

Multi-Objective Optimization of Diesel Engine Emissions and Fuel Economy using Genetic Algorithms and Phenomenological Model

T. Hiroyasu, M. Miki, J. Kamiura, S. Watanabe
Doshisha University

H. Hiroyasu
Kinki University

Copyright © 2002 Society of Automotive Engineers, Inc.

ABSTRACT

In this paper, the simulation of the multi-objective optimization problem of a diesel engine is performed using the phenomenological model of a diesel engine and the genetic algorithm. The target purpose functions are Specific fuel consumption, NO_x, and Soot. The design variable is a shape of injection rate. In this research, we emphasize the following three topics by applying the optimization techniques to an emission problem of a diesel engine. Firstly, the multiple injections control the objectives. Secondly, the multi-objective optimization is very useful in an emission problem. Finally, the phenomenological model has a great advantage for optimization. The developed system is illustrated with the simulation examples.

INTRODUCTION

Because of the merit of the durability and fuel efficiency, a diesel engine is loaded on from small to large vehicles. However, with increasing environmental concerns and legislated emissions standards, current engine research is focused on simultaneous reduction Soot and NO_x during maintaining reasonable fuel economy. The combustion improvement especially can be achieved designing a good injection system and characteristics of spray combustion.

To develop a good injection system, a parameter search to determine the influence an organization performance and an exhaust performance should be performed. However, when this parameter search is executed experimentally, the huge expense and huge time are needed. For this reason, the optimization of parameters by simulation on a computer is very useful.

When the parameter is optimized by the simulation, the

minimization of the fuel efficiency, the amounts of the nitric oxide (NO_x), and the amounts of the soot have been interested in many engine designer[1, 2, 3]. Therefore, these NO_x, Soot and fuel efficient become objective functions in optimization problems. There are some studies that solve this optimization problem[4, 5, 6, 7]. However, these problems are treated as single objective problems.

Since there are trade-off relationships between the fuel efficiency, NO_x and Soot, it is natural to handle these problems as Multi-objective Optimization Problems (MOPs). In this research, the minimization of fuel efficient, the amounts of NO_x, and the amounts of Soot are simultaneously performed by using the concept of multiple-purpose optimization.

To perform optimization by simulations, an optimizer (it determines the next searching point) and an analyzer (it evaluates the searching point) are needed.

The process of the combustion of the diesel engine is very complicated. At the same time, there are many requirement items for the models such as injection characteristics, spray characteristics, air-fuel mixing, ignition, heat release rate, heat losses, exhaust emissions, and so on. Thus, it is almost impossible to build the model of diesel combustion with the numerical expressions. On the other hand, several types of the models of diesel combustion have been proposed[8]. Those are roughly divided into three categories; thermodynamic model, phenomenological model and detailed multidimensional model. The thermodynamic model only predicts the heat release rate. In the phenomenological model, the prediction of equation which is derived by the fundamental experiment is used. The detailed multidimensional model predicts several items by solving differential equations with small time steps. In this paper, the HIDECS which is based on the phenomenological model is used since it does not need a

high calculation cost.

Many researchers are studying and developing several types of the optimization methods. Many algorithms that use the information about the gradient of the functions are developed and implemented into several commercial software[9, 10]. In this paper, the Genetic Algorithm (GA) is used for solving MOPs. The GA is an algorithm that simulates the heredity and evolution of creatures[11]. It is one of the multi-point search methods and probabilistic algorithm. It is said that it is easy to apply the GAs to several types of problems. It is also said that the GA is a robust algorithm for searching for an optimum solution even when the objective function has many local optimums. The GA especially is suitable for solving MOPs since the GA is a multi-point search.

In this paper, the simulation of a multi-objective optimization problem of a diesel engine is performed using the phenomenological model of a diesel engine and genetic algorithm. At first, the concept of multi-objective optimization problems is explained. Secondly, the GA and phenomenological model of diesel engine are illustrated briefly. In this paper, the extended GA that is developed by authors is applied. That is called the "Neighborhood Cultivation GA (NCGA)". The procedure of the NCGA is also mentioned. In the simulation, the target purpose functions are SFC, NOx, and Soot and the design variables are the shape of injection rate. Through this simulation, the effectiveness of the GAs for solving the diesel engine problem and the importance of phenomenological model in optimization problems are made clarified.

MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

Problems to find design variables \vec{x} that minimize or maximize k objective functions within the m constraints are called Multi-objective Optimization Problems (MOPs). MOPs can be formulated as follows[26, 27],

$$\begin{cases} \min \vec{f}(\vec{x}) & = (f_1(\vec{x}), f_2(\vec{x}), \dots, f_k(\vec{x}))^T \\ \text{s.t. } \vec{x} \in X & = \{\vec{x} \in R^n \\ & | g_j(\vec{x}) \leq 0 \ (j = 1, \dots, m) \end{cases} \quad (1)$$

Objective functions and constraints are consisted of design variables as follows,

$$\begin{cases} f_i(\vec{x}) = f_i(x_1, x_2, \dots, x_n), i = 1, \dots, k \\ g_j(\vec{x}) = g_j(x_1, x_2, \dots, x_n), j = 1, \dots, m \end{cases} \quad (2)$$

When the objective functions are in the trade-off relationship, it is difficult to minimize or maximize all objective functions at the same time. Therefore, the concept of the Pareto optimum Solution should be introduced in this case. **Definition (Dominant):** $\vec{x}_1, \vec{x}_2 \in R^n$.

When $f_i(\vec{x}_1) \leq f_i(\vec{x}_2)$ ($\forall i = 1, \dots, k$) and $f_i(\vec{x}_1) < f_i(\vec{x}_2)$ ($\exists i = 1, \dots, k$), \vec{x}_1 dominates \vec{x}_2 .

When \vec{x}_1 dominates \vec{x}_2 , \vec{x}_1 is the better solution than \vec{x}_2 . Therefore, it is a good way to select non-dominant solutions.

Definition (Pareto optimum solutions): $\vec{x}_0 \in R^n$.

- There is no solution $\vec{x} \in R^n$ that dominates \vec{x}_0 , \vec{x}_0 is a (strong) Pareto optimum solution.
- There is no solution $\vec{x}^* \in R^n$ that satisfies $f_i(\vec{x}^*) < f_i(\vec{x}_0)$ ($\forall i = 1, \dots, k$), \vec{x}_0 is a weak Pareto optimum solution.

Usually, there is not only one Pareto optimum solution but plural solutions in MOPs. In Figure1, the concept of the Pareto optimum solutions are illustrated in the case of two objectives.

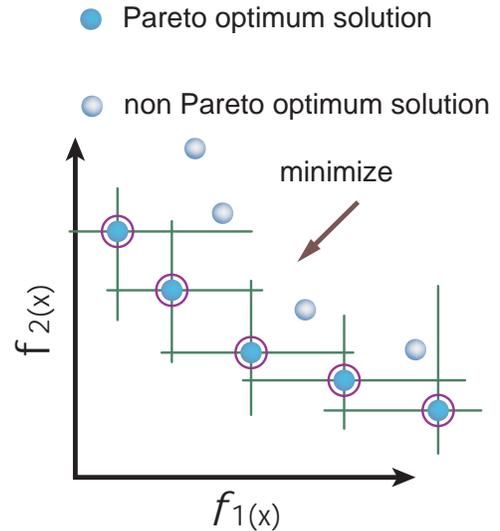


Figure 1: The Pareto optimum solutions

In this figure, the line of the Pareto optimum solution is called a Pareto front. In MOPs, to find Pareto optimum solutions is one of the goals.

GENETIC ALGORITHMS FOR MOPS

The Genetic Algorithm is an algorithm that simulates creatures' heredity and evolution[11]. Since the GA is one of the multi point search methods, an optimum solution can be determined even when the landscape of the objective function is multi modal. Moreover, the GA can be applied to problems whose search space is discrete. Therefore, the GA is one of very powerful optimization tools and is very easy to use. In multi-objective optimization, GA can find a Pareto optimum set with one trial because the GA is a multi point search. As a result, the GA is a very effective tool especially in multi-objective optimization problems. Thus, there are many researchers who are working on the multi-objective GA and there are many algorithms of the multi-objective GA[12, 13]. These algorithms of the multi-objective GA are roughly divided into two categories; those are the algorithms that treat the Pareto optimum solution implicitly or explicitly. The most of the latest methods treat the Pareto optimum solution explicitly. Typical

algorithms are SPEA2[14] and NSGA-II[15].

In the GAs, a searching point is called an individual. Usually, an individual is expressed as a bit string. There are many ways to convert design variables to bit strings. When the design variables are real numbers, the easiest way is to code the real number into the binary number. The following steps are the basic procedure of the GAs for MOPs.

Step 1: It supposes there are m individuals. This means there are m search points. These individuals are initialized. Since each individual is shown as a bit string, each bit is determined using the random number.

Step 2: Each individual has fitness value. In this step, the fitness value of each individual is determined. This operation is called "Evaluation". In MOPs, the Pareto ranking is often used for determining the fitness value[28]. The Pareto ranking is determined in the following procedure. For each solution, the number of the solution that are dominant to the focused solution is counted. The Pareto ranking is this number + 1. When the solution is non-dominant, the Pareto ranking becomes 1. The concept of the Pareto ranking is shown in 2. In this figure R denotes the Pareto ranking. The fitness value of each individual is a reciprocal number of the Pareto ranking.

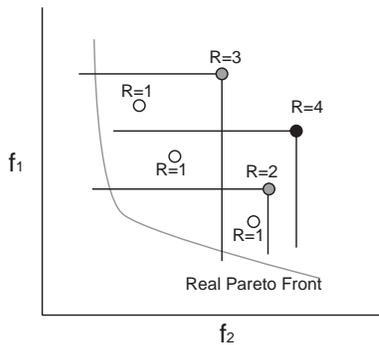


Figure 2: Pareto Ranking

Step 3: After the evaluation, with according to the fitness value, an individual is checked to remain for the next iteration. This checking is performed probabilistically. The individual whose evaluation value is big has a high possibility of remaining in the next iteration. There is a case where the individual who has high evaluation value may increase. On the other hand, the individual whose evaluation value is small may be disappeared. This operation is called "Selection". Usually, the roulette selection method is performed.

Step 4: New search point is created by operations of "crossover" and "mutation". Two individuals are chosen randomly. Those are called parents. The crossover point is determined randomly. Then the first part of parent 1 and the latter part of parent 2 are combined. Again, the latter part of parent 1 and the first part of parent 2 are combined. These are children and those are new search points. This operation is called "Crossover". In Figure 3,

the concept of crossover is shown.

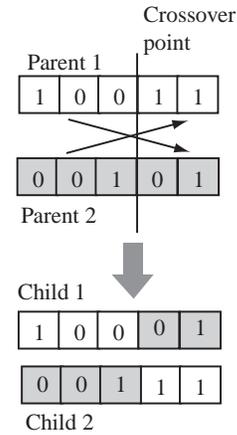


Figure 3: Crossover

In the operation of mutation, a certain bit of individual is chosen randomly. When this bit is equal 1, it is changed into 0. This operation also generates a new search point. In Figure 4, the concept of mutation is shown.

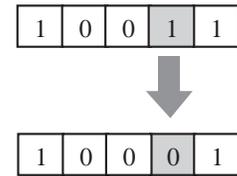


Figure 4: Mutation

Step 5: If the terminal condition is not satisfied, the routine is back to step 2. In GA, this one routine is often called "Generation". Usually, many generations are needed to find an optimum solution.

These steps are summarized in Figure 5.

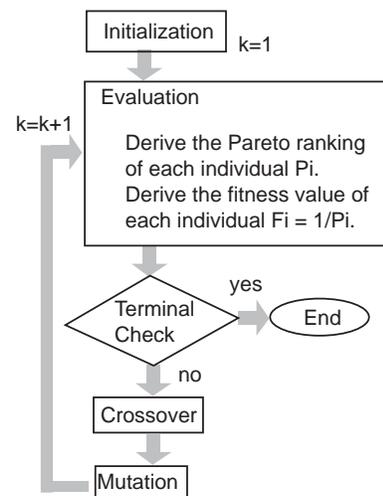


Figure 5: Flow of GA

NEIGHBORHOOD CULTIVATION GENETIC ALGORITHM (NCGA)

OVERALL In this paper, an extended GA that is called the Neighborhood Cultivation Genetic Algorithm (NCGA)

is used. The NCGA has the neighborhood crossover mechanism besides the mechanisms of SPEA2[14] and NSGA-II[15]. In the GAs, the exploration and exploitation are very important. By the exploration, an optimum solution can be found in a global area. By the exploitation, an optimum solution can be found around the elite solution. In the single object GA, the exploration is performed in the early stage of the search and the exploitation is performed in the latter stage. On the other hand, in the multi-objective GAs, both the exploration and exploitation should be performed during the search. Usually, the crossover operation helps both the exploration and exploitation. In the NCGA, the exploitation factor of the crossover is reinforced. In the crossover operation of the NCGA, a pair of the individuals for crossover is not chosen randomly, but individuals who are close each other are chosen. Because of this operation, the child individuals who are generated after the crossover may be close to the parent individuals. Therefore, the precise exploitation is expected.

THE FLOW OF NCGA The following steps are the overall flow of the NCGA where

P_t : search population at generation t

A_t : archive at generation t .

Step 1: Initialization: Generate an initial population P_0 . Population size is N . Set $t = 0$. Calculate fitness values of initial individuals in P_0 . Copy P_0 into A_0 . Archive size is also N .

Step 2: Start new generation: Set $t = t + 1$.

Step 3: Generate new search population: $P_t = A_{t-1}$.

Step 4: Sorting: Individuals of P_t are sorted with along to the values of focused objective. The focused objective is changed at every generation. For example, when there are three objectives, the first objective is focused in this step in the first generation. The third objective is focused in the third generation. Then the first objective is focused again in the fourth generation.

Step 5: Grouping: P_t is divided into groups which consist of two individuals. These two individuals are chosen from the top subsequently toward the bottom of the sorted individuals.

Step 6: Crossover and Mutation: In a group, the crossover and mutation operations are performed. From two parent individuals, two child individuals are generated. Here, parent individuals are eliminated.

Step 7: Evaluation: All of the objectives of individuals are derived. According to the values of objectives, the Pareto ranking of each individual is decided. Using the Pareto ranking, the fitness value of each individual is decided.

This operation is the same as the step 2 in the former section.

Step 8: Assembling: The all individuals are assembled into one group and this becomes new P_t .

Step 9: Renewing archives: Assemble P_t and A_{t-1} together. Then N individuals are chosen from $2N$ individuals. To reduce the number of individuals, the same operation of the SPEA2 (Environment Selection) is also performed.

Step 10: Termination: Check the terminal condition. If it is satisfied, the simulation is terminated. If it is not satisfied, the simulation returns to Step 2.

These steps are summarized as a schematic in Figure6.

In the NCGA, most of the genetic operations are performed in a group that is consisted of two individuals. That is why this algorithm is called "Neighborhood cultivation". This scheme is similar to the Minimum Generation Gap model (MGG)[16]. However, the concept of generation of the NCGA is the same as the simple GAs.

NUMERICAL EXAMPLE To demonstrate the searching ability of the NCGA, the NCGA is applied to the typical test function, KUR. The results are compared with those of the SPEA2[14] and NSGA-II[15]. KUR was used by Kursawa [17].

$$KUR : \begin{cases} \min & f_1 = \sum_{i=1}^n (-10 \exp(-0.2 \sqrt{x_i^2 + x_{i+1}^2})) \\ \min & f_2 = \sum_{i=1}^n (|x_i|^{0.8} + 5 \sin(x_i)^3) \\ s.t. & x_i \in [-5, 5], i = 1, \dots, n, n = 100 \end{cases} \quad (3)$$

It has a multi-modal function in one component and the pair-wise interactions among the variables in the other component. Since there are 100 design variables, it needs a high calculation cost to derive the solutions.

In the former studies, some methods used the real value coding and made good results[14]. In this paper, to discuss the effectiveness of the algorithm, the simple methods are applied for all the problems. Therefore, the bit coding is used in the experiments. Similarly, the one point crossover and bit flip are used for the crossover and mutation. The length of the chromosome is 20 bit per one design variable. Population size is 100 and the simulation is terminated when the generation is got over 250.

From Figures7 to 10, the derived Pareto solutions are shown. Figure10is the result of the NCGA but without the neighborhood crossover. In these figures, all the Pareto optimum solutions that are derived in 30 trials are figured

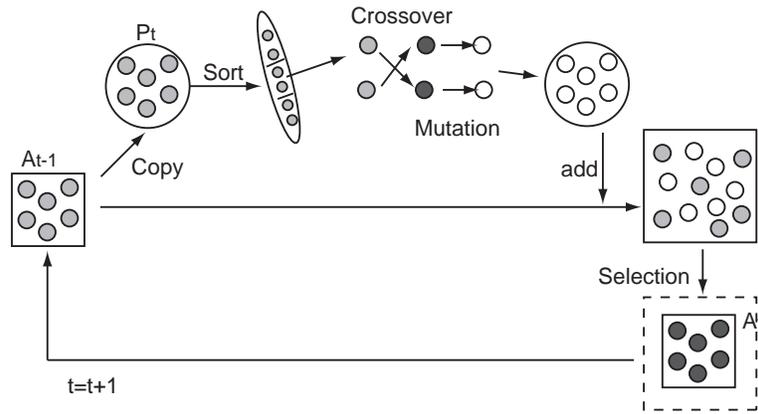


Figure 6: Flow of NCGA

out. There are several ways to compare the solutions[13]. One of them is to check the appearance of the derived solutions. Because this is the minimization problem, the solutions that are located in the left and bottom are better. At the same time, solutions should be spread instead of the concentration on one point. These two points can be ascertained by the appearance of the derived solutions. It is clear that the NCGA derived better solutions than the other methods. The solutions of the NCGA are also wider spread than those of the other methods. In this problem, the comparison between Figure7 and Figure10 shows that the mechanism of the neighborhood crossover acts effectively to derive the solutions. That is to say the neighborhood crossover is an operation to find the solutions that have the diversity and high accuracy.

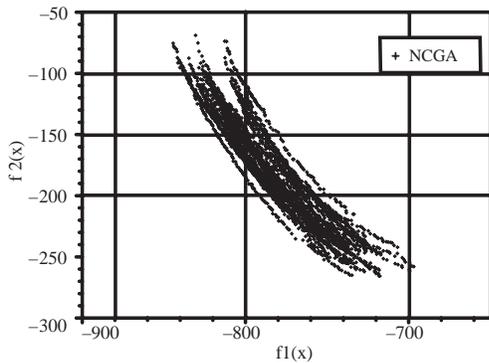


Figure 7: Results of KUR (NCGA)

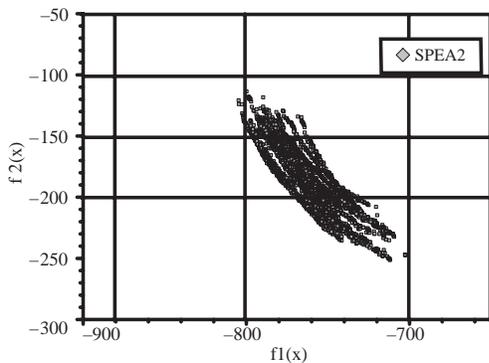


Figure 8: Results of KUR (SPEA2)

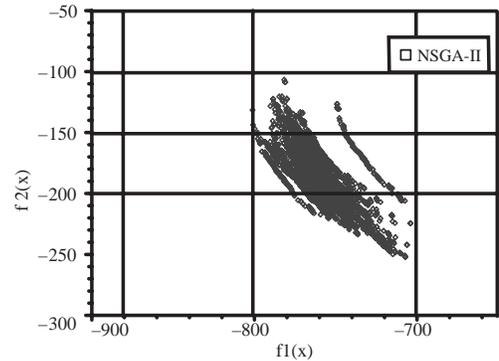


Figure 9: Results of KUR (NSGA-II)

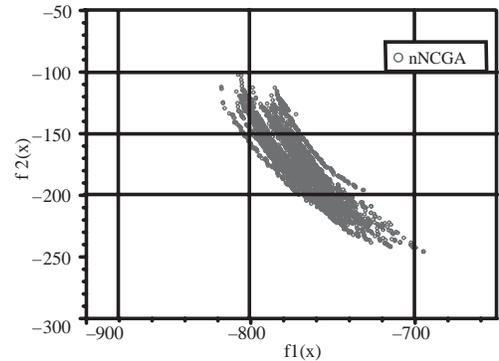


Figure 10: Results of KUR (NCGA without neighborhood crossover)

PHENOMENOLOGICAL MODEL AND HIDECS

In the work reported in this paper, the most sophisticated phenomenological spray-combustion model currently available, originally developed at the University of Hiroshima had previously demonstrated potential as a predictive tool for both performance and emissions in several types of the direct injection diesel engine. Recently, we call the HIDECS to this model code. A detailed discussion of the HIDECS spray-combustion model and some examples of its previous applications are given in Reference [18-25]. Therefore, only a brief description of the model is provided in this section.

The spray injected into the combustion chamber from the

injection nozzle is divided into many small packages of equal fuel mass as shown in Figure11. No intermixing among the packages is assumed. The spray characteristics are defined by the empirical equations of spray penetration. For example, the shaded regions shown in Figure11 are the fuel packages injected at the start of injection that constitute the spray tip during penetration. Air entrainment into a package is controlled by the conservation of momentum, that is, the amount of entrained air is proportional to the decrease in package velocity. The fuel, which is mixed with the air, begins to evaporate as drops, and ignition occurs after some ignition-delay period.

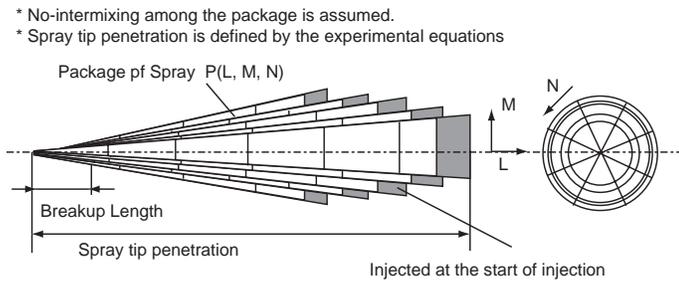


Figure 11: Schematic of the package distribution

The air-fuel mixing processes within each package are illustrated in Figure12. Each package, immediately after the injection, involves many fine drops and a small amount of air. As a package moves away from the nozzle, air entrains into the package and the fuel drops evaporate. Thus, the package consists of liquid drops, vaporized fuel, and air. After a short period of time following injection, ignition occurs in the gaseous mixture, resulting in the rapid expansion of the package. Therefore, more fuel drops evaporate, and more fresh air entrains into the package. The vaporized fuel mixes with fresh air and combustion products as the spray continues to burn.

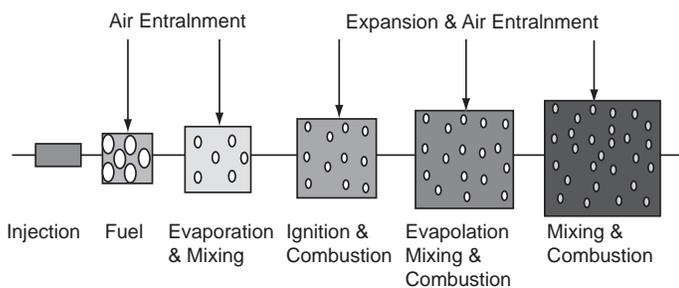


Figure 12: Schematic of the mass system during combustion

Figure13 shows two possible combustion processes for each package. Case A is called evaporation-rate-controlled combustion, while Case B is called the entrainment-rate-controlled combustion. When ignition occurs, the combustion mixture that is prepared before ignition burns in a small increment of time. The fuel-burning rate in each package is calculated by assuming stoichiometric combustion. When there is enough air in the package to burn all of the vaporized fuel, there are combustion products, liquid fuel and fresh air remaining in the pack-

age after combustion (Case A in Figure13). In the next small increment of time, more fuel drops evaporate and fresher air entrains into the package. At this point, if the amount of air in the package is enough to burn all the vaporized fuel at the stoichiometric condition, the same combustion process (Case A) is repeated. If the amount of air is not enough to burn all the vaporized fuel, however, the fuel-burning rate is dictated by the amount of air present (Case B in Figure13). Therefore, the combustion processes in each package always proceed under one of the conditions shown in Figure13.

The heat release rate in the combustion chamber is calculated by summing the heat release of each package. The cylinder pressure and bulk-gas temperature in the cylinder are then calculated. Since the time history of temperature, vaporized fuel, air and combustion products in each package are known, the equilibrium concentrations of gas composition in each package can be calculated. The concentration of NOx is calculated by using the extended Zeldovich mechanism. The formation of soot is calculated by assuming first-order reaction of fuel vapor. The oxidation of carbon is calculated by assuming second-order reaction between carbon and oxygen.

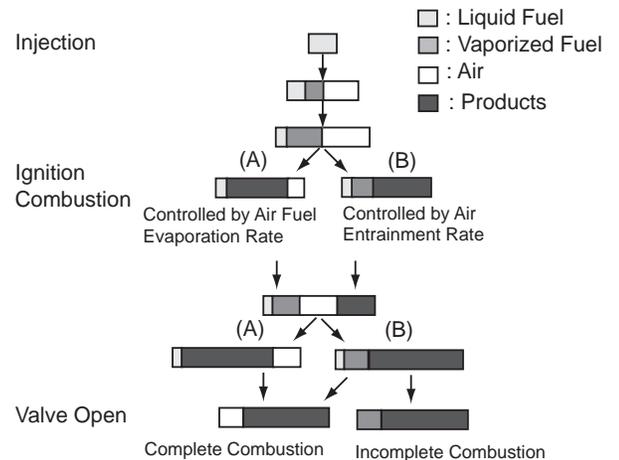


Figure 13: Schematic of the package combustion process

HIDECS/NCGA SIMULATION EXAMPLE

OVERALL The HIDECS can deal with several types of diesel engines. In this simulation, the specification of the target diesel engine is summarized in Table1.

In this engine used in a simulation, the fuel injection starts at -5.0 ATDC degree and the injection is lasted for 18 degrees. The total amount of fuel injection is constant, but the shape of the fuel injection can be changed. This shape of the fuel injection is a design variable in this simulation.

The HIDECS can derive several characteristics of engines. In this simulation, SFC, the amount of NOx and the amount of Soot are focused.

Table 1: Specification of the target diesel engine

Bore	102 mm
Stroke	105 mm
Compression Ratio	17
Engine Speed	1800 rpm
Swirl Ratio	1.0
Nozzle Hole Diameter	0.2 mm
Nozzle Hole Number	4
hline Injected Fuel Volume	40.0 mg/st
Injection Timing	-5.0 ATDC deg.
Injection Duration	18 deg.

SYSTEM CONSTRUCTION The overview of the system is written in Figure14.

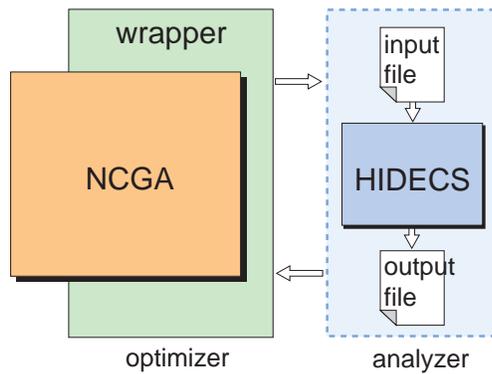


Figure 14: System construction

In Figure14, the NCGA is used as an optimizer and the HIDECS is used as an analyzer. Between the optimizer and analyzer, text files are exchanged. Therefore, basically several types of the GAs and analyzers can be used in this system.

In this simulation, the amount of SFC, the amount of NOx and the amount of Soot are the objectives. The split injection rate-shape is a design variable. In this simulation, the total amount of fuel injection, the start of the injection and the duration of the injection are fixed. On the other hand, the injection rate is a variable. The shape of the injection rate can be defined as follows. The duration of the injection is divided into 6 blocks. Each block has its own width and height. When these widths and heights are determined, the shape of the injection rate is determined. Therefore, the NCGA decides these values.

In Figure15, the concept of coding method is summarized. There are 12 variables (6 blocks have their widths and heights). These are real values which are from 0.0 to 1.0. They are coded into 8 bits by gray coding. Because the amount of the fuel and the duration of injection are fixed, the total area of 6 blocks is also fixed.

GA PARAMETERS In this simulation, the following parameters are used. The length of the chromosome is 8 bit per one design variable. Therefore, the total length of the chromosome is 96. The population size is 100 and the

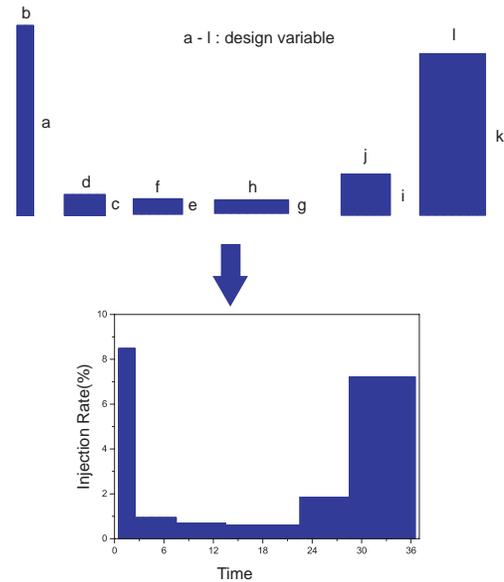


Figure 15: Coding method

number of sub population is 10. The crossover rate and mutation rate are 1.0 and 1/96 respectively. At the same time, migration rate and migration interval are 0.4 and 10 respectively. We use two point crossover and tournament selection. The simulation is terminated when the generation is over 200.

RESULTS In this section, the derived Pareto optimum solutions are described. The characteristics of the derived shape of injection rate are discussed briefly. The most important aspect of the multi-objective optimization problems is that the designers can find their design alternatives. The design alternatives are discussed using the derived Pareto solutions. The end of this section, the topic of calculation cost is mentioned.

Pareto-optimum solutions In Figure16, the derived Pareto solutions are plotted. In the figure, all the plotted solutions dominant to the other solutions that are derived during search. In Figures17, 18 and 19, the derived solutions are projected on SFC-NOx, SFC-Soot and NOx-Soot surface respectively.

From these figures, it is found that the Pareto solutions are derived.

In Figures20, 21 and 22, the solutions who have the best value of each objective function are illustrated.

In the solution who has the smallest value of SFC, the fuel injection pattern is characterized with the most fuel injected at the beginning of injection duration. In the solution who has the smallest value of NOx, the fuel is injected at two steps. In the solution who has the smallest value of smoke, the fuel is mostly injected in the middle of the injection period.

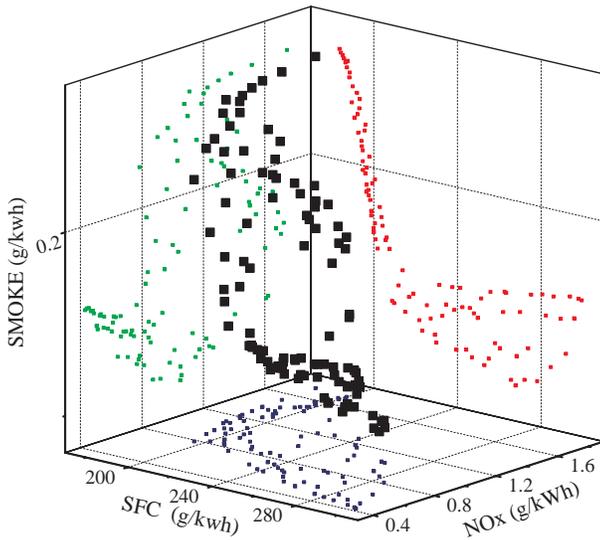


Figure 16: Derived Pareto solutions (SFC, NOx, Smoke))

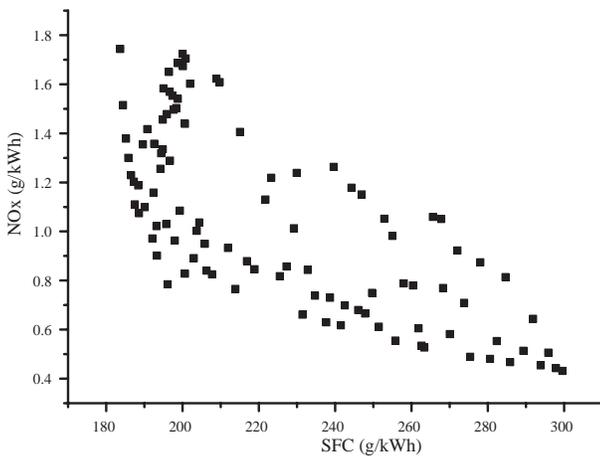


Figure 17: Derived Pareto solutions (SFC, NOx)

The early fuel injection gives the best solution of SFC (shown in Figure20). The early injection causes better fuel-air-mixing at the early stage of the combustion process, which results high maximum in-cylinder pressure and high engine output. In the pattern shown in Figure21, some of the fuel is injected at the beginning of injection and the rest of them at the end of injection. This double step injection, known as pilot injection, can reduce the NOx emission, because the medium in-cylinder pressure can be obtained to prevent the NOx formation. The optimum solution is in the agreement with the experimental studies on the pilot injection. It is very interesting to find out that the smallest smoke emission is obtained by injecting the most fuel at the middle of the injection period. This may be caused by the reduction of the incomplete fuel combustion in the combustion stroke. The small amount of fuel injected in the early stage evaporates and combusts. This operation may help the rest of fuel combust completely in a better environment.

From Figures16 to 22, it can also be found that there exists a conflict between economy and emissions control. There has to be a compromised fuel injection pattern to obtain the low emissions according to the increasing strict

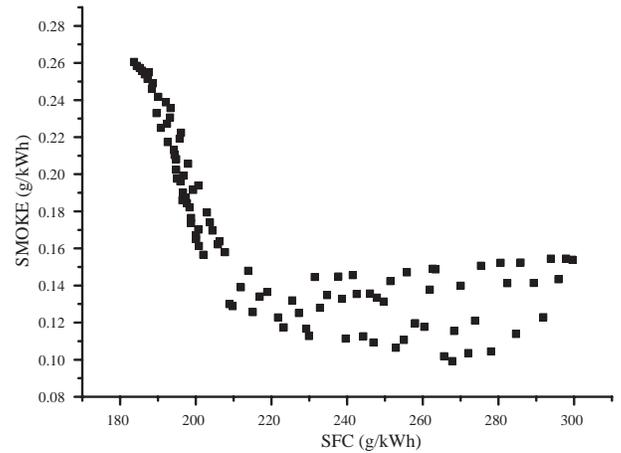


Figure 18: Derived Pareto solutions (SFC, Smoke)

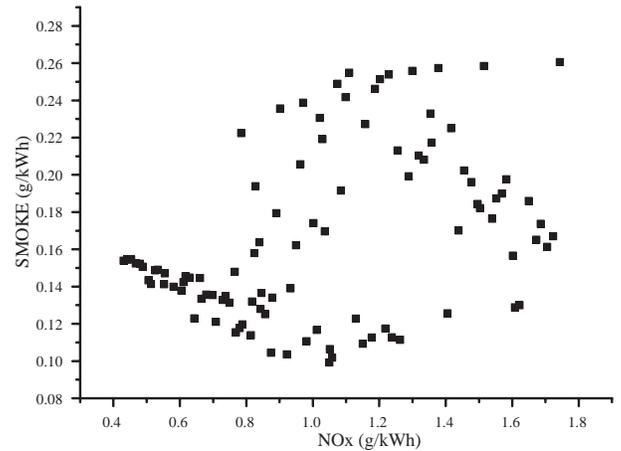


Figure 19: Derived Pareto solutions (NOx, Smoke)

regulations while keeping an acceptable SFC. It will be very costly to find such an injection pattern experimentally. Therefore, computation methods show the most advantage in model engine design. In the following session, more will be discussed how to use the HIDECS as a design tool with the aid of the NCGA.

Design alternative In Figure23, the Pareto optimum solutions are projected on the NOx and SFC surface. It is the same as Figure17. In this figure, we select the four design alternatives and they are plotted.

The selection method of design alternatives from the derived Pareto solutions is a hot topic in MOPs[13]. In this paper, the design alternatives are chosen in the following way. The candidate number one is the solution that has the best value of SFC. The candidate number two is the closest solution to the number one. The candidate number four is also the solution that has the best value of NOx.

The candidate number three is the divergence solution. Figure23 can be simplified and it is shown in Figure24. The change ratio of NOx with along to SFC is changed at the candidate 3. Therefore, the solutions can be classified into two groups those are shown in Figure24 as A and B. In A group, the change ratio is relatively big. Therefore,

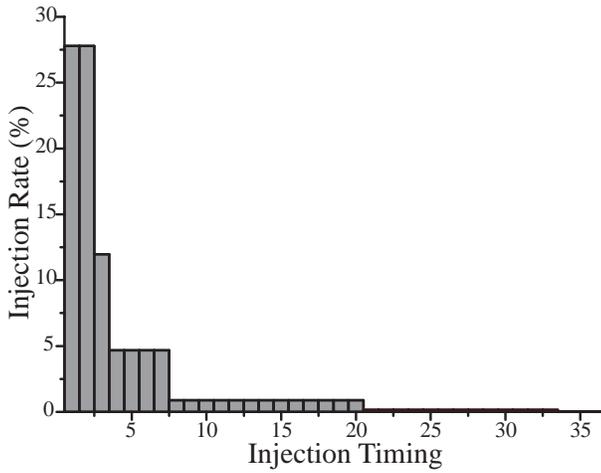


Figure 20: Pareto optimum solution that has the smallest value of SFC (SFC=183.7, NO_x=1.743, Smoke=0.2605) (Design candidate number 1 in Figure 20)

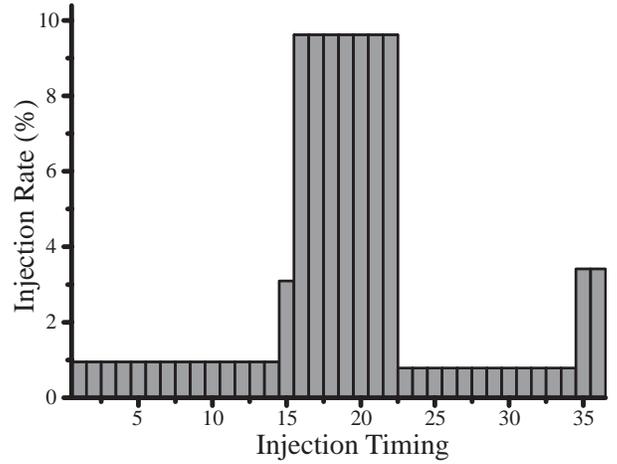


Figure 22: Pareto optimum solution that has the smallest value of Smoke (SFC=267.8, NO_x=1.050, Smoke=0.09924)

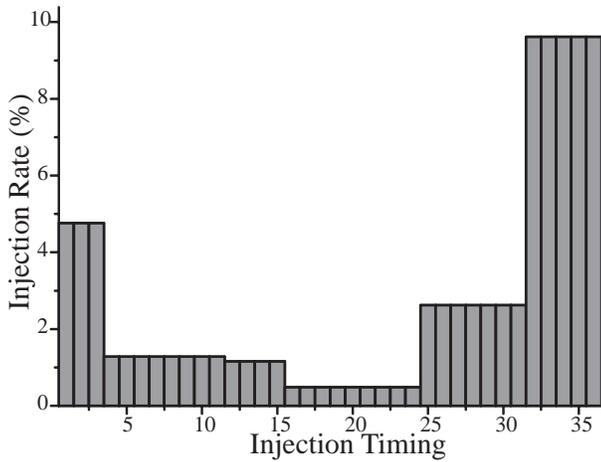


Figure 21: Pareto optimum solution that has the smallest value of NO_x (SFC=299.6, NO_x=0.4309, Smoke=0.1539) (Design candidate number 4 in Figure 20)

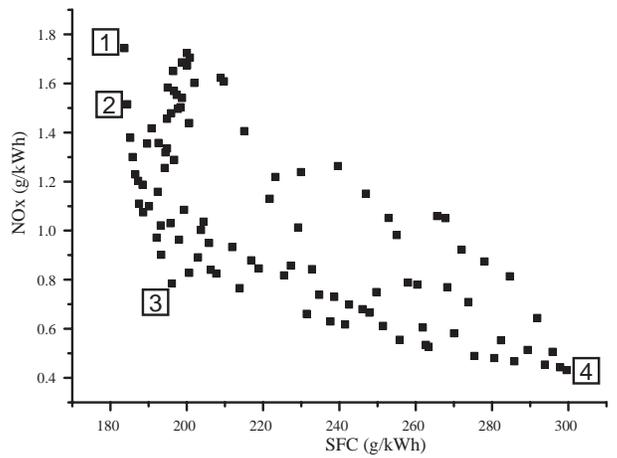


Figure 23: Pareto optimum solutions and design candidates

even when NO_x and SFC of two solutions are similar, the shape of the injection ratio of these solutions may be totally different. On the other hand, in B group, the change ratio is relatively small. Therefore, when the NO_x and SFC of two solutions are totally different, the shape of the injection ratio of these solutions may be similar.

The candidate number 1 is the same as the solution shown in Figure 20 and the candidate number 4 is the same as the solution shown in Figure 21. The injection rate shapes of the candidates of number 2 and number 3 are shown in Figures 25 and 26.

When the designer needs the good SFC, he chooses the candidate number 1. On the other hand, the designer needs the good NO_x, he chooses the candidate number 4. The candidate number 1 and 4 are the same results when the one objective is minimized. However, the most important fact is that these results are derived by one trial. At the same time, the designer can distinguish the solution distribution.

Compared to the candidate number 3 and 4, there are no big differences between them. Therefore, in this case, the candidate number 3 is the reasonable choice for the designer.

The following situation may be assumed. At first, the designer needs the result that has the lowest SFC. After, he gets this result, he may change his mind because he can find the candidate number 2 that has almost the same value for SFC but the value of NO_x is much smaller.

From these results, the following advantages of the GAs for multi-objective optimization problems are confirmed.

- the GAs can find the Pareto optimum solutions with one trial. In a single objective optimization problem, the GAs need the high calculation cost compared to the gradient search methods. On the other hand, in a multi-objective optimization problem, the gradient search methods also need many iterations to find the Pareto optimum solutions. The GAs are very easy to apply several types of problems. At the same time, the GAs have the robustness in finding the optimum

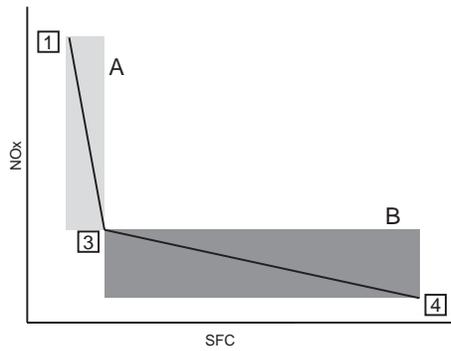


Figure 24: Design candidates

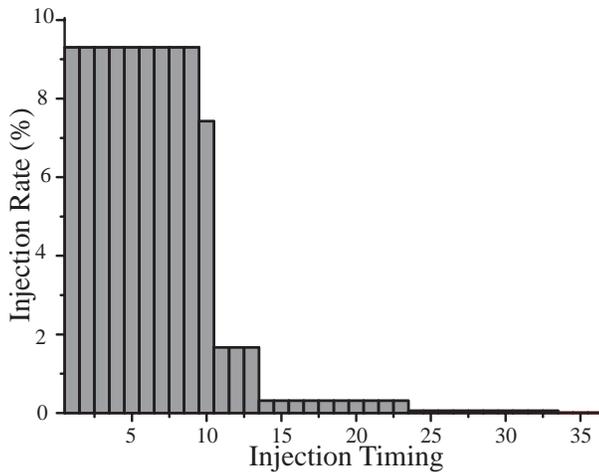


Figure 25: Design candidate number 2 (SFC=184.4, NOx=1.5149, Smoke=0.2585)

solution in a global area. Thus, the GAs are very useful tools to find Pareto optimum solution.

- Usually, a multi-objective problem is turned into a single objective problem by setting an evaluation function when the solutions are derived by the gradient search method. However, it is very difficult to set up this evaluation function. This evaluation function affects the results. On the other hand, GAs can find the Pareto optimum solutions without setting this excess evaluation function.
- In the results of this paper, the solutions that minimize each objective are totally different since there are the trade-off relations between the objective functions. Especially in the early stage of design, designers do not know the relationship between the objectives. Therefore, it is very useful for designers to show the Pareto optimum solutions. The designers can find solutions with their preferences.
- Even when the problems are in the bottom stage of design and the designers know the relationship between the objective functions, it is useful to derive the solutions by the GAs. To solve the problem, the designers have to define the objective function and the constraints. At the same time, they define the values of the constraints. Usually, the solutions are on the constraints. Therefore, the designers should be

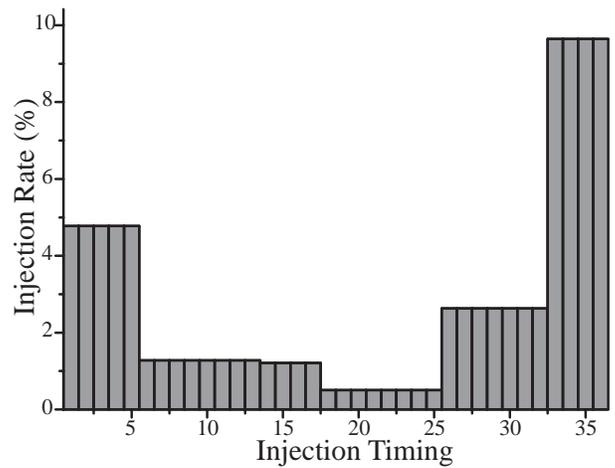


Figure 26: Design candidate number 3 (SFC=196.1, NOx=0.7846, Smoke=0.2224)

careful to decide the value of the constraints. When the designers set these constraints as objective functions, they can find several solutions around the constraints. Therefore, the information about the Pareto solutions is useful for the designers.

Calculation cost This simulation is performed on a PC cluster. The prescription of the used PC cluster is summarized in Table2.

Table 2: PC Cluster

Table 2: PC Cluster	
CPU	Pentium III (1GHz)*32
Memory	512 MB
OS	Linux 2.4.4
Network	FastEthernet TCP/IP
Communication Library	LAM

There are 32 CPUs in the PC cluster. This simulation is performed as a master slave model. There are 31 slaves and one master. Each HIDECS simulation is performed on each slave. The GA operations are performed on the master. Since, there are 100 individuals and 200 generations are performed, 20200 simulations of the HIDECS are performed. The average execution time of one trial of the HIDECS is 11.86 [s]. The total execution time is 11425 [s] and the total execution time for the GA operation is 525 [s]. Therefore, the parallel efficiency is more than 95 [%]. The important thing for the GAs is the calculation cost of evaluation of the function. In this simulation, the HIDECS only needs about 10 seconds. The GAs need many iterations. However, because of the small calculation cost of the HIDECS, the Pareto optimum solutions are derived within three hours using PC cluster. Comparing to the detailed multidimensional model, the phenomenological model has the higher advantage especially for GAs in MOPs.

CONCLUSION

In this paper, the multi-objective optimization problem is established for engine design using the phenomenological model and GAs. The HIDECS code which is based on the phenomenological model is used for analyzing the diesel engine. The NCGA which is an extended model of GA is applied. In this simulation, the amount of SFC, NO_x and Soot are minimized by changing the rate of fuel injection. Since there is trade-off relationship between SFC, NO_x and Soot, this problem becomes multi-objective optimization problem. By this simulation, the NCGA can successfully derive the Pareto optimum solutions. The information about these Pareto optimum solutions is very helpful for designer. The GA needs many iterations. It is also made clear that the phenomenological model is suitable for optimization by the GAs since the phenomenological model does not need a high calculation cost.

In the future work, we are planning to perform the following topics.

- In this paper, the only injection rate is treated as a design variable. The more factors will be targeted as design variables such as, boost pressure, EGR, start of fuel injection (SOI) and duration of the fuel injection.
- The alternate expression of the injection pressure shape is considered.
- In this paper, the derived solutions are not discussed the characteristics of the diesel engines precisely. These characteristics should be discussed in the future work.

ACKNOWLEDGMENTS

This work was supported by a grant to RCAST at Doshisha University from the Ministry of Education, Science Sports and Culture, Japan. The authors would like to thank Mr. S. Miyata, Ms. M. Fukumoto and Mr. M. Uchiyama for helpful comments.

REFERENCES

- [1] Walsh, M. P., "Global Trends in Diesel Emissions Regulation-A 2001 Up Date", SAE Paper 2001-01-0183, 2001.
- [2] Johnson, T. V., "Diesel Emission Control in Review", SAE Paper 2001-01-0184, 2001.
- [3] Moser, F. X., Sams, T. and Cartellieri, W., "Impact of Future Exhaust Gas Emission Legislation on the Heavy Duty Truck Engine", SAE Paper 2001-01-0186, 2001.
- [4] Senecal, P. K. and Reitz, R. D., "Optimization of Diesel Engine Emissions and Fuel Efficiency using Genetic Algorithms and Computational Fluid Dynamics", Eighth ICLASS, Pasadena, CA., July 2000.
- [5] Senecal, P. K. and Reitz, R. D. "A Methodology for Engine Design Using Multi-Dimensional Modelling and Genetic Algorithms with Validation through Experiments", International J. of Engine Research, vol.1, No.3, pp.229-248, I MechE, 2000.
- [6] Senecal, P. K., Pomraning, E. and Richards, K. J., "Multi-Mode Genetic Algorithm Optimization of Combustion Chamber Geometry for Low Emissions", SAE Paper 2002-01-0958, 2002.
- [7] Shrivastav, R., Hessel, R. and Reitz, R. D., "CFD Optimization of DI Diesel Engine Performance and Emissions Using Variable Intake Valve Actuation with Boost Pressure, EGR and Multiple Injections", SAE Paper 2002-01-0959, 2002.
- [8] Hiroyasu, H., "Diesel Engine Combustion and its Modeling", International Symposium on Diagnostics and Modeling of Combustion in Reciprocating Engines. Pp.53-75, 1985.
- [9] Nonlinear Programming Frequently Asked Questions, <http://www-unix.mcs.anl.gov/otc/Guide/faq/nonlinear-programming-faq.html>
- [10] iSIGHT, <http://www.engineous.com/specifications.htm>
- [11] Goldberg, D. E., "Genetic Algorithms in search, optimization and machine learning." Addison-Wesley, 1989.
- [12] Cantu-Paz, E., "A survey of parallel genetic algorithms.", *Calculateurs Paralleles*, 10(2), 1998.
- [13] Coello, C. A., "Handling preferences in evolutionary multiobjective optimization: A survey.", In 2000 Congress on Evolutionary Computation, volume 1, pages 30–37, 2000.
- [14] Zitzler, E., Laumanns, M. and Thiele., L. "Spea2: Improving the performance of the strength Pareto evolutionary algorithm.", In Technical Report 103, Computer Engineering and Communication Networks Lab (TIK), Swiss Federal Institute of Technology (ETH) Zurich, 2001.
- [15] Pratab, A., Deb, K., Agrawal, S. and Meyarivan, T., "A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II.", In KANGAL report 200001, Indian Institute of Technology, Kanpur, India, 2000.
- [16] Ono, I. and Kobayashi, S., "A Real-coded Genetic Algorithm for Function Optimization Using Unimodal Normal Distributed Crossover.", *Proc.7th Int.Conf.on Genetic Algorithms*, pp. 246–253, 1997.
- [17] Kursawe., F. "A Variant of Evolution Strategies for Vector Optimization.", In PPSN I, volume 496 of Lecture Notes in Computer Science, pp. 193–197, 1991.

- [18] Hiroyasu, H. and Kadota, T., "Models for Combustion and Formation of Nitric Oxide and Soot in Direct Injection Diesel Engines", SAE Paper 760129, 1976.
- [19] Hiroyasu, H., Kadota, T. and Arai, M., "Development and Use of a Spray Combustion Modeling to Predict Diesel Engine Efficiency and Pollutant Emissions (Part 1, Combustion Modeling)", Bulletin of the JSME, Vol.26, No.214, April, 1983.
- [20] Hiroyasu, H., Kadota, T. and Arai, M., "Development and Use of a Spray Combustion Modeling to Predict Diesel Engine Efficiency and Pollutant Emissions (Part 2, Computational Procedure and Parametric Study)", Bulletin of the JSME, Vol.26, No.214, April, 1983.
- [21] Kuo, T. W., "Evaluation of a Phenomenological Spray-Combustion Model for Two Open-Chamber Diesel Engines", SAE Paper 872057, 1987.
- [22] Nishida, K. and Hiroyasu, H., "Simplified Three-Dimensional Modeling of Mixture Formation and Combustion in a D.I. Diesel Engine", SAE Paper 890269, 1989.
- [23] Yoshizaki, T. Ishida, K. and Hiroyasu, H. "Approach to Low NOx and Smoke Emission Engines by Using Phenomenological Simulation", SAE Paper 930612, 1993.
- [24] Imanishi, H. Yoshizaki, T and Hiroyasu, H., "Simulation Study of Effects of Injection Rate Profile and Air Entrainment Characteristics on D.I. Diesel Engine", SAE Paper 962059, 1996.
- [25] Long, Y. S., Gakumazawa, H. and Hiroyasu, H., "The Simulation of the Distribution of Temperature and Mass of Liquid and Vapor Fuels, and the Wall Impinging Spray Pattern in a Diesel Combustion Chamber", SAE Paper 2000-01-1887, 2000.
- [26] Steuer, R. E., "Multiple Criteria Optimization: Theory, Computation, and Application", Wiley, New York, 1986.
- [27] Ringuest, J. L., "Multiobjective Optimization: Behavioral and Computational Considerations", Kluwer, Boston, 1992.
- [28] Fonseca. C.M, and Fleming, P. J., "An Overview of Evolutionary Algorithms in Multiobjective Optimization", Evolutionary Computation, Vol. 3, No. 1, pp. 1-16, 1995.

Hiro Hiroyasu: Research Institute of Industrial Technology, Kinki University, Takaya, Umenobe, Higashi Hiroshima, 739-2116, Japan. hiro@hiro.kindai.ac.jp

CONTACT

Tomoyuki Hiroyasu: Department of Knowledge Engineering and Computer Sciences, Doshisha University, 1-3 Tatara Miyakodani, Kyotanabe-shi, Kyoto, 610-0321, Japan, tomo@is.doshisha.ac.jp