

Real-time Engine Control Parameters Optimization Method for Small Diesel Engine by Multi Objective Genetic Algorithm

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ABSTRACT

Diesel fuel injection control systems, which are one of the expected solutions for meeting emission regulations, and achieving economical fuel consumption, consist of many parameters. To optimize this system, we have developed an adaptive multi-objective genetic algorithm (MOGA) method for real-time optimization. This method provides Pareto approximation set for the required objectives. Thus engine specifications can be precisely measured and minimize evaluation time. Pre-selection, which is an acceleration method for MOGA, is employed. By using this method we achieved the faster search of three-stage injection sets and PID controller gain.

1. INTRODUCTION

Recently, environment surrounding internal combustion engine for vehicle is getting stricter and stricter since it is required to reduce not only exhaust emissions but also CO₂ emission amount in social backgrounds such as promotion of anti-pollution in atmosphere, battle against global warming, and a rise in crude oil price. As a solution for the requirements for internal combustion engine, reduction of fuel consumption based on improvement of thermal efficiency should be considered. One example of the solution is a diesel engine. However, the conventional diesel engine has demerits such as noise, vibration, exhaust of emissions including PM, NO_x, and the like. However, according to introduction of a common rail diesel engine, it has been possible to improve combustion characteristics by multistage fuel injection, and thus the demerits have been mostly overcome. Nowadays in Europe, vehicles equipped with a diesel engine have come into widespread use.

Meanwhile, the common rail diesel engine also has a problem that calibration for electronic control becomes very complicated. Examples of the calibration include an injection calibration problem as to what timing is appropriate, how many stages are needed for injection, how much fuel amount is needed for each injection, and so on. Also included are a calibration problem considered by classification of a "constant drive" in which a condition for engine drive does not change and a "transient drive" in which the condition for engine drive changes every moment with the elapse of time, and a calibration problem as to how to determine control parameters for various feedback controls. It has been known that the number of combinations between parameters for calibration can be very large.

Generally, broad knowledge about calibration and skills therefore are necessary for the calibration of diesel engine.

In case of the manual optimization, some optimization needs long time to get optimal parameters by lack of controller parameters knowledge. Additionally, some parameters are not optimal enough to get the best performance, because it is hard to keep/use enough time of optimization during the product development term.

Because of the reason mentioned above, in order to embody these complicated calibrations logically with high speed, we started to study an automatic calibration technique to which a multi-objective genetic algorithm is applied in an online environment.

In this paper, in chapter 2, brief description of the proposed automatic calibration technique will be given.

In chapter 3, as an example of application for constant drive, an optimal point search method of a multistage injection for reducing NO_x, SOOT, and SOF and physical adequacy of the obtained results will be described. In chapter 4, as an example of application for transient drive, optimal point search means for a feedback control parameter used in a speed control of idling speed will be reported. In addition, the proposed method improved the convergence performance of engine speed to idling after sudden breaking acceleration for 30 minutes, which is considered a sufficiently favorable time. Chapter 5 shows a conclusion of this paper.

2. ONLINE OPTIMIZATION BASED ON MULTI-OBJECTIVE GENETIC ALGORITHM

2-1. MULTI-OBJECTIVE OPTIMIZATION PROBLEM AND MULTI-OBJECTIVE GENETIC ALGORITHM

Many practical optimization problems can be defined as a multi-objective optimization problem (MOP) for obtaining a Pareto optimal set which is a set of rational solutions satisfying plural evaluation criteria (objective functions) conflicting with each other [2].

An optimization problem having n variables and m objectives can be defined as:

$$\begin{aligned} \min_{\mathbf{x}} \quad & \mathbf{f}(\mathbf{x}) \\ \text{subject to} \quad & \mathbf{x} \in X = \left\{ \mathbf{x} \mid \mathbf{x} \in R^n, \mathbf{g}(\mathbf{x}) \leq 0 \right\} \end{aligned} \quad (1)$$

Where $\mathbf{x}=[x_1 \dots x_n]^T$ is n -dimensional decision variable vector, $\mathbf{f}(\mathbf{x})=[f_1(\mathbf{x}) \dots f_m(\mathbf{x})]^T$ is m -dimensional objective function vector, $\mathbf{g}(\mathbf{x})=[g_1(\mathbf{x}) \dots g_l(\mathbf{x})]^T$ is l -dimensional constraint condition vector.

When $\mathbf{x} \in X$ satisfying

$$\begin{aligned} f_i(\mathbf{x}) &\leq f_i(\mathbf{x}^*), \forall i = \{1, \dots, m\} \\ \wedge f_i(\mathbf{x}) &< f_i(\mathbf{x}^*), \exists i = \{1, \dots, m\} \end{aligned} \quad (2)$$

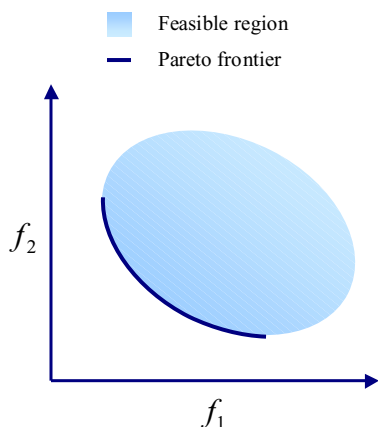


Fig. 2-1 Pareto frontier

does not exist, $\mathbf{x}^* \in X$ is referred to as Pareto optimal solution. Fig.2-1 shows the conceptual diagram Pareto frontier, which is Pareto optimal set in objective function space.

In the past, a scalarization method such as a weighted linear sum method or ϵ -constraint method has been widely used as an optimization method for MOP. Recently, attention has been focused on a multi-objective genetic algorithm (MOGA); a multi-objective optimization technique inspired by evolutionary biology [2]. MOGA is able to collectively find a Pareto approximation set of a Pareto optimal set by multi-point search; a feature of genetic algorithms. MOGA has been applied in various fields because the possible applications are numerous. In the field of engineering, a method in which the MOGA is combined with simulation is frequently used [5,8].

Traditionally in genetic algorithms, the decision variable vector (control parameter in calibration problem) is referred to as an individual, the aggregate of individual is referred to as a population, the objective function is referred to as a fitness function, and the objective function value is referred to as a fitness [4]. In this paper, if there is no alternative definition given, the standard definitions are used.

2-2. APPROACH TO CALIBRATION

Approaches to automation of calibration can be roughly classified into three categories.

2-2-1. Calibration using Physical Simulation

This is a method of constructing detailed physical models based on thermal, fluid, and mechanical dynamics of an engine and simulating calibration. The calibration can be performed completely in an offline environment without using a real engine. Hiroyasu et al. reported a case where MOGA is applied to a phenomenological model called HIDECS [5]. However, since action of an engine is complex, designing detailed physical models is difficult, and sometimes the calculation time may be longer than driving time of a real engine.

2-2-2. Calibration based on Response Surface Methodology

Response surface methodology (RSM) is a technique of measuring data with a measuring point generated on the basis of design of experiments (DoE), constructing approximation model on the basis of a statistic technique such as a second order polynomial or an artificial neural network, and performing optimization on the basis of the approximation model [9]. Shortening a calibration term is possible by greatly reducing the number of control parameters subjected to evaluation using a real engine. Many similar cases have been reported in other research papers [11,12]. However, it is difficult to reconstruct the approximation model whenever the

engine specifications are changed. It is also necessary to repeat model selection and design of experiments whenever controllable parameters increase.

2-2-3. Calibration of Experimental Base

This is a method of directly applying an optimization technique by installing a real machine in a part of simulation. Due to recent development in measurement control technology, use of such an experimental environment has been realized. Since a real machine is directly optimized, it is not necessary to construct a detailed physical model or an approximate statistic model. However, the problems arise that it is necessary to perform of having to perform measurements in real time arises and uncertainties such as, dynamics and observation noise of a sensor have to be included in evaluated values. Kaji and Kita proposed an approach in which MOGA is directly applied to a real machine as an optimization algorithm [6,7]. Through engine experiments, they succeeded in obtaining Pareto approximation set within a favorable optimization time.

In this paper, by employing the approach of experimental base described in 2-2-3, a set of diesel engine control parameters having trade-off relationship is collectively obtained.

2-3. ACCELERATION OF MULTI-OBJECTIVE GENETIC ALGORITHM BASED ON FITNESS ESTIMATION

Contrary to the simulation, the output of a real engine includes uncertainties such the observation noise of sensors and fluctuation caused by changing control parameters. It is commonly known that the optimization performance of the conventional MOGA deteriorates in environments of uncertainties. Additionally, MOGA requires a large number of evaluations, significantly increasing the time required for optimization.

To solve these problems simultaneously, a technique for accelerating a genetic algorithm by using approximation model has been proposed [7]. The approximation model is generated from the fitness and individuals already evaluated before, and it is used for noise filtering and fitness prediction. A conceptual diagram of the acceleration technique is shown in Fig. 2-2. Since the evaluation time required for an approximation model is negligibly smaller than that of a real problem, it is possible to reduce the number of practical evaluation. In addition, a large number of studies, which are mainly simulations having a long evaluation time per one trial such as computational fluid dynamics (CFD), have been reported.

Pre-selection is an acceleration technique, which is previously evaluating a lot of offspring individuals generated by using an approximation model and effectively performing optimization by evaluating only favorable individuals in a real environment. A conceptual diagram of pre-selection is shown in Fig. 2-3.

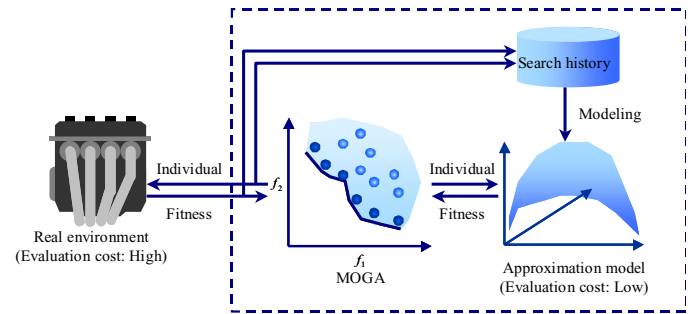


Fig. 2-2 An acceleration method using fitness estimation

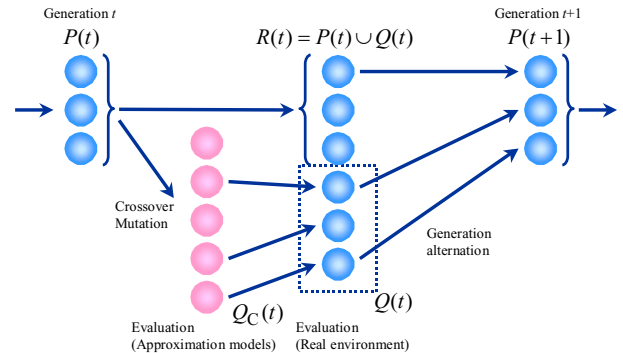


Fig. 2-3 Conceptual diagram of the Pre-selection algorithm

Although several pre-selection methods for MOGA have been proposed, Kaji and Kita have proposed a pre-selection algorithm appropriate for the optimization of an engine taking observation noise of demonstration into account.

The pre-selection algorithm is as follows.

Step 1. Evaluate all fitness vector $\mathbf{f}(\mathbf{x})$ in the initial population $P(0)$, $t=0$ in a real environment, and preserve individuals and their fitness vectors in search history set H .

Step 2. Generate a candidate offspring population $Q_c(t)$ from the achieved population $P(t)$ by applying selection, crossover and mutation operators.

Step 3. Calculate estimated value vectors $\hat{\mathbf{f}}(\mathbf{x})$ of $R_c(t) = P(t) \cup Q_c(t)$ by using the approximation model constructed by use of H .

Step 4. Assign the rank of the $R_c(t)$ based on the $\hat{\mathbf{f}}(\mathbf{x})$.

Step 5. Add a candidate offspring, which becomes a non-dominated individual to $P(t)$, and calculate its crowding distance (This operation is applied for all the non-dominated candidate offspring.).

Step 6. Select the evaluated offspring population $Q(t)$ from the q non-dominated candidate offspring assigned with good crowding distance.

Step 7. Evaluate offspring of $Q(t)$ in the real environment, and preserve the offspring together with the fitness vector in H .

Step 8. Assign the rank and the crowding distance of $R(t) = P(t) \cup Q(t)$ based on $\hat{f}(x)$ and select high-ranked $|P|$ individuals of $R(t)$ as next generation.

Step 9. If the termination condition is satisfied, finish this procedure; otherwise, set $t := t + 1$ and return to Step 2.

Here, t is the generation number, and q is the size of evaluated offspring population $Q(t)$. Until when the number of individuals preserved in the H reaches the number required for constructing an approximation model, evaluation is performed only in a real environment. In this paper, NSGA-II [3] known as a high precision MOGA is employed along with a locally weighted regression (LWR) [1] as the approximation modeling technique is employed. A crowding distance proposed by Deb et al. [3] is also employed as the crowding distance in the step 8. Note that the pre-selection proposed by Kaji and Kita was for unconstrained MOP, but in this paper, the pre-selection has been improved so as to be able to treat constrained MOP.

3. OPTIMIZATION EXPERIMENT OF THREE-STAGE INJECTION

To verify effectiveness of the proposed optimization technique, an experiment using a real diesel engine was performed. In this chapter, an example of a three-stage injection optimization in a constant drive will be introduced. Generally, due to multistage injection of diesel engine, it is possible to appropriately adjust a combustion state in a cylinder, and it is also possible to suppress exhaust and reduce noise. However, when the multistage injection is applied, the number of control parameters which ought to be set up increases, thus making it more difficult to find an optimal combination.

3-1. EXPERIMENTAL SETTING

Table 3-1 outlines principal specifications of the engine used in this experiment. Fig. 3-1 is a schematic diagram illustrating the engine system. The engine is a direct-injection diesel engine, in which a common rail is employed in a fuel injection mechanism and solenoid injector is used. Also, the engine has a variable vane turbo and an EGR system.

Table 3-2 shows the experimental condition. In this example, the optimization of the three-stage injection was set as a multi-objective optimization problem having 3 objectives and 7 variables. The detailed settings are given as follows.

Table 3-1 Engine specifications

Engine type	Parallel 4 cylinder, DI DieselSOHC 8 valve
Displacement	1.4 L
Bore x Stroke	73 mm x 81 mm
Fuel injection	Common rail system Solenoid injector
Compression ratio	18

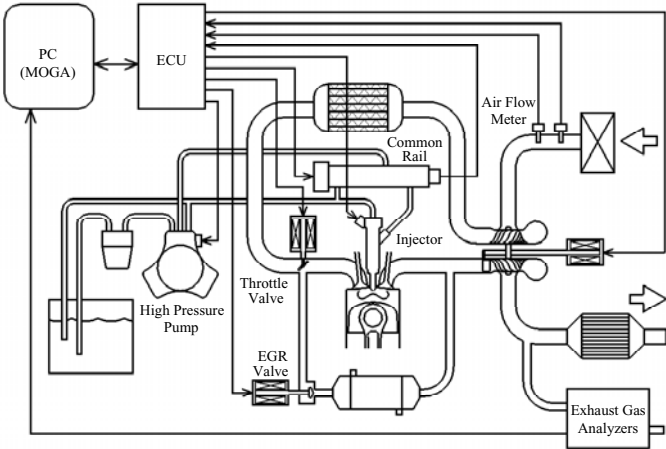


Fig. 3-1 Engine system

Table 3-2 Experimental condition of multi-injection

Engine speed	1200 rpm
Torque	46 Nm
Coolant temperature	80 degree C

Objective Functions (Measured Values): minimization of NOx, minimization of SOF, and minimization of SOOT.

Decision Variables (Control Parameters): Main-Injection(MI) Timing, Pre-injection(Pre)-MI Interval, Pre Quantity, Pilot-injection(Pil)-Pre Interval, Pil Quantity, Fuel Pressure, and Fresh Air Mass.

NOx, SOF and SOOT are measured fast and continuously by exhaust gas analyzers, HORIBA MEXA-1600DEGR and HORIBA MEXA-1230PM.

The MI Timing is the injector energization starting timing for main injection as viewed from the top dead center (TDC) in an advanced direction. The Pre-MI Interval is the interval between energization starting timings of the main injection and pre-injection. The Pre Quantity is the fuel injection quantity of the pre-injection. The Pil-Pre Interval is an interval between energization start timings of the pre-injection and pilot injection. The Pil Quantity is a fuel injection quantity of the pilot injection. The Fuel Pressure is the fuel pressure of the