

Assessment of Optimization Methodologies to Study the Effects of Bowl Geometry, Spray Targeting and Swirl Ratio for a Heavy-Duty Diesel Engine Operated at High-Load

Yu Shi and Rolf D. Reitz

Engine Research Center, University of Wisconsin-Madison

Copyright © 2008 SAE International

ABSTRACT

In the present paper optimization tools are used to recommend low-emission engine combustion chamber designs, spray targeting and swirl ratio levels for a heavy-duty diesel engine operated at high-load. The study identifies aspects of the combustion and pollution formation that are affected by mixing processes, and offers guidance for better matching of the piston geometry with the spray plume geometry for enhanced mixing. By coupling a GA (genetic algorithm) with the KIVA-CFD code, and also by utilizing an automated grid generation technique, multi-objective optimizations with goals of low emissions and fuel economy were achieved. Three different multi-objective genetic algorithms including a Micro-Genetic Algorithm (μ GA), a Nondominated Sorting Genetic Algorithm II (NSGA II) and an Adaptive Range Multi-Objective Genetic Algorithm (ARMOGA) were compared for conducting the optimization under the same conditions. Assessments of the optimization methodologies are provided and suggestions are given for the application of genetic algorithms in engine optimizations. A non-parametric regression analysis tool was also used to post-process the optimized results in order to provide an understanding of the effects of each optimized parameter on fuel economy and pollutant formation. It was found that an optimal combination of spray targeting, swirl ratio and bowl geometry exists that simultaneously minimizes emissions formation and offers improved fuel consumption.

INTRODUCTION

Due to its superior durability, drivability and fuel efficiency, the diesel engine has found broad application in both heavy-duty vehicles and off-highway engineering vehicles and equipment. With more and more stringent emission standards, the diesel is facing the challenge of meeting these more environmentally-friendly emissions regulations while maintaining fuel economy (a primary reason that diesel engine is considered as a good solution for reducing green-house gases). Low temperature combustion is receiving more attention due

to its ability to simultaneously reduce both NO_x and soot emissions as well as fuel consumption. Intensive studies on applying low temperature combustion strategies in diesel engines have been conducted recently, such as Premixed Charge Compression Ignition (PCCI) [1, 2], which realizes the low temperature combustion by injecting fuel very early to produce a premixed fuel-air charge prior to the ignition, and Modulated Kinetics (MK) [3, 4], which requires late injection with a large amount of cooled recycled exhaust gas to delay ignition timing and thus lower combustion temperature. Although the promising advantages of low temperature combustion have been explored, it is currently impossible to apply this combustion strategy to a heavy-duty diesel engine operated at high-load because of technical difficulties, such as ignition control and unacceptable engine knock. Thus, it is still of much interest to further investigate the traditional combustion regime for heavy-duty engines to be able to improve their performance and reduce emissions. For any combustion process, boundary and initial conditions are two dominating aspects, and particularly the preparation of the fuel-air mixture also critically influences compression ignition combustion. Combustion and pollution formation are significantly affected by the mixing processes in diesel engines, and thus it is necessary to identify a better method to match the boundary conditions, such as the piston geometry with the spray plume geometry, as well as good initial conditions, such as the initial flow motions like swirl.

The increasing capacity of computers enables wide application of CFD modeling to engine designs. Many researchers have shown that multi-dimensional CFD engine models are able to predict both combustion characteristics and pollution formation very well, and that the major trends of engine processes can be captured precisely [5,6]. Therefore numerical simulation is becoming a reliable way to evaluate real engine performance and emissions trends. This motivates the application of optimization methods to engine design. Compared to traditional experimental tests for engine optimization, numerical investigation promises to save cost and time, while maintaining relatively high reliability and accuracy. This methodology is becoming more

popular in both the industrial design process and in academic research.

Genetic Algorithm (GA) search techniques have become one of the main-stream optimization methods and are frequently used in engine design. The Single-Objective Genetic Algorithm (SOGA) has the goal of minimizing or maximizing a single desired objective. Both fuel economy and emissions are of the equal importance for engine design, and thus engine optimization is, naturally, a Multi-Objective Problem (MOP). However, by defining a merit function that includes each optimal objective in a mathematical expression, SOGA can still be employed to optimize engine designs with multi-objectives. Wickman et al. [7] conducted a study of engine combustion chamber geometry optimization for a small bore and a large bore engine with SOGA, and they achieved improved fuel economy and emissions for the two investigated engines. Bergin et al. [8] applied SOGA to their study of large diesel engines and discovered a promising new concept called “spin-spray” combustion. 2006 nonroad emissions targets were met by optimizing the spray events without other means of emissions reduction. But SOGA demonstrates dependency on the choice of merit function and unfortunately definition of an appropriate merit function is usually unclear to the decision maker prior to the optimization process. This motivates interest in studies and applications of Multi-Objective Genetic Algorithms (MOGA). MOGA is becoming a prominent method for use in optimization and design. Genzale et al. [9] investigated a heavy-duty diesel engine operated at low-load working under low-temperature combustion conditions, and a set of optimized combinations of the spray targeting, bowl geometry and swirl ratio was revealed through the use of MOGA.

The present paper assesses three different MOGAs including a Micro-genetic Algorithm (μ GA) [10], a Nondominated Sorting Genetic Algorithm II (NSGA II) [11], and an Adaptive Range Multi-Objective Genetic Algorithm (ARMOGA) [12]. Suggestions are provided for the application of GAs in engine optimizations. The study also identifies aspects of the combustion and pollution formation that are affected by mixing processes and offers guidance for better matching of the piston geometry with the spray plume geometry for enhanced mixing for a heavy-duty engine operated at high-load. A non-parametric regression analysis tool [13] is also used to post-process the optimized results in an attempt to provide more visible relations between design parameters and objectives.

SCOPE OF PRESENT STUDY

OBJECTIVES OF THIS WORK – The primary objectives of the present study include three aspects:

- 1. To evaluate computational efficiency of current MOGAs for the application of GAs to engine optimization.

- 2. To search for optimized combinations of piston bowl geometry, spray targeting, and swirl ratio to enhance the mixing and post-combustion oxidation processes in order to simultaneously reduce both NOx and soot emissions and improve fuel economy for a heavy-duty diesel engine at high-load condition.
- 3. To identify dominant design parameters that influence combustion and pollutant formation for this type of engine at the specific operating condition.

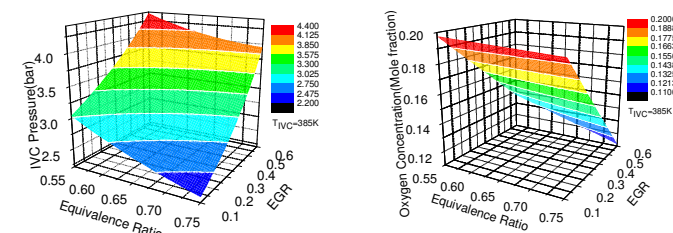
ENGINE DESCRIPTION AND OPERATING CONDITION – The modeled engine is a single-cylinder, direct-injection, 4-stroke diesel research engine, based on a Caterpillar production engine. The main geometric specifications and fuel injector parameters are summarized in Table 1. The injection pressure was increased to 2000 bar from the original 1600 bar in order to reduce the injection duration.

Table 1: Engine and Injector Specification

Engine base	Caterpillar DI Diesel
Combustion chamber	Quiescent, direct injection
Swirl ratio	0.5
Bore×Stroke [mm]	137.16×165.1
Bowl width [mm]	97.8
Displacement [L]	2.44
Connection rod length [mm]	261.6
Geometric compression ratio	16.1:1
Fuel injector nozzles	8 holes, equally spaced
Spray pattern included angle	154°
Rail pressure [bar]	2000
Nozzle orifice diameter [mm]	0.217

The investigated operating condition was determined at Mode 4 [14] that corresponds to 95% load and high speed. However, slight changes were made for the present modeling work. High global equivalence ratios deteriorate soot emissions but lower equivalence ratios require more intake charge and that is limited by current turbo chargers, especially for the high-load condition. High large EGR rates can suppress NOx formation by lowering combustion temperatures and in-cylinder oxygen concentration but the soot emissions increase with the increasing EGR levels. In this situation, the global equivalence ratio and EGR levels need to be balanced by considering both the intake charge conditions and emissions trade-off relations. A simple program was written to study the relationship between the intake charge conditions, the global equivalence ratio, and the EGR level based on the complete combustion assumption. This is believed to be valid for a global equivalence ratio less than about 0.75. Figure 1 gives estimated results for an intake valve closing (IVC) temperature of 385K that is used to guide the baseline operating conditions, which are listed in Table 2. The start of injection (SOI) timing was determined by maximizing the gross indicated mean effective pressure

by performing a SOI sweep for the engine at the baseline operating condition.



a. IVC pressure b. Oxygen concentration
Figure 1: Relationship of intake charge conditions, and global equivalence ratio and EGR levels

Table 2: Baseline Operating Condition

Speed [rev/min]	1672
IVC temperature [K]	385
IVC pressure [kPa]	310
SOI [deg BTDC]	13
Injection quantity [mg/cyc]	229
Injection duration [CAD]	19
EGR level [%]	25
Global equivalence ratio	0.6
O ₂ Concentration [vol. %]	17.65

OPTIMIZATION PARAMETERS AND OBJECTIVES –
The primary goal of the present study is to find optimal combustion boundary conditions, including the geometrical boundary, i.e., combustion chamber (bowl) shapes, for a high-load heavy-duty engine. In addition, optimal combinations of spray targeting and swirl ratio levels with the combustion chamber shape were searched for simultaneously in order to further understand the effects of the flow initial conditions and the spray development on combustion with the objectives of reducing both NO_x and soot emissions and improving fuel economy. Therefore, seven parameters, including injector spray angle, swirl ratio, and five different parameters that define the bowl geometry were studied in the present paper. The five bowl geometry parameters enable a search of a wide range of bowl shapes, and also allow for the consideration of reentrant-type bowls. The searched number of geometry parameters gives a reasonable search space for the meshing software program kwickgrid [9], although more parameters are available in the grid generator to define the bowl shape. Figure 2 illustrates the five bowl geometry parameters optimized in present paper. Furthermore, Table 3 gives the ranges of the parameters, including Bezier curves, and main bowl geometry, which were determined so as to also avoid infeasible bowl designs but still to maintain diversity [31]. The thickness of the bowl lip was given as 2.8 mm based on previous experience and the radius was automatically determined by the grid generator. More detailed descriptions of the grid generator and parameterized bowl shapes are given below.

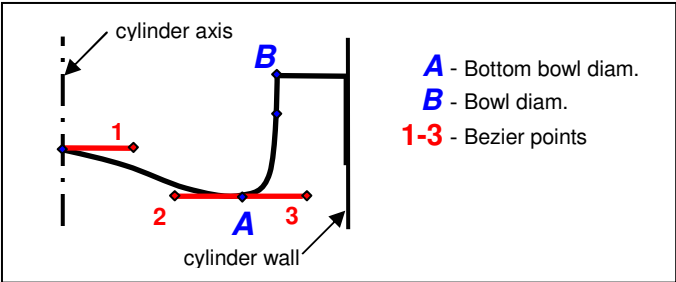


Figure 2: Parameters of bowl geometry [9]

Table 3 also lists the ranges of spray angle and swirl ratio considered. The spray angles target a wide region of the piston curvature, from the bowl floor up to the bowl lip. Considering the ability of the intake system of the experimental engine [14], the range of swirl ratio was restricted to a relatively narrow range.

Table 3: List of optimization parameters and their ranges

Parameter	Range
A- diam. of bowl bottom	74-80% bowl diameter
B- bowl diameter	71-84% cylinder diameter
1 – Bezier curve control point (from 1 to 2)	0.1-0.7
2 – Bezier curve control point (from 2 to 1)	0.3-0.9
3 – Bezier curve control point (from A to B)	0.8-1.5
Injector spray half-angle	60°-85°
Swirl ratio	0.5-2.0

NO_x and soot emissions are two of the most important concerns in the upcoming stringent 2010 heavy-duty regulation requirements, and the existence of a trade-off relation is well known to engine researchers. Therefore reductions of these two emissions were two main objectives in this study. Gross indicated specific fuel consumption (GISFC) was also investigated to understand the contradiction that results by suppressing the combustion temperature to reduce NO_x emissions and its effect on deterioration of fuel economy.

OPTIMIZATION METHODOLOGIES – Before GAs were widely employed as an optimization tool in engineering designs, traditional optimization methodologies, such as gradient-based methods, dominated applications. These methods are sensitive to derivatives of the parameter-space, and have difficulty in finding global optimal solutions. However, engine design requires diverse global solutions for multi-objectives and the design spaces are generally non-smooth, which limits the search capacity of traditional optimization methodologies. Goldberg [15] was the first to suggest use of GAs in engineering problems [16]. GAs are mathematical algorithms that simulate the evolutionary processes of ecosystem, which obeys the Darwinian idea of “survival of the fittest”. It is a simple search technique that utilizes the “fittest” attributes of previously created designs to generate new designs with the aim of

moving the evolution process towards better solutions. In this process, the design-space is coded in mathematical expressions (representing “genes”), either with binary strings or real numbers, which are evaluated to provide the “fittest” information for the crossover of genes. The crossover gives higher possibility to those genes with better merit to survive to the next generation. Mimicking natural evolution, random changes of genes (mutation) are introduced to avoid local optimization and to maintain the diversity of solutions. SOGAs aim at finding global solutions for a single objective, and thus are easier to use and analyze. The application of SOGAs to Multi-Objective Problems (MOPs) with a predefined mathematical merit function, however, hides the relationships among multi-objectives.

It is necessary to understand if a solution with multi-objective is optimized since trade-offs always exist in MOPs. The notion of “optimum” that is most commonly adopted in such problems is that originally proposed by Francis Ysidro Edgeworth and later generalized by Vilfredo Pareto, and it is normally referred as the Pareto optimum. The Pareto optimality can be defined as:

A point $\vec{x}^* \in \Omega$ is Pareto optimal if for every $\vec{x} \in \Omega$ and $I = \{1, 2, \dots, k\}$ either,

$$\forall_{i \in I} (f_i(\vec{x}) = f_i(\vec{x}^*)) \quad (1)$$

or, there is at least one $i \in I$ such that

$$f_i(\vec{x}) > f_i(\vec{x}^*) \quad (2)$$

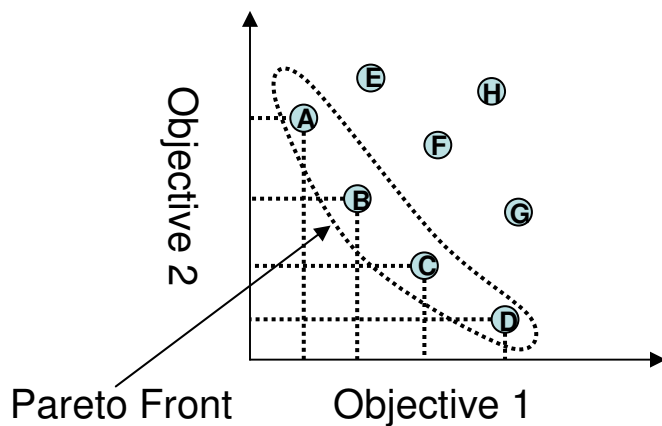


Figure 3: Definition of Pareto optimal

In words, this definition says that $\vec{x}^*$ is Pareto optimal if there exists no feasible vector $\vec{x}$ which would decrease some criterion without causing a simultaneous increase in at least one other criterion [17]. Figure 3 gives a more visible illustration on the Pareto optimum. As it shows, Cases A-D are Pareto optimal cases because neither of them are out-performed by other cases in this problem with the aim of minimizing both objectives. This also

highlights another terminology, dominance, which is frequently used in descriptions of MOGAs. One design is said to be dominated because at least one of its objectives is worse than other cases. Obviously, designs A-D are not dominated by other cases. However, designs E-H are dominated cases. Based on the relationships between dominated and dominating, the cases that are not dominated by each other can be grouped together, and the best group in the objective-space where all Pareto optimal solutions are located is called the Pareto front. Therefore, it can be conjectured that there are two goals in multi-objective optimizations [18]:

1. To find a set of solutions as close as possible to the Pareto-optimal front.
2. To find a set of solutions as diverse as possible.

In engine design problems, in-cylinder clean combustion techniques are usually combined with aftertreatment methods for the reduction of emissions. In this case, optimal solutions of in-cylinder combustion can guide the selections of aftertreatment devices. This enables engine designers to have more options for the selection of aftertreatment devices.

A considerable number of MOGAs have been proposed in the past, among which μ GA, NSGA II and ARMOGA have been widely applied to many engineering optimization problems [7-12]. The three MOGAs share a common feature that an elite-preserving operator is utilized. i.e., the genetic algorithms allow the parents to compete with their offspring and elite designs have opportunity to be directly carried over to the next generation. It has been proved that GAs converge to the global optimal solution for some functions in the presence of elitism. Moreover, the presence of elites enhances the probability of creating better offspring [18]. However, the three GA methods differ in details, such as their gene coding and ranking techniques.

Micro-Genetic Algorithm – Coello et al. [10] proposed a Micro-GA with a very small population size and a reinitialization process, combined with an external file to store nondominated cases previously generated, as well as an additional efficient mechanism to keep diversity. They showed that a Micro-GA carefully designed is sufficiently able to produce the Pareto front of a multi-objective optimization problem.

Differing from other MOGAs, the population memory of μ GA is divided into two parts: a replaceable and a non-replaceable portion. They are initially fed by randomly generated populations for the first optimization cycle, and the non-replaceable portion will keep its initial populations during the entire run. Therefore this algorithm induces an additional variable that is the percentage of each portion to be predefined for the optimization problem. μ GA employs conventional genetic operators for each cycle, but a tournament

selection, two-point crossover, uniform mutation, and elitism. At the end of each cycle, two nondominated populations (if there are two or more, otherwise, only one is selected) are compared with the external memory and the replaceable population memory, and if either of them or both dominate any population in the compared population memories, the dominated population will be replaced. In this way, both the external and the replaceable memory will tend to have more nondominated cases. Some of the replaceable populations will be used as initial populations to start a new evolutionary cycle.

There are three types of elitism involved in the μ GA which are described in details by Coello, et al. [10]. The technique of selecting nondominated populations discussed above is to converge the evolution to the true Pareto front. In order to keep diverse solutions distributed on the Pareto front, an approach similar to the adaptive grid proposed by Knowles and Corne [19] is also employed in μ GA. Briefly the selection of nondominated solutions is based on their locations in the objective-space once the defined limit of the external memory has been reached, and the less crowded regions are given preference. This procedure also induces two extra parameters for the optimization problem, which are the expected size of the Pareto front and the number of positions that determines how to divide the objective-space for each objective defined by the user. In general, μ GA focuses on the utilization of elitism to converge the optimization process, and reducing the population size and keeping diverse solutions by preserving the initial randomness and judging the locations of solutions. However, additional user-defined parameters have to be specified.

Nondominated Sorting Genetic Algorithm II – Motivated by the fact that elitism helps achieve better convergence in multi-objective evolutionary algorithms (MOEAs), Deb et al. [11] proposed a new elitist nondominated sorting GA. It employs both the elite-preserving strategy, as well as an explicit diversity-preserving mechanism. The evolution process of NSGA II is that it first randomly generates a predefined size (N) population, which undergoes conventional selection, crossover, and mutation procedures to produce offspring for the next generation. From the second generation, the parent generation (size N) competes with its offspring generation (size N) to introduce elitism. In this procedure, the crowding tournament selection is used and two rules are applied to the selection operator: 1. Solutions with higher ranks are given preference to be selected; 2. If they have the same rank, the less crowding distances cases are assigned higher priority.

Figure 4 illustrates the concepts of rank and crowding distance. As shown, solid circles dominate other cases. However, they do not dominate each other, and thus they form a nondominated front defined as the first rank. The same procedure can be applied to the rest of the solutions to find the second rank and so on until every

solution is assigned a rank. The crowding distance is defined by the average distance of a solution to its nearest neighbors. For example, the crowding distance of solution i in Figure 4 is the average side-length of the rectangle (the dashed box). The mathematic definition of the crowding distance can be also applied to higher dimensions, although it is only shown in a 2-D plot for a clear view. Therefore, N populations will be selected from 2N combined populations based on the aforementioned competition rules. These N populations will later undergo conventional selection, crossover, and mutation to complete an optimization cycle. It is apparent that the elitism makes the GA converge to the optimal solutions and the assistance of the explicit crowding distance maintains the diversity of solution. In addition, the crowding distance concept needs no extra user defined niching parameter (such as σ_{share}) that is used by many other MOGAs, such as the ARMOGA discussed next.

Deb et al. [11] also improved the computational efficiency of the sorting algorithms applied in NSGA II and reduced the computational burden from its original version NSGA [20]. However, this characteristic is not attractive in the present study, since the main calculation burden is on the evaluation process for engine optimization with CFD.

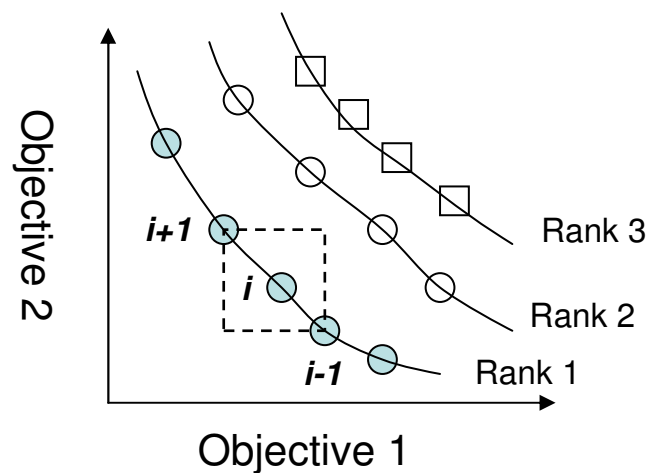


Figure 4: Definitions of the Rank and the Crowding Distance

Adaptive Range Multi-Objective Genetic Algorithm – An adaptive range technique was proposed by Arakawa, et al. [16]. Sasaki, et al. [12] extended and improved the method with a MOGA that is similar to that proposed by Fonseca and Fleming [21] to reduce the number of evaluations. The idea is that instead of searching the predefined design-space, an adaptive range, based on statistical study of the distribution of the preceding optimized solutions is utilized as the search range for the optimization cycle. The starting generation is determined by the user. As illustrated in Figure 5, ARMOGA focuses its search on a concentrated promising design-space where most of the potential optimal solutions are located, giving fast convergence to the Pareto front.

Mathematical descriptions of the statistical method of determining the adaptive range are given by Sasaki et al. [12].

$$d_{ij} = \sqrt{\sum_{k=1}^M \left(\frac{f_k^i - f_k^j}{u_k - l_k} \right)^2} \quad (7)$$

where u_k and l_k are the maximum and minimum k objective values in the present generation respectively, and M is the total number of objectives. Finally, the niching parameter δ_{share} is

$$(1 + \delta_{share})^M - 1 = N \cdot (\delta_{share})^M \quad (8)$$

and a similar sharing parameter α_{share} is user-defined. Thus, if the distance between two populations is lower than δ_{share} , then the niche count increases to reduce the fitness of the solution, and thus the diversity is preserved. In addition to the niching technique, ARMOGA also improves the real-coding method detailed in Ref [12] and introduces mutations helpful to diversity-preservation. Other than the above features, ARMOGA uses conventional GA operators.

The above three MOGAs also differ in coding systems. μ GA uses a binary coding for all operators, but ARMOGA is based on a real number coding system. NSGA II enables the user to choose either binary or real number coding, and the present study used the binary one for NSGA II. It was found from the authors' research that the real coding for NSGA II gave similar results as obtained using a binary one, and thus it was not included in this paper. Future study focusing on NSGA II will demonstrate more on the real coding method. Note that the constraint-handling technique of GAs is a very important feature, and the three GAs employ different constraint-handling techniques, such as the penalty function approach. However, the present study showed that all calculated results were located within the constrained space.

The three MOGAs utilize conventional GA operators and also share the common feature of the use of the elitism mechanism. They differ in coding method, ranking treatment, design space assignment, and niching technique. Furthermore, they require different parameter setups for the control of the algorithms. It is of much interest to assess these MOGAs based on their characteristics by conducting numerical experiments and parametric studies. The present paper focuses on the effects of population number on the performance of MOGAs. In addition, the effect of the starting generation of adaptation was also investigated for ARMOGA. Table 4 lists the five groups of setup considered for the present numerical experiments and parametric studies.

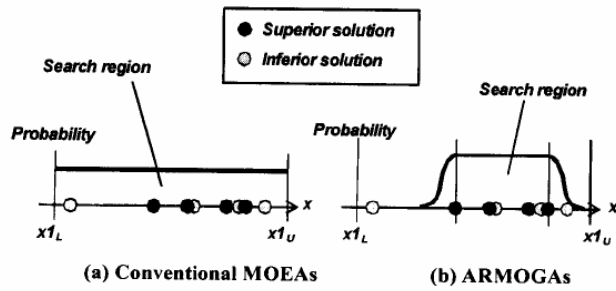


Figure 5: Sketch of search region of ARMOGA [12]

It is apparent that the implementation of range adaptation for the design space contradicts with the goal of achieving diverse optimal results to a certain degree. Therefore, techniques that aim to distribute optimal solutions uniformly need to be applied to ARMOGA. Similar to NSGA II, a rank is assigned to each individual. However, instead of using the rank and the explicit crowding distance directly, ARMOGA uses a fitness function with the assistance of the standard sharing approach to determine the preference of population of being selected for the next GA operation and thus for the next generation. The fitness value of each population is calculated from

$$F_i = N - \sum_{k=1}^{R_i-1} \mu(k) - 0.5(\mu(R_i) - 1) \quad (3)$$

where N is the number of solutions, and $\mu(R_i)$ is the number of solutions in rank R_i . The fitness value is then weighed divided by the niche count:

$$F'_i = \frac{F_i}{nc_i} \quad (4)$$

where the niche count is calculated from a sharing function

$$nc_i = \sum_{j=1}^N sh(d_{ij}) \quad (5)$$

$$sh(d_{ij}) = \begin{cases} 1 - \left(\frac{d_{ij}}{\delta_{share}} \right)^{\alpha_{share}} & d_{ij} < \delta_{share} \\ 0 & \text{others} \end{cases} \quad (6)$$

d_{ij} is the normalized distance summation between population i and j , which is as

Table 4: Groups for the assessment of MOGAs

Group	1	2	3	4	5
MOGAs	μ GA	NSGA II	ARMOGA	NSGA II	ARMOGA
Coding	Binary	Binary	Real	Binary	Real
Crossover possibility	0.7	0.9	0.9	0.9	0.9
Mutation possibility	0.1	0.143	0.143	0.143	0.143
Start gen. of adaptation	N/A	N/A	20	N/A	15
Pops.	4	4	4	32	32
Gens.	320	320	320	40	40
Total Evas.	1280	1280	1280	1280	1280

Since it has been claimed that μ GA is able to produce Pareto solutions with a very small population size, this paper only studied population of 4. But for NSGA II and ARMOGA the population size of 4 and 32 were also investigated. 3 random populations out of an initial 10 (larger than population size of 4) were used as the non-repeatable part for μ GA to introduce diversity for later generations, which is required by this algorithm.

In order to compare the efficiency of different MOGAs, the numerical experiments were done with the same total evaluation number of 1280. The mutation possibility of NSGA II and ARMOGA is the reciprocal of the number of design parameters (7 in this paper) to be optimized, which is the default set of modeFRONTIER™. The intervals of the design parameters that are required by the binary coding system are small enough to remove their sensitivity to solutions. For ARMOGA, the starts of generation of adaptation are 20 and 15 for group 3 and 5, which correspond to the 77th and 609th evaluations, respectively. The rest of the parameters were selected based on our previous experience.

Non-parametric Regression Analysis Method – In order to offer visible relations between the design-space and the objective-space, and also to create response functions of the parameter values mapping to objective values, a non-parametric regression (NPR) method was used in this work as a post-processing and optimization data analysis tool. A recently developed method for model selection and model fitting in nonparametric regression models, the COmponent Selection and Smoothing Operator (COSSO) [13] was applied in this paper. COSSO is based on smoothing spline analysis of variance (SS-ANOVA) model, and within this framework, the response function can be expressed as following:

$$f(x) = b + \sum_{j=1}^d f_j(x^{(j)}) + \sum_{j < k} f_{jk}(x^{(j)}, x^{(k)}) + \dots \quad (9)$$

where b is a constant for fitting, f_j are the main effects of each inputs, f_{jk} are two-way interactions for each pair of input parameters, and the sequence can be

continued for higher order interactions, but it is usually truncated to enhance interpretability. In this work, only two-way interactions were considered. The response function f is determined by minimizing:

$$\frac{1}{n} \sum_{i=1}^n [y_i - f(x_i)]^2 + \lambda J(f) \quad (10)$$

where y_i is the i^{th} measured data point and $f(x_i)$ is the corresponding predicted value with the form of Eq. (9). Therefore the first term of Eq. (10) ensures a square fit of the data. The role of the second term is to penalize the roughness of the response function to avoid an excessively noisy fit, and $J(f)$ quantifies the roughness of the response function f . The smoothness parameter λ works as a weight to control the trade-off between fitting data and removing noise. The COSSO determines the penalty function J from the sum of component norms and the smoothness parameter λ , from a cross validation technique. An iterative technique to optimize the number of components to be included in Eq. (9) is also employed in COSSO to determine the response function based on the framework of the SS-ANOVA. The reader can refer to Ref. [13] for more details. After the response function is determined, the magnitude and response shape that each design parameter will produce on the objective-space is quantified, and can be further visualized by graph analysis and generating tools, such as Matlab in this study. It is also worth noting that a design needs to be selected as the reference point (center id) for the non-parametric study, and in this sense, the study can be regarded as sensitivity analysis of all parameters on the reference design of interest.

COMPUTATIONAL MODELS

CFD MODELS – An improved version of the KIVA-3V code was used as the evaluation tool for the optimization process in this study. It was used to simulate the close-valve portion of the engine cycle. In the simulations, the turbulent flow was modeled by a modified RNG $k - \varepsilon$ model within the framework of the Reynolds Averaged Navier-Stokes (RANS) theory developed by Han and Reitz [22] in order to consider the effects of variable gas density for high-speed flow in engine simulations. The spray models are based on the wave breakup model proposed by Reitz [23], which accounts for the effects of drop breakup. Kelvin-Helmholz jet stability theory was implemented to simulate the atomization and breakup as described by Beale and Reitz [24]. The KIVA standard spray impingement model was used to account for the impact of drops on walls. The ignition process was modeled using the Shell model proposed by Halstead et al. [25] and applied in KIVA by Kong et al. [5]. The Shell model is able to predict the cool flame and two-stage ignition phenomena that are observed during the