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REAL-TIME AND ROBUST ESTIMATION OF BIODIESEL BLENDS USING CRANKSHAFT POSITION SENSOR: EXPERIMENTAL VALIDATION

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ABSTRACT

Biodiesel is a renewable alternative fuel that produces lower exhaust emissions with the exception of nitrogen oxides (NO_x) when compared to conventional diesel fuel. Fuel blend information is useful during engine operation for optimizing emissions and performance. Therefore, online estimation of biofuel content is a critical step in allowing diesel engines to maintain performance while simultaneously meeting emission requirements when operating on biodiesel blends. Presented in this paper is a model-based biodiesel blend estimation strategies using crankshaft torsionals. A sensitivity analysis investigation is conducted for the method to quantify robustness of the proposed fuel blend estimation methods.

INTRODUCTION

Biodiesel usage has a direct impact on reducing tailpipe emissions. Specifically, Carbon Monoxide (CO), Hydrocarbons (HC) and Particulate Matters (PM) decrease by about 50%, 50% and 65% on average, respectively. In spite of all these environmental benefits, there is an increase of 10% in NO_x formation approximately. Such an increase in NO_x emission is counterproductive in meeting ever restricting EPA requirements. Solutions to NOx reduction have been proposed as using exhaust gas recirculation (EGR) systems or adding chemicals to biodiesel fuel. Regardless of the NO_x reduction approach, there is a need for accurate estimate of the biocontent of the fuel in real–time. This information is useful in optimization of the engine control parameters after each tank refill to mitigate the negative aspects of using biodiesel [1].

Biodiesel content can be estimated utilizing the differences between its chemical properties and those of the conventional diesel fuel. There have been studies on biodiesel blend estimation in the past decade [2][3][4][5][11]. Some of these studies propose laboratory–based method to measure the biodiesel blend [2][3], and other are oriented towards application for automotive industry[4][5].

The first proposed method in the literature is using fiber–optic Near–Infrared (NIR) spectroscopy and H nuclear magnetic resonance spectroscopy for biodiesel blend estimation [4]. The author claims that the NIR spectroscopy is an easy method providing that the hardware is available for monitoring biodiesel production transesterification. Near–infrared spectroscopy (NIRS) uses the near–infrared region of the electromagnetic spectrum (from about 800 nm to 2500 nm). Typical applications include pharmaceutical, medical diagnostics (including blood sugar and oximetry), food and agrochemical quality control, and combustion research, as well as cognitive neuroscience research. The spectrum of the fuel is used to determine the blend. Two different methods are investigated and the consistency of the results is shown through comparison [4]. In the same year, a biodiesel blend estimation method was proposed by M. Tat *et al.* [2] using a commercial flexible fuel composition sensor. This kind of sensor is used to measure the fuel blend for gasoline engines or determine the quality of gasoline fuel. There are two different types of fuel composition sensors. The first type works based on optical method and second type is based on measuring the dielectric of the material. Interested reader is referred to [2] for further information. The output frequency of the sensor shows a difference of about 7 Hz for switching from diesel to biodiesel. The method is tested for different types of diesel and biodiesel types and is reported to be able to estimate the blend with up to 10% error. There is no uncertainty or sensitivity analysis of the method against operating condition and the model variations.

Ultra violet (UV) absorption method has been also ptoposed for biodiesel blend estimation [3]. Unlike NIR spectroscopy that uses invisible beams (with much higher wavelengths) UV absorption uses visible beams for spectroscopy. The root mean square error (RMSE) of the method is reported to be 2.88%. However, the method is too complicated to be applied to automotive application. A recent biodiesel blend estimation study belongs to Snyder *et al.* [5] which is based on the oxygen content of biodiesel. They estimated the blend using an exhaust path oxygen sensor measurement. Based on the chemical content of the biodiesel, there is about 10% oxygen in biodiesel combination while diesel fuel is oxygen free. This difference in oxygen content will affect the amount of oxygen in the combustion chamber and exhaust path. A universal exhaust gas oxygen (UEGO) sensor is used for this method. The fuel fraction of the fuel and air mixture in the combustion chamber along with the exhaust path oxygen content measurement is used in this method. The method is reported to be able to determine the blend within 4% of the actual blend. The method is very sensitive to the operating condition and the estimation error is very large for small mixture fractions. The work is completed by adding a Kalman Filter in the system to mitigate the large errors in some operating conditions [6]. The main drawback of this method is the need of an additional UEGO sensor in the exhaust path.

The mentioned biomass fuel estimation methods and concepts are not attractive for the engine manufacturers due to the following reasons:

- Complexity of the methods
- Addition of a new sensor
- Robustness against model variation
- Sensitivity to measurement errors.

Complexity of some of the proposed method prevents their real application in the engine industry. As mentioned before, adding a new sensor to the diesel engine will increase the production and maintenance cost resulting in an increase in the final product price and complexity of the periodic maintenance. In addition, new sensor requires diagnosis and it makes the on board diagnosis (OBD) system more complicated. The inclusion of a new sensor also introduces robustness and sensitivity issues with regards to ambient environmental changes and reliability challenges.

A robust applicable estimation method is required to address all of the above issues. A new fuel blend estimation methods using crankshaft position sensor measurements are presented in this study [7]. The approach utilizes the produced torque of the engine as manifested in the crankshaft torsionals. The fundamental principle driving the proposed method is the difference between the energy content of conventional diesel and biodiesel fuels.

A model-based estimation method is used for the method to address the robustness of the method against measurement errors and model variations. The method is explained in details in the following sections.

MODEL–BASED ESTIMATION AND REAL-TIME ADAPTATION

The proposed biodiesel blend estimation method is based on an online adaptive model [12][13] whose parameters depend on the fuel type in the combustion chamber. To illustrate this approach, assume that the following equation is representing the parametric model

$$y = c_1 f_1(x_1, \dots, x_n) + c_2 f_2(x_1, \dots, x_n) + c_3 f_3(x_1, \dots, x_n) \tag{1}$$

where y is the output and $x_1, \dots, x_n$ are the inputs of the model. The f_i's are the regressors of the model and c_i's are the coefficients (Fig. 2-1). The objective is to compare the output of the model with the measurement from the engine and adapt the coefficients (c_i's) based on the error $E = y - \tilde{y}$. For the nominal system, the coefficients are $(c_{1n} \quad c_{2n} \quad c_{3n})$ and the difference between the set of the online estimated model coefficients and set of nominal model coefficients results in a parameter variation vector represented by $(\Delta c_1 \quad \Delta c_2 \quad \Delta c_3)^T$. This vector is represented in Figure 2. The parameter variation vector that corresponds to the nominal model is the null vector, but in case of any discrepancy or model mismatch with the nominal model, there would be a non-zero vector as shown in Figure 2. For biodiesel blend estimation, the model representing the conventional diesel fuel is considered to be the nominal model. Any biodiesel blend in the fuel leads to a nonzero parameter variation vector due to a change in the coefficients of the model. The length of this non-zero parameter variation vector can provide information on biodiesel blend content.

The proposed model–based approach is used for all of the proposed biodiesel blend estimation methods in the next sections. The goal is to drive the appropriate model from the principal equations of the internal combustion engines and tune it for the specific method and construct the final estimator.

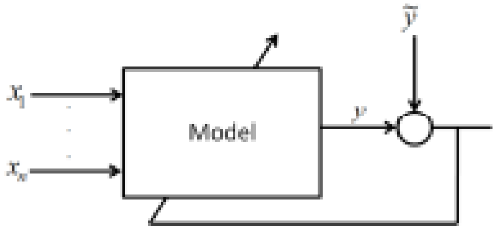

FIGURE 1 MODEL WITH ADAPTIVE COEFFICIENTS

Crankshaft torsionals method

The energy content of biodiesel is almost 12% less than that of the conventional diesel fuel. This difference leads to a reduction in torque production from the engine since the energy release of the fuel is converted to mechanical torque. This difference between produced torque of the hydrocarbon diesel fuel and biodiesel fuel can exploited for biomass content estimation provided that engine torque can be estimated. Concerning the torque estimation, the crankshaft torsionals due to the engine firing event can be employed [8]. This estimation method is based on the fact that the crankshaft twist during a power stroke is directly related to the engine brake torque. However, instead of estimating the torque as in [8], the twist of the crankshaft during a power stroke will be directly used in our approach. This torque estimation methodology is explained in details in the next section. Combining the crankshaft twist with nominal engine speed and the mass of fueling command from the engine control enables the biomass content estimation.

Torque estimation and notch filtering

The estimation of the brake torque of the internal combustion engines has been widely reported in the literature. Franco *et al.* [8] showed that the frequency content of the engine speed signal is strongly correlated with the engine load. The Fast Fourier transform (FFT) of the engine speed signal for the developed model in the previous chapter is shown in Figure 3. As it is shown in the figure, the value for 6 events/engine cycle is dominant for the whole frequency range. This value is related to the engine load. The value increases as the load on the engine increases.

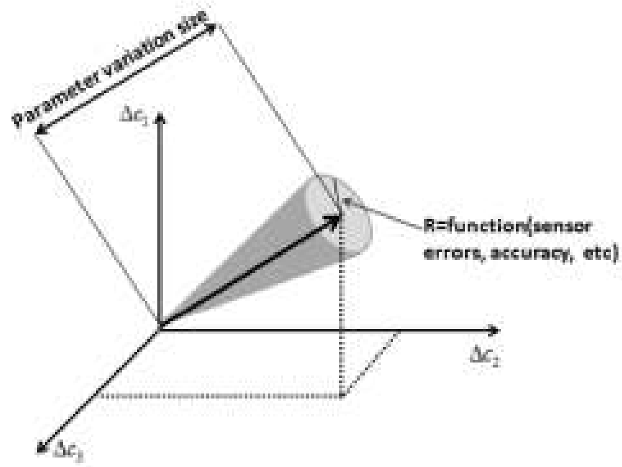

FIGURE 2 BIODIESEL BLEND ESTIMATION USING PARAMETER VARIATION VECTOR SYNTHESIS

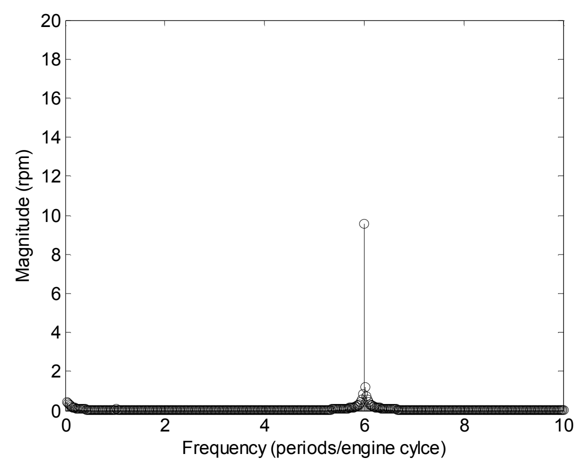

FIGURE 3 FREQUENCY CONTENT OF THE INSTANTANEOUS ENGINE SPEED SIGNAL AT 1500 RPM

Digital Fourier Transform (DFT) computation is really expensive online and must be replaced by simple filtering approaches. To extract different components of the engine speed frequency, we use an infinite impulse response (IIR) notch filter [15]. The notch filter has zero response for the frequency of interest and nonzero response for all other frequencies. Ideally a finite impulse response (FIR) filter is used to extract one frequency of interest. FIR filter has nonzero response for the frequency of interest and zero response for all other frequencies. The disadvantage of using this type of filter in our application is the phase shift of the filter which causes problems in the real–time implementation of the filter. The phase shift of IIR notch filter is minimum compared to FIR filter. The desired notch filter can be easily obtained by placing two complex conjugate poles at the frequency of interest and two complex conjugate zeroes on the unit circle at the same frequency [13]. The transfer function of the filter in crank angle domain is

$$G(z_\theta) = K_f \frac{1 - 2.\cos(\omega_n).z_\theta{}^{-1} + z_\theta{}^{-2}}{1 - 2.r.\cos(\omega_n).z_\theta{}^{-1} + r^2.z_\theta{}^{-2}}$$

where z_θ is the z–transform parameter in crank domain, r is the radial location of the filter poles, K_f is the filter static unity gain, and ω_n is defined as

$$\omega_n = \frac{2\pi}{f_s} f_n \qquad (3)$$

where f_s is the sampling frequency in samples per engine cycle and f_n is the frequency of interest. The filter frequency diagram is shown in Figure 4 for two different values of r. The configuration of notch filtering is shown in Figure 5. The notch filter output is subtracted from the original signal and the result is the frequency of interest wave.

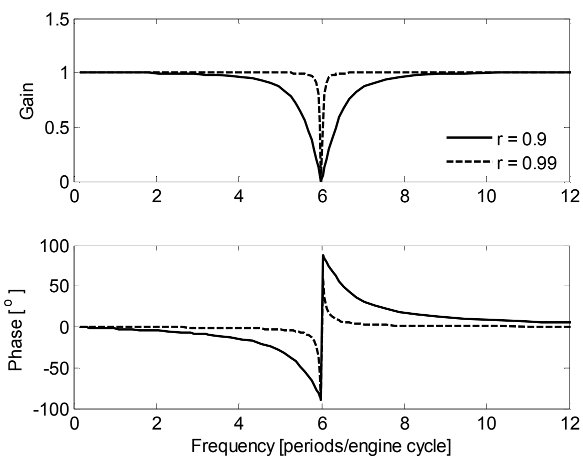

FIGURE 4 NOTCH FILTER FREQUENCY DIAGRAM (SOLID: R=0.9, DASHED: R=0.99) [8]

Theoretical background

The relation between produced power and torque in an internal combustion engine is

$$P = 2\pi NT \qquad (4)$$

where P is the engine power (in kW), N is the engine rotational speed (in rev/s) and T is the produced torque (in N.m) [9]. The power in (4) is called *brake power*. A measure of fuel efficiency is the *fuel conversion efficiency* η_f defined by

$$\eta_f = \frac{P}{\dot{m}_f Q_{HV}} \qquad (5)$$

where $\dot{m}_f$ is fuel rate injected per cycle (in kg/sec) and Q_{HV} is the heating value of the fuel (in kJ/kg). It is shown that the heating value of the fuel linearly depends on the biodiesel blend [10]. This efficiency measure is determined in a standardized test procedure in which a known mass of fuel is fully burned with air, and the thermal energy released by the combustion process is absorbed by a calorimeter as the combustion products cool down to their original temperature [9]. From (4) and (5)

$$Q_{HV} = \frac{2\pi}{\eta_f} \frac{NT}{\dot{m}_f} \qquad (6)$$

which indicates the relation between heating value of the fuel and a combination of torque and fuel consumption. The final model after some mathematical approximation is as follows

$$M_6 \approx c_1 \dot{\tilde{m}}_f + c_2 \dot{\tilde{m}}_f \tilde{N} + c_3 \qquad (7)$$

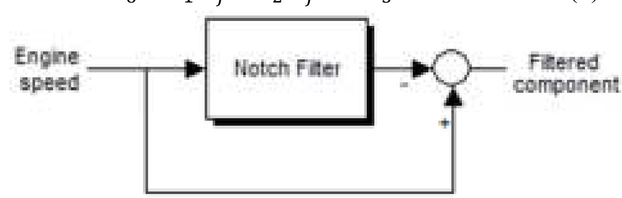

FIGURE 5 NOTCH FILTERING CONFIGURATION

Further details about the model derivation are derived in [7][14]. The block diagram of the estimation approach is shown in Figure 6. As shown in this figure, the inputs to the model are fueling rate and average engine speed signal and the output is the crankshaft torsionals which is an indicator of produced brake torque of the engine. Equation (7) is valid in steady–state conditions and the coefficients carry the information on the heating value of the fuel that we seek to determine the biodiesel blend.

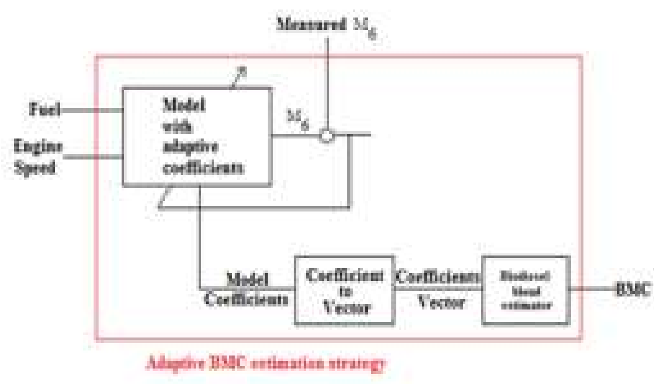

FIGURE 6 BLOCK DIAGRAM OF THE ROBUST ESTIMATION STRATEGY

EXPERIMENTAL SETUP

To validate the proposed concepts in biodiesel blend estimation methods, we test the performance of the designed estimators in the real engine applications. All of the tests are done in the Engine Control Research Laboratory at the University of Houston. The lab is equipped with a diesel engine, water brake dynamometer, data acquisition system (dSpace), Fast NO_x analyzer, and Claterm III to control the engine. Every part is described in the following subsections. The engine is shown in Figure 7.

FIGURE 7 CUMMINS DIESEL ENGINE

Experimental results

The difference in energy content is used to develop the crankshaft torsionals approach for biodiesel blend estimation.

Every operating point has been tested for four different biodiesel blends {B0, B20, B50, B100}. Moreover, the whole experiment has been repeated several times to compensate the effect of any uncertainty in diesel engine system, dynamometer, and measuring devices.

The following model is derived for this method

$$M_6 \approx c_1 \tilde{\dot{m}}_f + c_2 \tilde{\dot{m}}_f \tilde{N} + c_3. \qquad (8)$$

The engine is run in different speed and load operating points and the data is collected from crankshaft position sensor and fueling rate (Calterm) in steady-state and is averaged in 5 seconds to avoid small fluctuations of data in steady-state. The model structure for coefficient adaptation is shown in Figure 8. The coefficients of the model (8 are shown in Table 1. These coefficients are obtained from experimental results data. The M_6 component and average engine speed is calculated offline and used for the model adaptation. This test has been repeated for all of the blends (B0, B20, B50, and B100). Then, least squares method has been used to achieve the coefficients in Table 1. The one difference between simulation and experiment is that in simulation the engine speed signal is one of the outputs of the diesel engine model but it must be calculated from the crankshaft position sensor raw data in the experiment.

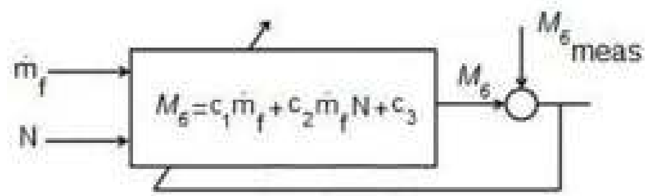

FIGURE 8 ADAPTIVE MODEL FOR CRANKSHAFT TORSIONALS APPROACH

TABLE 1 MODEL (8 COEFFICIENTS FOR DIFFERENT BLENDS

Biodiesel blend	c_1	c_2	c_3
B0	-4.06	1.91	1.97
B20	-3.82	1.80	1.77
B50	-3.42	1.52	1.90
B100	-2.14	1.00	1.70

As mentioned before, the first two terms coefficients of the model (7) are used for biodiesel blend estimation. The *parameter variation vectors* (variation from the vector B0) are shown in Figure 9.

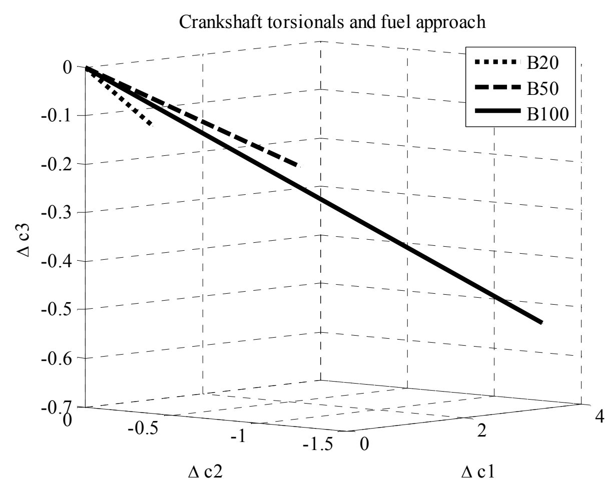

FIGURE 9 MODEL (7) PARAMETER VARIATION VECTORS

For the biodiesel blend estimation purposes, we calculate the projection of all parameter variation vectors on the largest vector (which is related to B100) and for each vector, we just use the first two coefficients (the projection of all vectors on the plane $c_1 - c_2$). The length of the projected vectors is plotted in Figure 10. The values are given in Table 2. As observed from this figure, a second order polynomial can be fitted to this set of points. The equation of the line plotted in Figure 10 is

$$BD = -23.42L^2 + 175.52\,L - 1.98 \tag{9}$$

where L is the length of the projected parameter variation vectors on the reference vector (solid line in Figure 9)

$$L = \frac{\bar{V}.\bar{V}_{100}}{|\bar{V}_{100}|} \tag{10}$$

with

$$\bar{V} = (c_1 - c_{1,B0}^{TF} \quad c_2 - c_{2,B0}^{TF})^T \tag{11}$$

and

$$\bar{V}_{100} = (c_{1,B100}^{TF} - c_{1,B0}^{TF} \quad c_{2,B100}^{TF} - c_{2,B0}^{TF})^T \tag{12}$$

where "TF" stands for crankshaft torsionals and fueling method.

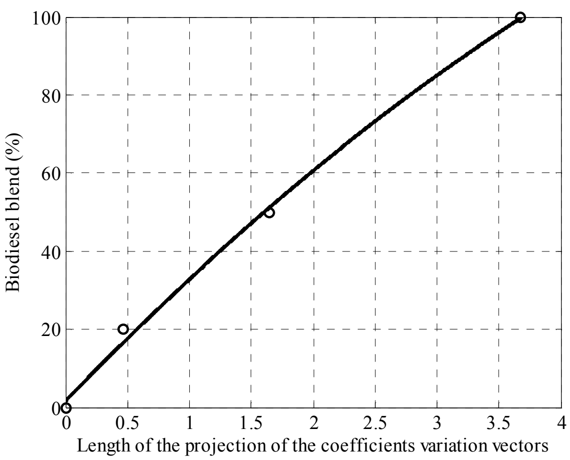

FIGURE 10 LENGTH OF THE PROJECTION OF THE PARAMETER VARIATION VECTORS VS. BIODIESEL BLEND

To validate the designed biodiesel blend estimator, we run B70 biodiesel blend on the engine and estimate the blend using the collected data from the engine and the estimator (9). The parameter variation vector for B70 is shown in Figure 11. The coefficients of the model adapted for this blend are

$$(c_{1,B70}^{TF} \quad c_{2,B70}^{TF} \quad c_{3,B70}^{TF}) = (-2.97 \quad 1.37 \quad 1.79). \tag{13}$$

Using equation (10) to (12), the length of the projection of the vector in Figure 11 is calculated

$$L|_{B70} = 1.22. \tag{14}$$

Then the estimated blend from (9) is "73.5".

TABLE 2 LENGTH OF THE PROJECTED VECTOR ON THE REFERENCE VECTOR FOR DIFFERENT BIODIESEL BLENDS (CRANKSHAFT TORSIONALS APPROACH)

coefficients	Projected vector length
B0	0
B20	0.26
B50	0.75
B100	2.13

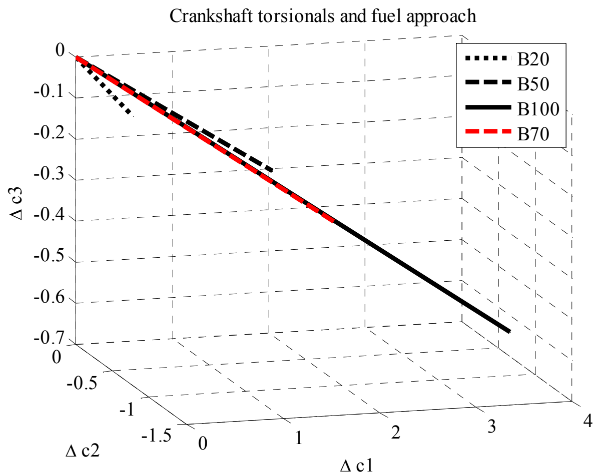

FIGURE 11 PARAMETER VARIATION VECTOR (CRANKSHAFT TORSIONALS APPROACH) FOR B70 (RED) COMPARED TO THE VECTORS USED FOR ESTIMATOR DESIGN

CONCLUSIONS

An adaptive model estimation approach for biodiesel blend estimation in diesel engines is presented in this paper. The proof of concept using a diesel engine model developed in GT-Power is presented in a previous paper by the authors [7]. Experimental results are shown to validate the concepts proposed in the simulation. Crankshaft torsionals method uses the current sensor set of the engine and shows the best estimation results. The parameter variation vectors are plotted and it has been shown that the vector length is related to biodiesel blend. A second order regression is used to relate the biodiesel blend to the length of the vector.

Experiment and simulations show promising results for biodiesel blend estimation. One of the most important features of a biodiesel blend estimator is its performance for various biodiesel feed stocks. According to the literature [11], the heating value of most biofuels is almost within the same range. Conducting a series of tests using different types of biodiesels is interesting to check the ability of the methods in handling the estimation for different fuels.

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