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MULTI-OBJECTIVE OPTIMAL DESIGN OF AUTOMOTIVE ENGINE USING GENETIC ALGORITHM

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ABSTRACT

A genetic algorithm based optimization method is proposed for a multi-objective design problem of an automotive engine, that includes several difficulties in practical engineering optimization problems. While various optimization techniques have been applied to engineering design problems, a class of realistic engineering design problems face on a mixture of different optimization difficulties, such as the rugged nature of system response, the numbers of design variables and objectives, etc. In order to overcome such a situation, this paper proposes a genetic algorithm based multi-objective optimization method, that introduces Pareto-optimality based fitness function, similarity based selection and direct real number crossover. This optimization method is also applied to the design problem of an automotive engine with the design criteria on a total power train. The computational examples show the ability of the proposed method for finding a relevant set of Pareto optima.

1 INTRODUCTION

A typical configuration of automotive power trains is composed of an engine, a torque converter, a gear train and a final gear, and it is a main subsystem of an automobile that determines the product characteristics. Especially, a gasoline internal-combustion engine is a most important subsystem for the aspects of fuel consumption, acceleration performance, maximum speed, etc. While the engineering and marketing circumstances justify the application of design optimization through mathematical means to such an engine system, there are many factors that do not make such applications so easy. For instance, the physical phenomenon includes fuel combustion in engine chambers, coupled air oscillations in intake and outlet pipes and so forth, and it is also necessary to coordinate with nonlinearity caused by interactions with other parts of a power train such as shift changing. All of these factors bring trivial rugged nature in system response, and such characteristic prevents the traditional optimization techniques based on gradient information from finding optimal design solutions. For instance, the design optimization integrated with finite element analysis is getting to be introduced into practical use in the field of structural optimization, but the objective phenomenon of an engine is rather different from such problems in the aspects of the above issues. As for the optimization criteria, since automobiles are used by human passengers, it is

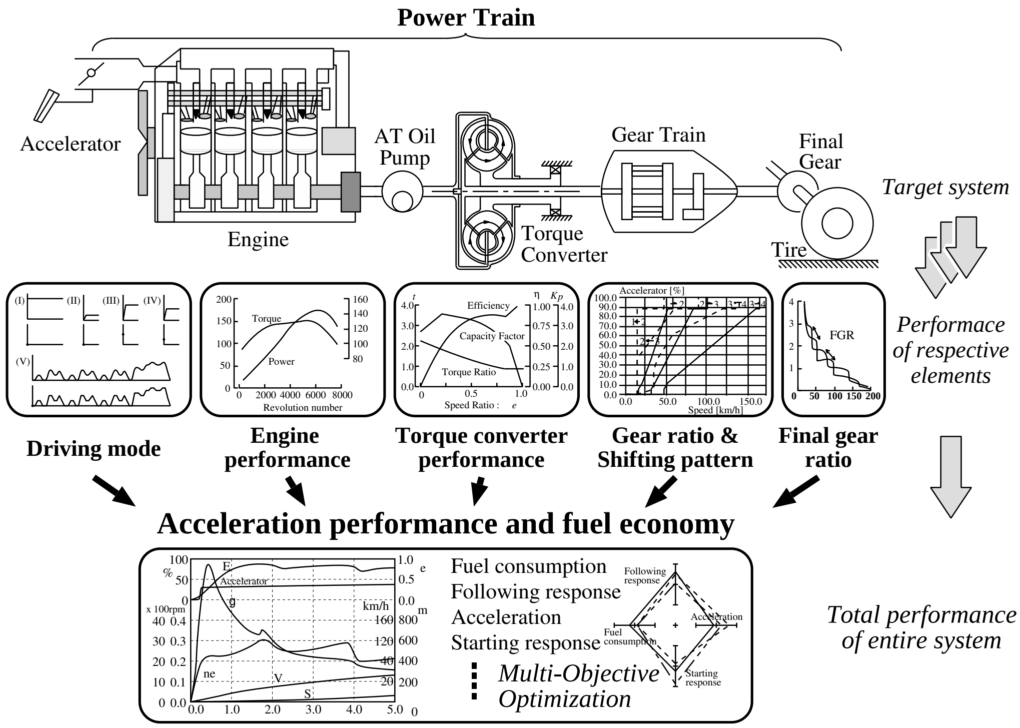


Figure 1. Power train design problem

also a difficult part of mathematical formulation, which leads the design problem to a typical situation of multi-objective optimization (Eschenauer *et al.*, 1990).

This paper develops a genetic algorithm based optimization method for the design problem of an automotive engine for total power train performance, which includes several optimization difficulties in practical mechanical engineering problems. After discussing the difficulties in optimal design of an engine and a power train, we review the advantages of genetic algorithms toward such a direction. Based on them, we propose an optimization method based on the framework of genetic algorithms (Goldberg, 1989), which can optimize real design variables and multi-objectives under rugged system constraints. We also develop an optimal design system for an automotive engine, where engine chamber shapes and intake and exhaust system parameters are taken as design variables, based on it. Some computational examples are shown in order to demonstrate its effectiveness and validity.

2 OPTIMIZATION OF AUTOMOTIVE ENGINE FOR POWER TRAIN

2.1 Automotive Power Train and Optimal Design

An automotive power train is composed of an engine, a torque converter, a gear train, a final gear, etc. (Fig. 1) and it is a key subsystem for automotive characteristics. The performance of a power train includes fuel economy and acceleration performance in various driving modes. Among those subsystems and these performance indexes, a gasoline internal-combustion engine is the main component that affects all aspects of automotive drivability, economy, safety and so forth. Thus, the optimization of an engine and its coordination with other components are essential for optimal design of not only a power train but also an automobile. Under the up-to-date engine technology, various subsidiary components and adaptive digital control functions are successfully introduced to enhance engine performance. However, system-level optimization for fundamental issues related to principal particulars should be considerably important for achieving totally optimal design as well, and systematic optimization is more promising for total system performance, if the simulation model for physical phenomena of the target system is available in a reasonable level.

2.2 Compromise between Analysis Accuracy and Global Synthesis

Since an engine system includes combustion chamber, intake pipe, exhaust pipe, etc., its total physical phenomenon is a complicated time-varying oscillation caused by mass transfer, shock wave, combustion, heat transfer and so forth. After the progress in computational mechanics and computation power, some parts of phenomena can be individually simulated in high-performance computers with appropriate accuracy for the final ascertainment of design results, while it takes tremendous computational cost in both hardware and time. On the other hands, such simulation codes are not enough and appropriate for usage in design optimizations due to not only expensive computational requirement but also the nature of the target system.

A typical conventional method for facilitating design or design optimization is to establish simple design formulas based on experiments or computational simulations. Since design is natively an inverse-problem, the simple proxy model for a exact model or a complicated computer code can bring a straightforward design rule that can immediately solve the design problem, if such a model is available. Even for a complicated system, if an entire system is quasi-independently decomposed into a set of subsystems, similar straightforward design must be possible. For instance, in the field of structural optimization, the sensitivity analysis based on finite elements has been successfully combined with optimization, since it underlying phenomenon is fairly simple and locally decomposable.

To the contrary, a power train is composed with several subsystems and their causes and effects are tightly connected though time-varying oscillation as aforementioned (Fig. 1). This implies that any simple proxy model cannot stand for the corresponding subsystem as a straightforward design rule because of complicated interactions among subsystems. Consequently, simplified proxy models that are representative for respective subsystems are indispensable, but they should be combined into a total simulation model for evaluation of total objectives. This may lead the various types of noise factors and rugged nature in real phenomenon and simulation model. Further, the computational expense for design optimization will be still much as compared with the situation where a well-natured set of proxy models can be used. Under these points, it is important that a set of computational models should compromise analysis accuracy and global information of the entire system, for the optimization of a power train system including an engine.

2.3 Subsystem Optimization toward Total Performance

Since physical phenomenon of a power train is tightly interconnected, the entire system model is necessary for optimization evaluation. As well, the original performance measures for a power train include various aspects of an automobile that also relates to operation modes of a system, that is, driving modes. This implies that the design problem is multi-objective.

As shown in Fig. 1, the performance indexes include stationary performance such as maximum speed of an automotive, acceleration performance under several situations, total fuel economy under a regulated situation such as 10.15-mode fuel consumption. The reason why these various indexes must be simultaneously considered is that the performance emerges from combinations of partial performance of respective components and individual operation modes that are assumed against typical driving situations. In the figure, the partial performance of a component corresponds to a specific area of each diagram shown for every subsystem. This kind of combinatorial performance requires the simultaneous evaluation of all aspects of the total performance of an entire power train system toward total design optimization. In the other words, while for instance maximum power and torque of an engine itself would be able to be taken as objectives for optimization, it is not enough since the compromise among performance indexes as well as among components is significant for a superior engine.

Under the viewpoint of developing a design optimization method, various performance indexes leads the formulation to be multi-objective. Furthermore, the combinatorial characteristics of respective indexes make the mathematical nature of the target system considerably ill-posed in the aspects of rugged system response and computationally expensive even after the introduction of simple proxy models that are appropriate for optimization calculation.

2.4 Design Optimization and Genetic Algorithms

As discussed in the above, the optimization problem of a power train where the principal particulars of an engine are taken as design variables belongs to a typical class of difficult optimization problems in real engineering applications. The difficulties discussed are itemized as follows:

- Rugged and noisy system response due to physical characteristics of the time-varying oscillation phenomenon, combinatorial factors related to driving modes, etc.
- Computation time for design evaluation caused by the evaluation of time-varying physical phenomenon and the overall system configuration.
- Multi-objectives of the entire power train system, which is necessary for total performance optimization of an entire system.

All of these must be counted as disadvantages for applying gradient-based optimization methods for this problem. As for rugged and noisy system response, local information represented with gradient is not accurate enough for gradient-based algorithms. Moreover, the nature of time-varying oscillation phenomenon in intake pipes and combustion chambers also leads the optimization situation to multi-peak characteristics. As for computation time, while multi-peak characteristic requires any global optimization mechanism, uniformly searching design solutions over full design space is too expensive, and any means to intensively search promising regions for saving computation time, i.e., the calculation number of simulation analysis. As for multi-objectives, several techniques for seeking a set of Pareto optimal solutions have been proposed, such as the weighting objective method, the constraint oriented transformation method, etc. (Eschenauer *et al.*, 1990). However, most of traditional methods for multi-objective optimization problems need iterative use of optimization calculations for a scalarized objective after the feedback from designer's preference.

Against the above disadvantages of gradient-based methods, genetic algorithm based optimization methods are promising for the design optimization the characteristics of which was discussed in the above. Goldberg (1989) denoted that the most important advantage of genetic algorithms as optimization methods is *robustness* against ill-natured property of the target problems. Indeed, genetic algorithms can be robust enough for noisy situation, since they do not use any gradient information of design space. They also have some ability for searching globally optimal solutions against multi-modality. Filho *et al.* (1994) categorized genetic algorithms into guided random search techniques as well as simulated annealing. This intention well corresponds to how to save computation times of design evaluation when some kinds of random search mechanisms are significantly necessary. As for multi-objective optimization, recently, several extensions of genetic algorithms for multi-objective optimization problems have been developed (Tamaki, 1996). The fundamental idea for multi-objective optimization is that a set of tentative solutions used in genetic algorithms can be finally converged into a set of Pareto optimal solutions.

3 GENETIC ALGORITHM BASED OPTIMIZATION METHOD

3.1 Fundamentals of GA Based Optimization Method

The genetic algorithm based optimization method for an automotive engine proposed in this paper is fundamentally followed to the simple GA, that consists of the iterations of selection, crossover and mutation, described by Goldberg (1989). Based on it, we introduce the following extensions for the specific class of design optimization problems, where the automotive engine design problem is included:

- Fitness function for the constrained multi-objective optimization problem and wide design space.
- Selection based on similarity between a pair of design solutions and elite preserve strategy with life span limit.
- Direct crossover of design variables represented as real numbers within side constraints.

Figure 2 illustrates the optimization situation through the genetic algorithm based optimization method with the above extensions. While the usual optimization converges the solution(s) toward a single optimal solution, the algorithm developed in this paper converges a set of solutions from randomly generated initial solutions to Pareto optimal solution surface as close as possible within the inferior limits of respective criteria. The following parts of this section describe the contents of the above extensions.

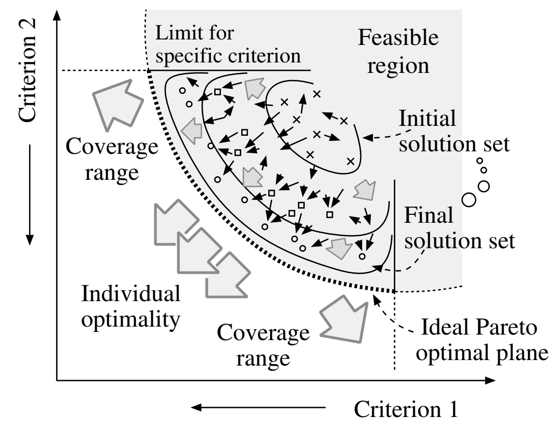


Figure 2. GA based multi-objective optimization

For the description of the proposing method, we denote a multi-objective optimization problem as follows with a design variable vector $\boldsymbol{x} = [x_1, x_2, \cdots, x_n]^T$.

$$\left.\begin{array}{rll} \text{minimize} & f_i(\boldsymbol{x}) & (i = 1,2,\cdots,r) \\ \text{subject to} & h_j(\boldsymbol{x}) = 0 & (j = 1,2,\cdots,p) \\ & g_k(\boldsymbol{x}) \leq 0 & (k = 1,2,\cdots,q) \\ & x_l^L \leq x_l \leq x_l^U & (l = 1,2,\cdots,n) \end{array}\right\} \quad (1)$$

This form considers the side constraints with lower bounds x_l^L and upper bounds x_l^U for design variables specifically.

3.2 Fitness Function for Constrained Multi-Objective Optimization Problem

A genetic algorithm optimizes an optimization problem by a measure of a fitness function. Although an objective function can be used as such a fitness function for simple problems with a single objective and without constraints, the target problem includes multiple objective functions and constraints. It is necessary to define a fitness function for this kind of problems. In this paper, we use a similar method to the conventional genetic algorithms for multi-objective optimization (Tamaki, 1996; Osyczka and Kundu, 1995). The detail procedure to calculate the fitness functions is described in the following:

First, a set of arranged objective functions, $f'_i(\boldsymbol{x})$, $(i = 1,2,\cdots,r)$ for respective objectives are defined with the

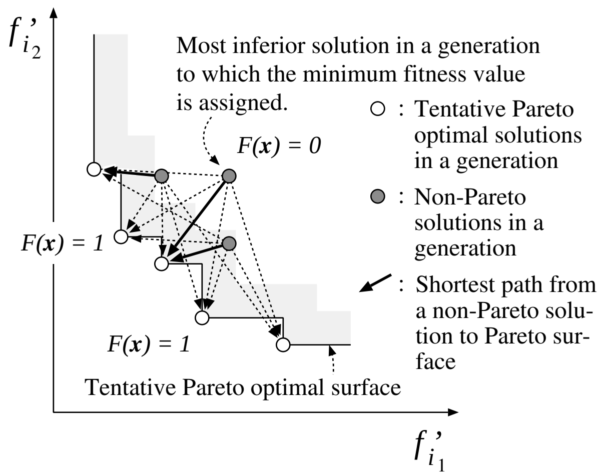


Figure 3. Fitness function for multiple objectives

following equation in order to eliminate constraints:

$$f'_i(\boldsymbol{x}) = f_i(\boldsymbol{x}) + p_E(t) \sum_{j=1}^{p} \left| h_j(\boldsymbol{x}) \right|^2 + p_I(t) \sum_{k=1}^{q} \{\max(g_k(\boldsymbol{x}), 0)\}^2 \quad (2)$$

Where, $p_E(t)$ and $p_I(t)$ are the penalty coefficient functions for equality and inequality constraints, respectively, that are grown as the generation t gains. The enlargement of $p_E(t)$ and $p_I(t)$ enables that the algorithm can explore the wide range of design space in early generations and that the algorithm can converge into feasible design space in the final generations. Equation (2) does not consider the side constraints, and they are managed in crossover operation.

Second, the algorithm eliminates the solutions such that any arranged objective function $f'_i(\boldsymbol{x})$ is larger than the upper bound f'^U_i from the following operations. The value of f'^U_i is assigned to each objective function beforehand in order to avoid meaningless solutions in the aspects of both objective inferiority and constraint violation in a set of Pareto optimal solutions.

Third, a set of arranged objective functions $f'_i(\boldsymbol{x})$, $(i = 1, 2, \cdots, r)$ is unified into the fitness function, $F(\boldsymbol{x})$, so as that $F(\boldsymbol{x}) = 1$ for every Pareto optimal solution in a generation and so as that other non-Pareto solution has a value corresponding to how far a solution is from a set of Pareto optimal solutions, as shown in Fig. 3 (Osyczka and Kundu, 1995). Among non-Pareto solutions, the solution that is the most far from any Pareto optimal solution with the measure of Euclidean norm in r-dimensional space defined with $\boldsymbol{f}'(\boldsymbol{x})$ has $F(\boldsymbol{x}) = 0$. The values for other non-Pareto solutions are assigned values that are linearly interpolated between $F(\boldsymbol{x}) = 0$ to $F(\boldsymbol{x}) = 1$ based on Euclidean norm from the solution to the closest Pareto optimal solution. This arranges the fitness functions so as that the solutions on the frontier of Pareto optimal surface have the best value and the other has inferior value according to how far it is from the frontier.

Fourth, 'σ-truncation' and 'linear scaling' (Goldberg, 1989) are applied to F_i as similar to conventional genetic algorithms in order to distribute fitness values to an appropriate range for selection. The resulting fitness functions are denoted as $F'(\boldsymbol{x}_i)$.

Finally, the sharing function (Goldberg, 1989; Horn *et al.*, 1994) is applied to the arranged fitness functions in order to adjust the fitness values based on the crowdedness of solutions, since the solutions should be scattered toward a set of Pareto optima. The procedure used for the sharing is as follows (Horn *et al.*, 1994):

$$F''(\boldsymbol{x}_i) = \frac{F'(\boldsymbol{x}_i)}{nc_i} \quad (3)$$

$$\begin{cases} nc_i = \sum_j sh\left(d\left(\boldsymbol{f}'(\boldsymbol{x}_i), \boldsymbol{f}'(\boldsymbol{x}_j)\right)\right) \\ sh(d) = \max\left(0,\ 1 - \dfrac{d}{\sigma_{share}}\right) \end{cases} \quad (4)$$

Where, nc_i is the niche count and σ_{share} is the niche size. The distance d is Euclidean norm in the objective function space, $\boldsymbol{f}'(\boldsymbol{x})$. $\sum_j$ means the sum across the solutions in a generation.

The niche size means the region of Pareto surface that the individual solution should stand for, and the niche count means the duplicated count of solutions that practically exist within such a region. The niche size σ_{share} can be determined by the following equation based on Fonseca and Fleming (1993)'s method :

$$N = \frac{\prod_{i=1}^{r}(f'_{i,max} - f'_{i,min} + 2\sigma_{share}) - \prod_{i=1}^{r}(f'_{i,max} - f'_{i,min})}{(2\sigma_{share})^r} \quad (5)$$

Where, $f'_{i,max}$ and $f'_{i,min}$ are the maximal and minimal values of $f'_i(\boldsymbol{x})$ in each generation, and N is the number of solutions in a generation.

3.3 Selection based on Similarity and Life Span

The fitness function, $F''(\boldsymbol{x}_i)$, described above ranks the solutions in a generation based on the Pareto optimality and solution distribution over the Pareto optimal surface. As shown in Fig. 2, the optimization method is seeking a set of solutions rather than a single solution. For this purpose, the diversity of solutions in a generation should be preserved as possible. On

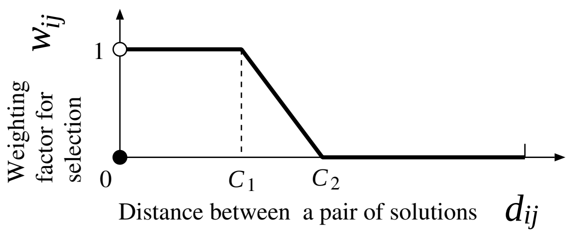


Figure 4. Mating probability for diversification

the other hand, mating a pair of solutions that have considerably different tendency each other for crossover fails into inferior search performance, since such pairs can generate new solutions that do not inherit the properties of both parents or that violate constraints. In order to avoid these situations and to find a superior Pareto optimal solution set, the algorithm limits the crossover between a pair of similar solutions.

Figure 4 shows how to calculate the selection probability for a pair of solutions, $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, not for a solution. First, the distance d_{ij} is calculated as Euclidean norm in the uniformed design variable space, where the minimum value is arranged to 0 and the maximum value is arranged to 1 for every design variable. Second, the weighting factor w_{ij} for selection probability of a pair of solutions F''_i and F''_j is determined by the relationships shown in the figure, where C_1 and C_2 are the coefficients for controlling the selection mechanism. Finally, selection is performed for all possible pairs of solutions based on the probability distribution calculated by $w_{ij}F''_iF''_j$ with the remainder-stochastic-sampling-without-replacement strategy (Goldberg, 1989). Here, $w_{ij} = 0$ for $d_{ij} = 0$ means that crossover between an identical solution is prohibited.

The 'elitist plan', where the best solution is preserved to the next generation without any genetic operations (Goldberg, 1989), is known as an effective strategy for superior optimization performance. Its modification for multi-objectives is the preservation of tentative Pareto optimal solutions, and it is also known as an effective strategy (Tamaki, 1996). However, in some cases, if all of Pareto optimal solutions are left without genetic operators generation by generation, preserved solutions may occupy most of solutions in a generation and it may result in less crossover operations and a kind of premature convergence. The algorithm introduces the life span limit for the elitist plan, where every Pareto optimal solutions preserved during a certain number of generations T are forcibly eliminated from the next generation. This is effective for increase the updates of solutions through crossover operations.

3.4 Design Variable Representation and Crossover

Genetic algorithms were originally designed for discrete design space that can be directly represented with genotype such as bit vectors or character sequences. However, the practical engineering optimization problems are usually represented with real numbers. Typically, bit vectors are used for real numbers, but such methods cannot guarantee the representation precision of design variables. The algorithm proposed in this paper uses the direct coding of real numbers (Furukawa and Yagawa, 1995). In the direct coding, a sequence of real design variables is used as genotype representation, that it is identical to phenotype representation, and interpolation is used for crossover operation. Further, the paper introduces a monotonously increasing threshold mapping between design variables and intermediate variables so as that the design variables can be constrained between the upper and lower bounds of side constraints x_i^L and x_i^U in Eq. (1).

The crossover operation from two design variable vectors $\boldsymbol{x}^\alpha$ and $\boldsymbol{x}^\beta$ in a parent generation to two ones $\boldsymbol{x}^\gamma$ and $\boldsymbol{x}^\delta$ in a child generation is performed with the following linear interpolation equation over the intermediate variables translated with the sigmoid function $Sig_i(\widehat{x}_i)$:

$$\begin{cases} x_i^\gamma = Sig_i\left(\mu_i \cdot Sig_i^{-1}\left(x_i^\alpha \right) + (1-\mu_i) \cdot Sig_i^{-1}\left(x_i^\beta \right) \right) \\ x_i^\delta = Sig_i\left((1-\mu_i) \cdot Sig_i^{-1}\left(x_i^\alpha \right) + \mu_i \cdot Sig_i^{-1}\left(x_i^\beta \right) \right) \end{cases} \tag{6}$$

$$Sig_i(\widehat{x}_i) = \frac{x_i^U + x_i^L \exp(-\widehat{x}_i)}{1+\exp(-\widehat{x}_i)} \tag{7}$$

Where, $x_i^{(\bullet)}$ is the i-th design variable of a solution $\boldsymbol{x}^{(\bullet)}$ in the generation, and μ_i is an interpolation coefficient that is randomly generated for each design variable under a normal distribution $N(0, \sigma^2)$. This crossover operation can be arranged by standard deviation σ and crossover probability P_c.

The above crossover can restrict the design variables within the side constraints because the range of $Sig_i(\widehat{x}_i)$ is from x_i^L to x_i^U and its domain is infinite. Since this crossover operation includes the nature of mutation in genetic algorithms, the algorithm does not introduce any mutation operation.

4 FORMULATION OF OPTIMIZATION PROBLEM OF AUTOMOTIVE ENGINE

As aforementioned, a gasoline internal-combustion engine is a key subsystem of an automotive power train. This section briefly shows the mathematical formulation of the engine design problem and the analysis model used for design evaluation in optimization calculation.

4.1 Optimization Problem Formulation

This paper considers the design problem of a four-cylinder gasoline engine, where a series of principal particulars that dominate the basic characteristics of the engine should be

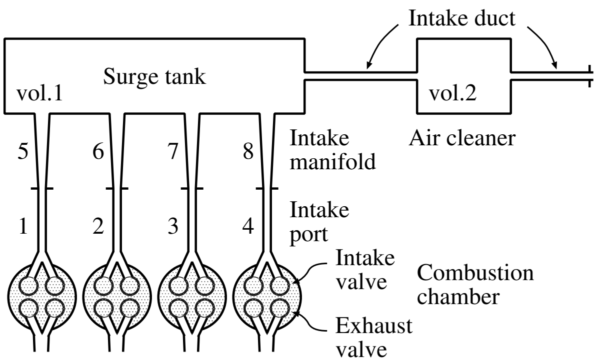


Figure 5. Schematic of Engine Model

optimally determined rather than all detail design variables. For this purpose, we use the engine model that consists of four combustion chambers and intake and exhaust systems composed of pipes and chambers (Fig. 5).

(1) Design variables Under the model shown in Fig. 5, we introduce eleven independent design variables. As for the combustion chambers, since four chambers have the same shape and since the displacement can be treated as a given condition, two variables, bore and compression ratio, are used as design variables. As for intake and exhaust valves, while the engine has 16 valves (four valves per cylinder), it can be assumed that all intake values share a set of variables and all exhaust values share another set of variables. Since each valve of intake or exhaust can be represented with three variables for open timing, close timing and maximum lift, and since the valve radius can be determined from the bore size, six variables are required for values in total. As for the intake system, it consists of two ducts, an air cleaner, a surge tank, four intake manifolds and intake ports for every chamber as shown in Fig. 5. Among them, four intake manifolds and intake ports are considered as the design target, and the other parts are assumed to be constant. All series of a manifold and a port for cylinders are same, the output side diameter of a manifold is equal to the input side diameter of a port, the output side diameter of a port is dependent to the intake valve diameter, and the input side diameter of a port is equal to its output side diameter. Thus, three variables, the port length, the manifold length and the taper ratio of a manifold, are counted as design variables for the intake system.

(2) Objective functions The design evaluation of an engine system is based on the total performance of an automotive power train as shown in Fig. 1. The objectives to be considered can be itemized as follows:

(i) Fuel consumption ··· a mileage, typically 10.15-mode mileage.
(ii) Acceleration performance ··· the time required until the driving speed is reached from 0 km/h to 100 km/h.
(iii) Starting response ··· an index showing the powerfulness at starting.
(iv) Follow-up response ··· an index showing the ability to follow another vehicle with keeping a certain distance.
(v) Blowup feeling ··· an index showing slipping situation in a torque converter.
(vi) Full acceleration characteristic ··· an index showing pitching motion on a vehicle at full acceleration.
(vii) Flat spot feeling ··· an index showing the smoothness during the increase of engine revolutions.
(viii) Stole revolution number ··· the revolution number of an engine at stole.

Among these, the items from (i) to (iv) are arranged to the objective functions to be minimized, and the others from (v) to (viii) are translated to the constraints where their grades should be superior to the minimum level. Thus, the problem is formulated as a multi-objective optimization problem with four objective functions.

The evaluation of items listed in the above requires full simulation of the entire power train system for drivability or fuel consumption under specific driving modes and time charts, respectively.

(3) Constraints In addition to the above four constraints on design criteria, the maximum lifts of intake and exhaust valves are constrained with the relationships with open and close timings of the corresponding valves, respectively. Further, the upper and lower bound constraints are introduced for every design variable as side constraints, that are necessary for preventing the algorithm from generating any meaningless solutions. Practically, these constraints are rather significant, since the computer simulation code for engine performance fails for unexpected design variables.

4.2 Simulation Model for Engine System

The automotive industries face demands on a wide variety of models, they have been seeking the handy and precise prediction methods of engine performance for rapid design cycles (e.g., Ohnishi *et al.*, 1988; Yamashita *et al.*, 1993). Such simulation and analysis models are appropriate for the computational optimization purpose, as well.

The fundamental configuration of the simulation model for an engine system was shown in Fig. 5, and it consists of chambers and pipe elements. The physical phenomenon is cyclic due to twice shaft rotation of a four-cycle engine. The interactions among four chambers that occurs through the connections via intake and exhaust systems are effectively utilized for performance enhancement in various ranges of power output and shaft revolution. The prerequisites for the simulation model are to evaluate the effects of valve timing, length of manifolds and ports, etc. The representative phenomena in an engine system are mass and heat flow in/though pipes and chambers and fuel combustion in the combustion chambers (Ohnishi *et al.*, 1988).

The mass flow and heat transfer in pipes can be modeled as a series of one-dimensional time-varying compressible flow equations for respective parts and their joint parts and heat transfer equations between flow and walls. The non-mesh method (Benson method) based on characteristic curves is used for numerically solving the flow equations. The phenomenon in combustion chambers is modeled with energy balance, mass balance and gas state equations, under the assumptions that their inside is uniform and that inflow gas is instantaneously mixed into a homogeneous state. The state transition in the chambers is predicted by solving the simultaneous equations. The boundary conditions at respective joint parts are modeled with energy and mass balance equations and the equation on adiabatic throttling, while the details are different among the pipe-and-chamber joints, pipe branch/merge joints and pipe joints between different diameters.

The above series of models can represent the chained phenomenon, and they include various coefficients on physical equations. While some of them can be based on theories, the other must be arranged based on past design data and experiments with real engines. The tuning of the latter kind of coefficients is essential for the use of the above models for not only analysis but also optimization calculation, and they are arranged by means of computer database and statistical techniques (Yamashita *et al.*, 1993).

By means of these simulation models, the power and torque chart for different throttle lift and shaft revolution numbers can be drawn by iterative calculations as the base for the total drivability and fuel consumption simulations.

4.3 Design Evaluation of Power Train

The configuration of an overall power train consists of an oil pump for automatic transmission, a torque converter, a gear train and a final gear in addition to an engine (Fig. 1). As similar to the engine, the torque converter has response characteristics against speed ratio, which is determined by stationary fluid phenomenon, and the map representing the characteristics can be generated by computer simulation with the pressure balance method (Numazawa *et al.*, 1983) in advance for the design optimization of an engine system. The shift pattern of gear train is another important design factor, but the map is also given beforehand, since it is not considered as the design variables.

The objective functions and constraints aforementioned are the measure under the particular driving situations, respectively. By using the performance maps for all subsystems, driving simulations for several modes are performed for calculating them. The modes are *full acceleration mode*, where the vehicle is driven with full throttle lift from zero initial speed for 30 seconds, for evaluating acceleration performance, full acceleration characteristic and stole revolution number, *starting response mode*, where the vehicle is driven with 25 percent throttle lift from zero initial speed for five seconds, for starting response and flat spot feeling, *follow-up response mode*, where the vehicle is driven with 75 percent throttle lift from 50 km/h initial speed for five seconds, for follow-up response, *tight feeling mode*, where the vehicle is driven with 50 percent throttle lift from 20 km/h initial speed for five seconds, for blowup feeling, and *fuel consumption mode* for evaluating 10.15-mode mileage, where the vehicle is driven under the regulated driving pattern.

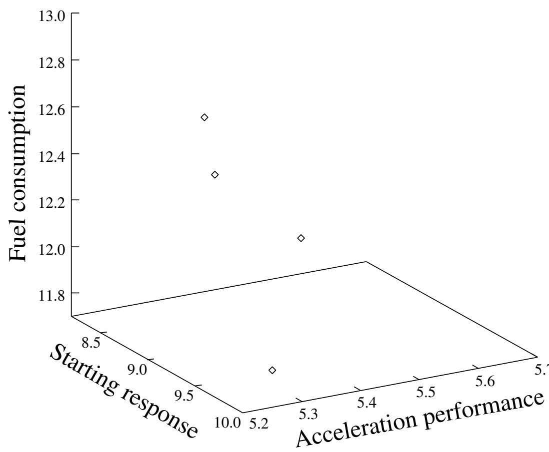
All the above five time-response simulation calculations are required for design evaluation in an engine design optimization. While the simulation model is reduced by introducing the handy and precise prediction methods for saving the computation time, an evaluation of a design still requires about seven minutes on Sun Ultra SPARC Station Model 140 (SPECint92 215.0, SPECfp92 303.0). Due to this computational expense, the optimization computation shown in the next section is implemented on a workstation cluster by parallelizing the design analysis computations based on concurrency in genetic algorithms.

5 COMPUTATIONAL EXAMPLES

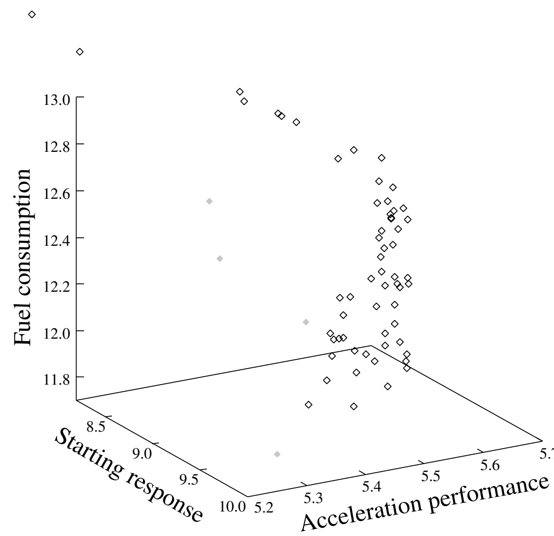
This section shows several computational examples of the optimization calculation. The default setting for optimizations shown in this section is as follows: The number of individuals is 100. The penalty coefficient function for inequality constraints is $p_I(t) = 100 \times 2^{\frac{t}{10}}$, while the formulation includes no equality constraint. The parameters for similarity-based selection are that C_1 is equal to the average distance across all possible pairs of solutions in design variable space minus its standard deviation, and C_2 is the average distance, in respective generations. The life span limit T is 10 generations. The crossover probability is $P_c = 1.0$. The standard deviation for crossover operation is $\sigma = 0.5$.

5.1 Optimization Results and Convergence History

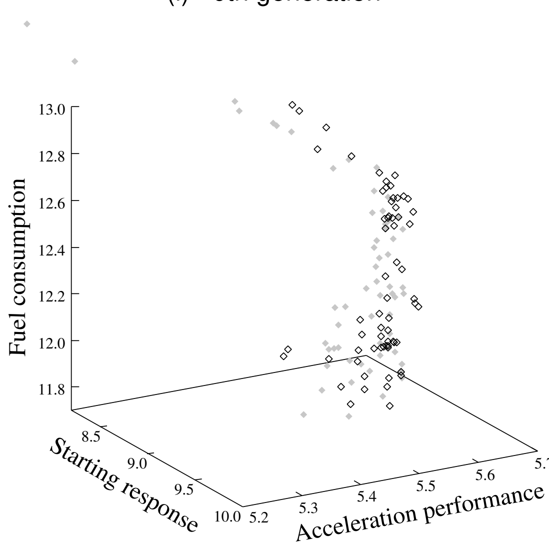
Figure 6 shows an optimization history in concerns with Pareto optimal solution distribution in each generation over the objective function space (non-Pareto solutions are eliminated in the figure). While there are four objective functions, the figure shows the space on fuel consumption, acceleration performance and starting response, where the maximum values are optimal. As shown in the figure, a set of solutions is converged into the



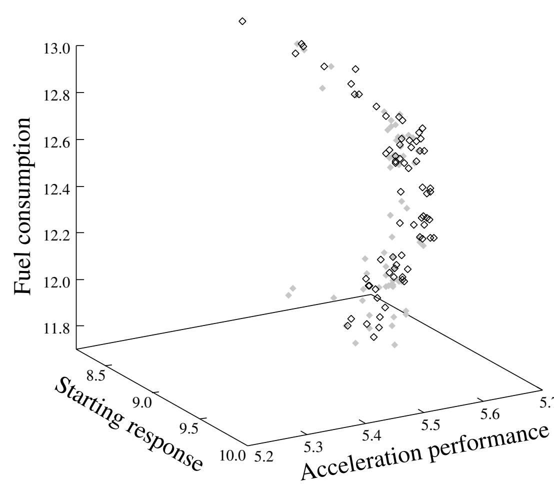
(i) 0th generation



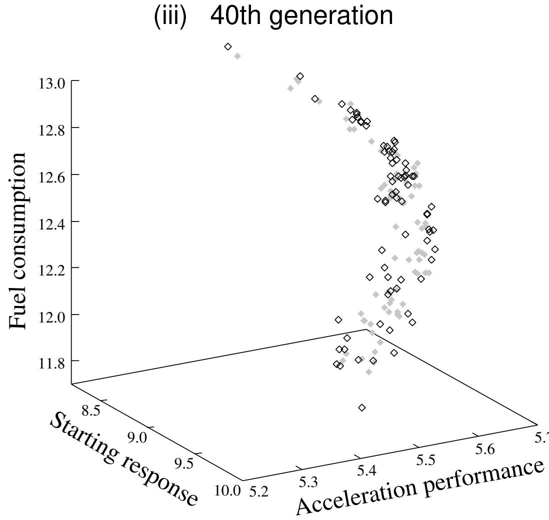
(ii) 20th generation



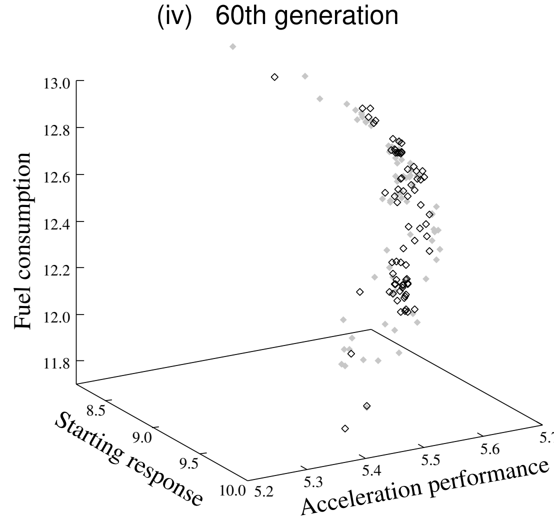
(iii) 40th generation



(iv) 60th generation



(v) 80th generation



(vi) 100th generation

Figure 6. Convergence history of Pareto optimal solutions

Pareto optimal solutions generation by generation, as the number of generations is gained. As for the respective objectives, all objectives are evenly much improved from the initial solutions that are randomly generated around an existing design. This optimization result shows the effectiveness of the application of the genetic algorithm based optimization method to the automotive engine toward the optimal performance of a power train.

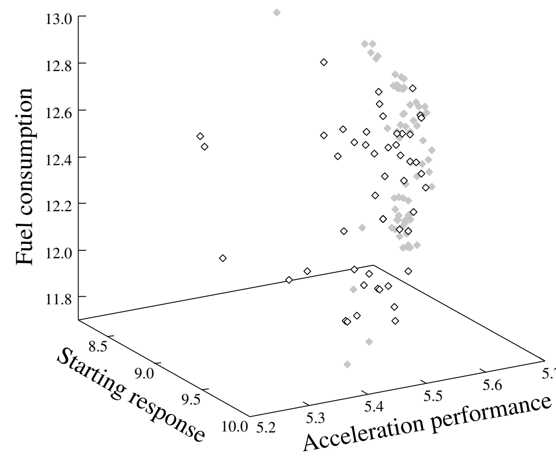
5.2 Effects of Diversification

Since the genetic algorithm based optimization method proposed here includes several extensions for diversification of individuals and so forth, their effects are discussed in the following.

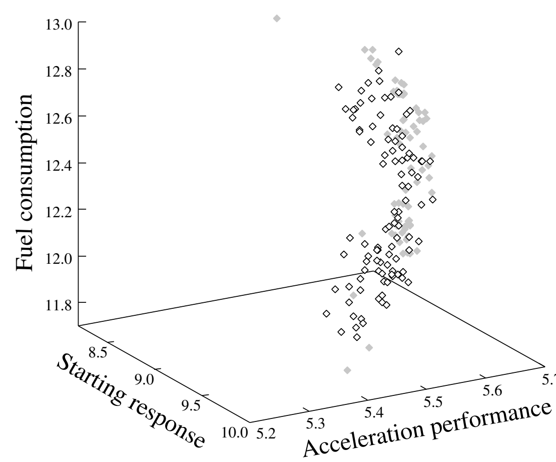
Figure 7 shows two optimization results with less effects in the 100th generation, where gray-scale plots are the Pareto optimal solutions gotten with all effects in the 100th generation. Figure 7 (i) is the result where similarity-based selection, i.e., mating probability arrangement with w_{ij} is not taken, and (ii) is the result where life span limit with T is eliminated (There is no progress after the 67th generation due to occupation of individuals by Pareto optima). As compared with Fig. 6 (vi), the result without similarity-based selection shown in Fig. 7 (i) includes less number of Pareto solutions and they are are fairly inferior in all objectives. As for the result without life span limit shown in Fig. 7 (ii), it is better than the result shown in Fig. 7 (i), but most solutions are behind the Pareto optimal solutions gotten with all effects.

The effects of life span limit can be more clearly recognized with how many elite solutions are preserved generation by generation, i.e., *Pareto ratio*. Figure 8 shows optimization history in concerns with Pareto ratio in every generation for the results of Fig. 7 (ii) and Fig. 6. The optimization history without life span limit, shown in Fig. 8 (i), that corresponds to Fig. 7 (ii) is that the population is occupied by elite solutions after the 67th generation, and it means that any new solutions are not generated after the generations. On the other hands, the optimization history with life span limit, shown in Fig. 8 (ii), that corresponds to Fig. 6 shows that it is effective for protecting such a situation.

Besides, we apply the successive quadratic programming (SQP) technique to this optimization problem as a gradient based optimization method under the weighted sum of four objective functions in order to confirm that the optimization problem is hard due to rugged nature of system response. The result shows that the SQP algorithm easily falls into local optimal solutions and that it cannot optimize the problem.



(i) Optimization without similarity-based selection (100th generation)

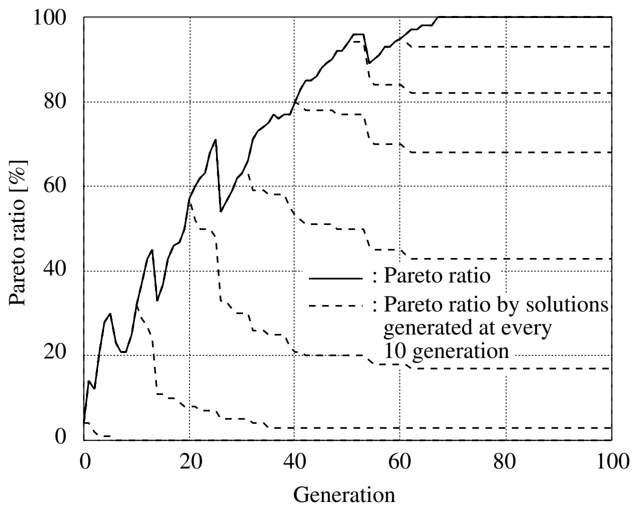


(ii) Optimization without solution life span limit (67th generation)

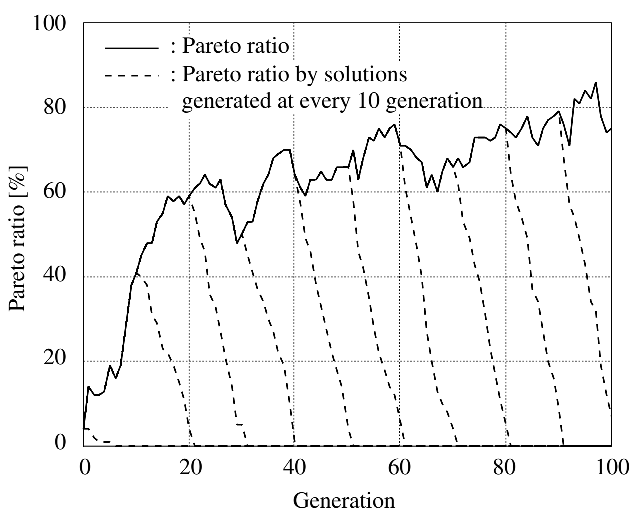
Figure 7. Comparison of optimization results

6 SUMMARY

This paper discussed the optimal design of an automotive engine in concerns with the total power train performance. After investigating the difficulties in design optimization for practical, complicated engineering systems, we proposed a genetic algorithm based optimization method for multi-objective constrained optimization problems with real design variables. The algorithm is based on the simple GA and includes several extensions for the class of optimization problems such as similarity based selection, life span limit, etc. Its application to the optimization problem of an automotive engine showed its optimization ability and the effects of the extensions introduced in this paper.



(i) Optimization without life span limit



(ii) Optimization with life span limit

Figure 8. History of Pareto ratio

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