine speed, load, ignition timing and excess air coefficient on the ionization current and presents an artificial neural network model to predict the in-cylinder air-fuel ratio by using data of the ionization current. A secondary spark plug was used as an ionization current sensor. Experimental studies were conducted on a spark-ignition engine at variable speed, load, ignition timing, and excess air coefficient. The effects of these parameters on the ionization current were investigated individually. For modeling of the excess air coefficient, an artificial neural network model was developed with the experimental results. The network was trained with Levenberg-Marquardt and Scaled Conjugate Gradient training algorithms. Performance of the network was measured by comparing the predictions with the remaining experimental results. The excess air coefficient can be predicted with the network with a coefficient of determination of 0.99508. This study shows, the ionization current signal can be used to predict the in-cylinder excess air coefficient as a feasible alternative to the production air-fuel ratio sensors.

1. Introduction

In internal combustion engines, one of the most important parameters affecting the emissions and performance of the engine is the excess air coefficient (λ). To measure the excess air coefficient, step type and wide band lambda sensors are used. Step type lambda sensors have an output characteristic that, changes the voltage level from high to low or low to high at stoichiometric ratio. These type lambda sensors do not provide information about the exact value of lambda. On the contrary, wide band lambda sensors provide information about the lambda value that is more accurate. Both sensors are located on the exhaust pipe of the engine and they measure the average lambda of the cylinders. In addition, both sensors have a high cost. Fast and accurate measurements of the excess air coefficient are essential for precise air-fuel ratio (AFR) control. In addition, in-cylinder measurements of lambda make AFR control easier.

Researchers proposed different methods of estimating the excess air coefficient using engine parameters. In-cylinder pressure traces of the engine can be used to predict the excess air coefficient; however, this is an impractical method. In a previous study, the estimation of the excess air coefficient by analyzing the low sample rate in-cylinder pressure was performed with a 1% error approximately [1]. In another study, a principal component analysis of the spark ionization signal with manifold absolute air pressure, fuel pulse width and engine speed were used in an artificial neural network (ANN) to estimate the AFR in transient and steady state operations. In that study, a three-layer NARX network was used and the prediction performance of AFR was 0.9724 of R^2 [2]. The use of

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Nomenclature

λ	excess air coefficient
AFR	air fuel ratio
ANN	artificial neural network
ECU	electronic control unit
TDC	top dead center
BDC	bottom dead center
CA	crank angle
UEGO	universal exhaust gas oxygen
BTDC	before top dead center
MBT	maximum brake torque
BMEP	brake mean effective pressure
LM	Levenberg-Marquardt
SCG	scaled conjugate gradient
RMSE	root mean square error
MAPE	mean absolute percentage error
R^2	coefficient of determination
t	target value
o	output value
n	engine speed
z	ignition angle
iv	peak ionization current value
il	peak ionization current location

spark plug voltage characteristics in an ANN to achieve a cheap solution for the AFR measurement was investigated by Walters et al. According to results of the study, the excess air coefficient could be measured with ±0.1 accuracy using an ANN-based spark voltage characterization method [3]. Cycle-resolved AFR and in-cylinder pressure were estimated using an ionization current-based stochastic estimation method with a maximum 2% of errors by Lee et al. [4]. The effects of the equivalence ratio, engine load, engine coolant temperature, and engine speed on the ionization current signal were investigated by Huang et al. It was shown that the ionization current signal could be used with ANNs for the prediction of the equivalence ratio [5]. The estimation of the peak pressure position and AFR using the ionization current and ANNs was investigated by Wickström et al. According to the results of this study, the estimation performance of the peak pressure position with ANN was two times better than a linear model and the estimation performance of the AFR with the ANN was 10 times better than the linear model [6]. The estimation of the AFR using the ionization current and neural networks was studied by Hellring et al. For estimation with an un-normalized ionization current, a network with two hidden layer consisting of 20 neurons was selected and for a normalized ionization current, a network with two hidden layers with 10 neurons was selected. According to the results of the study, the neural network model without normalization of the ionization current was 20 times better than a linear model and four times better than the corresponding linear model with normalization [7]. Klövmark et al. estimated of the AFR by modeling of the ionization current as a sum of two Gaussian functions. The AFR was estimated using the parameters of Gaussian functions with correlation plots, linear regression modeling, Bayesian classification, and ANN modeling methods. It was mentioned in the results that the ANN approach was the best solution among the methods with a 0.1% mean square error [8].

Modeling with ANNs is an intelligent solution for systems whose behaviors are difficult to describe mathematically. The principle of ANN is based on a human brain neuron cell, which has a learning ability. ANNs have a wide application field, including estimation, classification, data binding, filtering, recognition and matching, diagnostics, and optimization [9–13]. Also ANNs have been applied to several problems in internal combustion engines, as with in other fields. Some studies dealt with the estimation of the performance characteristics of the internal combustion engines with different types of fuels [14–16]. On the other hand, some studies are related to the modeling of alternative combustion mode engines with ANNs [17,18].

The ionization current occurs in two phases during combustion. The first phase is flame front and the second is post flame. In the first phase, the ionization current is formed by the combustion of hydrocarbons. The second phase of the ionization current results from the NOx formation during combustion [19].

Hydrocarbon molecules react with oxygen and at the end of the reactions, carbon monoxide and water release as products during combustion.

$$C_8H_{18} + \frac{25}{2}O_2 \rightarrow 8CO_2 + 9H_2O \quad (1)$$

During some combustion steps, free electrons, which can be used to generate a current, release due to chemical ionization. Some examples of these reactions are given in Eq. (2).

$$\begin{array}{ccc} CH + O & \rightarrow & CHO^+ + e^- \\ CHO^+ + H_2O & \rightarrow & H_3O^+ + CO \\ CH + C_2H_2 & \rightarrow & C_3H_3^+ + e^- \end{array} \quad (2)$$

In addition to hydrocarbon oxidation reactions, ionization takes place during NOx formation depending on the temperature increase in the combustion chamber [20–22].

The amount of the ionization current depends on the quantity of the ionic agent in the field, the strength of the electrical field (bias voltage), the spark gap distance, the electrode shapes, the temperature, and the humidity. Therefore, the ionization current contains information about combustion phases and cylinder pressure [23,24]. Consequently, the ionization current measurement is a feasible method that can be used to determine combustion parameters [2,25].

The purpose of this study is to investigate the effects of the engine speed, ignition timing, and excess air coefficient on the ionization current and present an ANN model that can be used to predict the in-cylinder AFR using ionization current information. The expected benefit of the study is to examine a feasible and faster solution for measuring the excess air coefficient instead of the production sensors. For this purpose, a secondary spark plug was mounted to the cylinder head for use as an ionization current sensor. Experiments were performed on a single cylinder engine at variable engine speed, load, ignition timing, and excess air coefficient. Experimental results were used to examine the effects of these parameters on the ionization current and generate an ANN model. The engine load was kept at full to simplify the model and reduce the number of experiments.

2. Methodology

2.1. Experimental setup

The experimental study was carried out on a single cylinder four-stroke spark ignition (SI) engine. Technical specifications of the engine are given in Table 1. A Cussons P8160 type standard