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Modeling and optimization of biodiesel engine performance using kernel-based extreme learning machine and cuckoo search

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ABSTRACT

This study presents the optimization of biodiesel engine performance that can achieve the goal of fewer emissions, low fuel cost and wide engine operating range. A new biodiesel engine modeling and optimization framework based on extreme learning machine (ELM) is proposed. As an accurate model is required for effective optimization result, kernel-based ELM (K-ELM) is used instead of basic ELM because K-ELM can provide better generalization performance, and the randomness of basic ELM does not occur in K-ELM. By using K-ELM, a biodiesel engine model is first created based on experimental data. Logarithmic transformation of dependent variables is used to alleviate the problems of data scarcity and data exponentiality simultaneously. With the K-ELM engine model, cuckoo search (CS) is then employed to determine the optimal biodiesel ratio. A flexible objective function is designed so that various user-defined constraints can be applied. As an illustrative study, the fuel price in Macau is used to perform the optimization. To verify the modeling and optimization framework, the K-ELM model is compared with a least-squares support vector machine (LS-SVM) model, and the CS optimization result is compared with particle swarm optimization and experimental results. The evaluation result shows that K-ELM can achieve comparable performance to LS-SVM, resulting in a reliable prediction result for optimization. It also shows that the optimization results based on CS is effective.

1. Introduction

Recently, biodiesel has become a popular alternative fuel for diesel engines because it can be produced from many different biological sources and can significantly reduce the diesel engine emissions [1,2]. In practice, biodiesel is used together with diesel fuel at some specific ratios (e.g., B5 and B20) and no significant engine modification is required [1]. However, the volume content of biodiesel in the diesel fuel (i.e., biodiesel ratio) can sensitively affect the engine performance and its emission characteristics. Recent studies and reviews [3–6] have investigated the effect of different biodiesel ratios on diesel engine performance and emissions at different engine speeds and loads. They showed that for a higher biodiesel ratio, more nitrogen oxides (NO_x) emissions are emitted and more fuel are consumed (leading to higher fuel cost), but fewer hydrocarbon (HC), carbon monoxide (CO) and particulate matter (PM) emissions are produced. Hence, an optimal biodiesel ratio that has the best comprise between engine emissions and fuel cost at all engine loads is desired. Determining this optimal biodiesel ratio becomes an interesting topic as the fuel cost and some of engine emissions are in trade-off relationship.

One very straight-forward method for determining this ratio is by conducting numerous experiments and comparing the results to obtain the optimal ratio based on the user's requirements. The disadvantage of this method is that a lot of time and money are required for the huge demand of experiments, and the resulting procedure is not flexible since the constraints, like fuel cost, might vary. Another suitable method is by creating a mathematical model for biodiesel engines so that the optimal biodiesel ratio can be determined by applying computer-aided optimization methods to the engine model. The constraints can easily be provided in the design of objective function. Nevertheless, an exact mathematical biodiesel engine model still remains unknown as the relationship between the parameters of biodiesel engines are very complicated. Most of the biodiesel engine models in the current literature were constructed using traditional artificial neural network (ANN) based on experimental data [7–10]. The optimization based on ANN models for renewable energy application could also be found in a

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latest work [11]. However, traditional ANNs have many drawbacks for its learning process, such as multiple local minima, user burden on selection of optimal network structure, slow learning speed, large training data size and poor generalization performance [12]. Moreover, an accurate model is very important for conducting optimization; otherwise, the result may not be reliable. Therefore, traditional ANN model is not preferred in this study due to its poor generalization performance.

A recent approach entitled extreme learning machine (ELM) [13,14] has been introduced to solve most of the aforesaid problems. It is a single-hidden layer feedforward neural network where the parameters of the hidden layer are initialized randomly. Moreover, unlike traditional ANNs where the output weights are iteratively learned (e.g., gradient-descent), ELM calculates the output weights analytically using a Moore–Penrose generalized inverse. Therefore, it has the advantages of extremely fast learning speed and better generalization capability. A few recent studies [15–19] have already demonstrated the use of basic ELM on some engineering applications. A kernel-based ELM (K-ELM) has also been developed lately [20–22], where the hidden layer feature mapping is determined by the kernel matrix. In this version, only the kernel function and its parameters are needed to be defined; the number of hidden nodes is not required. With the use of kernel function, K-ELM is expected to achieve better generalization performance than basic ELM. Furthermore, as randomness does not occur in K-ELM, the chance of result variations could be reduced. As a result, instead of basic ELM, K-ELM is adopted in this paper to model the engine performance and emissions. A famous kernel-based method called least-squares support vector machine (LS-SVM) is employed as a comparison basis to demonstrate the effectiveness of K-ELM because it has been used in many recent engine modeling studies [23–26]. For fair comparison, the engine models are created using these two methods under the same data sets and same hyperparameter tuning methods. From the comparison, the most accurate model is selected to determine the optimal biodiesel ratio using optimization methods.

As the estimated performance model is very complicated, discontinuous and out of gradient information, traditional optimization methods cannot be used in this application. Therefore, some advanced optimization methods are proposed to study. Since many optimization techniques are available today and each of them has its own advantages and disadvantages, it is impossible to study all techniques in one study. Cuckoo search (CS) [27,28], as one of the modern optimization techniques, has not been explored in engine optimization problem yet. CS is a population-based algorithm that inspired by the brood parasitism of some cuckoo species. It has a more efficient randomization property (with the use of Levy flight) and requires fewer parameters (population size and discovery probability only) than other optimization methods [27]. The evaluation results from Refs. [27,29] also show that CS can achieve more robust performance than other famous techniques such as genetic algorithms, particle swarm optimization (PSO) and artificial bee colony algorithm. Thus, CS is chosen in this study for the determination of optimal biodiesel ratio. Similar to K-ELM, the performance of CS is evaluated by comparing with a traditional method. PSO is employed as the comparison basis because it has been shown in some previous studies that PSO outperforms many optimization techniques in engine optimization problem [26]. The optimization results are further verified through the experimental data.

In a nutshell, this research proposes a new biodiesel engine modeling and optimization framework based on K-ELM and CS in order to determine the optimal biodiesel ratio subject to various user-defined constraints.

2. Experimental setup

As K-ELM and LS-SVM are data-driven methods, sample datasets from experiments are required for model training and verification. A naturally aspirated, water-cooled, 4-cylinder, direct-injection diesel engine was employed as the test engine for the experiments in this study. The specifications of the test engine are provided in Table 1, and the experimental setup is illustrated in Fig. 1.

In the setup, an eddy-current dynamometer with a control system was used to adjust the engine speed and load. Three gas analyzers were adopted to measure the engine emissions on a continuous basis: a heated flame ionization detector (HFID) was used for HC, a heated chemiluminescent analyzer (HCLA) was used for NO_x, and non-dispersive infra-red analyzer (NDIR) was used for CO and carbon dioxide (CO_2). These gas analyzers were calibrated with standard and zero gases before each experiment. A tapered element oscillating microbalance (TEOM) was used to measure the PM mass concentration. Before pass through the TEOM, the engine exhaust gas was diluted with a Dekati mini-diluter, and the dilution ratio was around 8.

Six fuels, including pure diesel, pure biodiesel, and four blended fuels (20%, 40%, 60%, 80% of biodiesel by volume), were used for the experiments. The experiments were conducted at engine speeds of 1800 revolution per minute (rpm) and 2400 rpm, with five different engine torque of 28, 70, 130, 190 and 230 Nm for each engine speed and fuel blend, resulting in 60 sets of sample data. In each test, the fuel consumption was measured using a measuring cylinder and the volumetric fuel consumption rate was then calculated. To ensure the repeatability and comparability of the measurements, the cooling water temperature was automatically controlled by a temperature controller to 80 °C, and held to within ±2 °C, while the lubricating oil temperature varied from 90 to 100 °C, depending on the engine load. At each load and blend, data were recorded after the engine had reached the steady state, which was indicated by the lubricating oil temperature, the coolant temperature and the CO_2 concentration. The data were recorded continuously for 5 minutes to reduce experimental uncertainties. Each test was carried out three times and the average values were used. The experimental results have previously been presented in Refs. [3], so the corresponding experimental uncertainty and standard errors could be found from Ref. [3].

3. Data processing

In order to collect the sample data within a reasonable time and cost, together with the narrow range of operating speeds of diesel engines, only 60 sets of experimental data were acquired, resulting in data scarcity. Moreover, some performance outputs of the sample data, such as PM mass concentration and CO emissions, also suffer from the problem of data exponentiality (i.e., the output *y* increases or decreases exponentially along input x; refers to the

Table 1
Engine specifications.

Model	Isuzu 4HF1
Type	In-line four-cylinder
Maximum power	88 kW/3200 rpm
Maximum torque	285 Nm/1800 rpm
Bore × stroke	112 mm × 110 mm
Displacement	4334 cc
Compression ratio	19.0:1
Fuel injection timing (BTDC)	8°
Injection pump type	Bosch in-line type
Injection nozzle	Hole type (with five orifices)