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A GA-based Comparative Study of DI Diesel Engine Emission and Performance Using a Neural Network Model

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Abstract: In diesel engines, applying design techniques such as computer simulations has become a necessity in view of the fact that these methods can result in small amounts of NOx and SOOT and a reasonable fuel economy. To achieve such a target, multi-objective optimization methodology is a good choice In this paper, this technique is implemented on a closed cycle two-zone combustion model of a DI diesel engine. The combustion model is developed by Matlab programming and validated by a single cylinder Ricardo data obtained from the engine. The main outputs of this model are NOx, SOOT and engine performance. The optimization goal is to minimize NOx and SOOT at the same time while maximizing engine performance. Injection timing, injection duration and AFR (Air-fuel ratio) are selected from engine inputs as design variables. A neural network model of the engine is developed based on model data as an alternative for the complicated and time-consuming combustion model in a wide range of engine operation. Design variables are optimized using GA (Genetic Algorithm). Here, three common algorithms for multi-objective optimization, MOGA, NSGA-II, and SPEA2+ are applied and the results are compared.

Keywords: Genetic Algorithm, Diesel Engine, Multi-objective Optimization, Neural Network.

1. INTRODUCTION

Public concern about environment is increasing in consequence of daily growth of diesel engine usage in industry and transportation. To reduce the allowable limits of exhaust emissions, stringent emission standards are being legislated. In this paper a two-zone combustion model of a diesel engine, which yields the quantities of engine emissions (NOx and Soot) and performance (IMEP) in a closed cycle, is applied. The target is to perform a simultaneous optimization of NOx and Soot in a way that a reasonable engine performance is achieved. For the optimization problem three factors are selected as design variables: start of injection (SOI), injection duration and AFR (air to fuel ratio). The influence of these design variables on the engine operation is assessed by varying each parameter in a specific range and sampling the model outputs; thereby, a data sheet can be obtained. The aforementioned data sheet will be used to generate a neural network model of the engine as an alternative to the combustion model. Due to the fast and accurate responding of ANNs in prediction, there are more advantages in comparison with alternative modeling techniques. Results of trained neural network will be used for optimization. Numerical methods for optimization present some limitations such as the difficulty to escape from local minima and the dependence of the solution on the initial value chosen. On the other hand, genetic algorithm methods suggest an easy and trustable way to solve optimization problems, especially when there is more than one objective. Although the computational time may be larger than that of numerical methods, where the search domain is rather large, GA is much more applicable.

Considering these constraints, some valuable GA methods called MOGA, NSGA-II, and SPEA2+ is used as the optimization techniques in the present work.

2. COMBUSTION MODEL

In a two zone combustion model, the combustion chamber is divided into two zones. The first zone is the unburned zone, which includes the unburned mixture of fuel, air and residual gas and the second zone is the burning zone. The current two zone model includes processes occurring during the closed cycle (compression and expansion strokes). Main in-cylinder processes which are air motion, fuel spray development and mixing, spray impingement on the wall, turbulent heat transfer and chemistry of combustion are modeled here. The fuel considered here is dodecane (C12H26), representing a common fuel for commercial diesel engines. The main calculation procedure is based on the integration of the first law of thermodynamics and the perfect gas state equation combined with the various sub-models, for each zone separately. The semi-empirical model of Whitehouse and Way is used for calculating the rate of combustion. The injected fuel in the burning zone mixes up with the air entrained from the air zone via a mixing and diffusion process, while the burning rate of the fuel is affected by an Arrhenious-type expression. The generally accepted kinetics formation scheme proposed by Lavoie et al.

(1970) [1] is used for calculation of nitride oxide. The net soot formation rate is calculated by using the model proposed by Hiroyasu et al. (1983) [2], as modified by Lipkea and Dejoode (1994) [3]. Detailed explanation of the model can be found in [4, 5]. Engine descriptions are shown in table 1. Fig. 1 illustrates the predicted and measured quantities of pressure in the case of 80% load and 2500 rpm. As can be seen there is a good agreement between measured and predicted data.

Table 1. Specifications of the Target Diesel Engine

Bore	0.08026 (m)
Stroke	0.0889 (m)
Connecting rod	0.1788 (m)
Compression ratio	19.81
Nozzle diameter	0.00025 (m)
Intake valve close	40° *ca* after BDC
Exhaust valve open	60° *ca* before BDC
Engine speed	2500 (rpm)

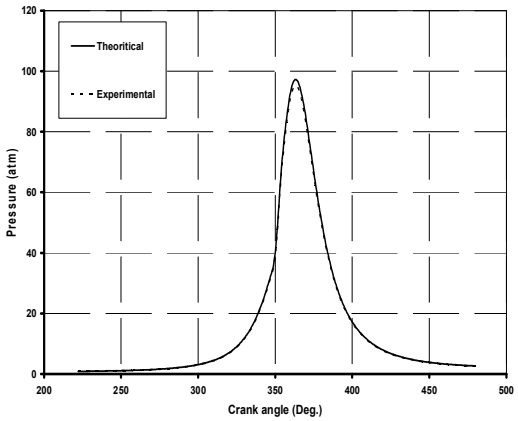


Fig. 1 Calculated And Experimental Pressure Diagram, At 80% of Full Load, 2500 rpm and a Static Injection timing of 340° crank angle.

3. NEURAL NETWORKS

Artificial Neural Network (ANN) is a tool used in modelling of time series processing and pattern recognition, and also has its root in engineering, neuro-science and mathematics. ANN consists of simple and adaptive processing units which is often called neurons. A simple neuron is an information-processing unit that is fundamental to operation of neural network. Neurons are interconnected and form a large network. In neural modelling, the inputs are known or they can be measured and the behaviour of outputs is investigated when input varies. Three basic elements of the neuronal model are as follows [6]:

A set of synapses or connecting links, each of which is characterized by a weight or strength of its own as W_{ki}.

1. A summer for adding input signals, weighted by the respective synapses of the neuron.
2. An activation function $\varphi(\cdot)$ for limiting the amplitude of the output of a neuron.

The activation function limits the amplitude range of the output signal to some finite value. There are various types of activation functions, such as threshold function, piecewise-linear function, and sigmoid function. Here, we have made use of a certain ANN architecture known as the Multilayer Feed-forward Neural Network or Multilayer Perception (MLP).

3.1. NETWORK IMPLEMENTATION

The range of variation of the design parameters is shown in Table 2. These data are used for training and testing the neural network. For every set of engine load and speed a network is trained with SOI, AFR and injection duration as inputs and NOx, Soot and IMEP as outputs. 256 samples are applied for training in each set of data. The input layer uses 3 nodes, two hidden layers are constructed of 15 nodes in each layer and the output layer includes 3 nodes. The training procedure is based on "Quick Propagation" algorithm. 128 samples were used in testing procedure of each data set. A sample validation for NOx and Soot quantities at 80% load and 2500 rpm is displayed in Fig. 4. Surprisingly the results are satisfactory such an extent that the blue and red curves are matched, not being able to be distinguished from each other.

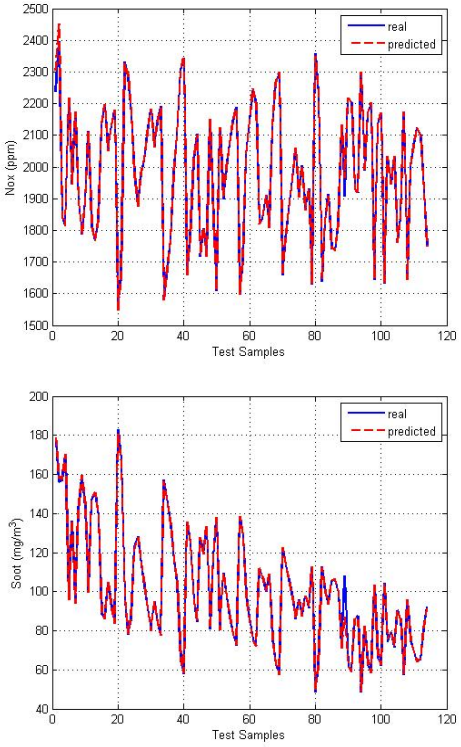


Fig. 4 Results of ANN Testing For NOx and Soot at 80% Load and 2500 rpm

Network errors are calculated based on mean square error (MSE) formula given as below:

$$MSE = \sum_{p=1}^{P}\sum_{i=1}^{N}\left(Y_{real}^{p,i} - Y_{predicted}^{p,i}\right) \quad (1)$$

Where i is number of nodes in output layer, p is the number of samples and $Y_{predicted}$ is network outputs and Y_{real} is the correct data of well depths, which extracted before. MSE value is 0.0035 for the trained data. This value for test data is equal to 0.0083.

Table 2. Ranges of the Designed Parameters Used for Data Generation

Design Parameter	Range of Variation
SOI	330-350 crank angle
AFR	24-66
Injection Duration	16-41 crank angle
Engine Load	40%-100%
Engine RPM	1500-4000

4. MULTI-OBJECTIVE OPTIMIZATION

In reality, most optimization problems deal with more than one objective. Usually, the target is to find design variables like *x* that minimize or maximize *k* objective functions within *m* constraints. This type of optimization problems is called Multi-objective Optimization Problems (MOPs) and can be formulated as follows [7]:

$$\min \vec{f}\left(\vec{x}\right) = \left(f_1\left(\vec{x}\right), f_2\left(\vec{x}\right), ..., f_k\left(\vec{x}\right)\right)^T$$
$$s.t.\ \ \vec{x} \in X = \left[\vec{x} \in R^n \mid u_j\left(\vec{x}\right) \le 0\,(j = 1, ..., m)\right] \quad (2)$$

If the objective functions are in the trade-off relationship, it is difficult to minimize or maximize all objective functions at the same time. In this case the concept of dominancy and Pareto optimum solution should be utilized.

Dominant solution definition: Suppose $\vec{x}_1, \vec{x}_2 \in R^n$ are two solutions, when:

$$f_i\left(\vec{x}_1\right) \le f_i\left(\vec{x}_2\right)\,(\forall_i = 1, ..., k)\ and\ f_i\left(\vec{x}_1\right) \prec f_i\left(\vec{x}_2\right)\ (\exists i = 1, ..., k)$$

Then $\vec{x}_1$ dominates $\vec{x}_2$ and is a better solution. In Fig. 5, the concept of the Pareto optimum solutions is illustrated in case of two objectives, which are supposed to be minimized. Solution A yields better results for both f_1 and f_2 than solution C. In this case, it is said that C is dominated by A. Therefore, A is better than C. On the other hand, the value of f_1 of A is better than that of B, but f_1 for B is better than that of A. Therefore, it is not possible to conclude which of the two solutions is better. In this case, A and B are called non-dominant solutions. A set of these non-dominant solutions is called a Pareto optimum set. The line of the Pareto optimum solution is called Pareto front.

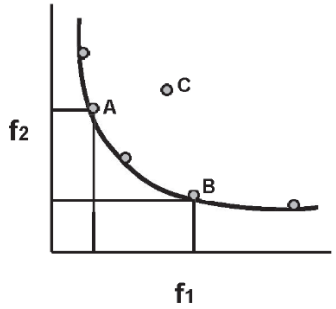


Fig. 5 Pareto Optimum Solutions

4.1 Genetic Algorithm for MOPs

The Genetic Algorithms can be applied to problems whose search space is discrete. Since GA's are multipoint search methods, these algorithms are very suitable for finding a Pareto optimum set [8]. Several algorithms for multi-objective optimization problems have been reported up to now [9]. MOGA, NSGA-II and SPEA2+ are three well-known examples of these algorithms, which we discuss here. In multi-objective GAs, the Pareto ranking is often used for determining the fitness value [10]. The Pareto ranking is determined according to the following procedure. For each solution, the number of the solutions that are dominant to the focused solution is counted. Pareto ranking is this number +1. The concept of the Pareto ranking is shown in Fig. 6 [11].

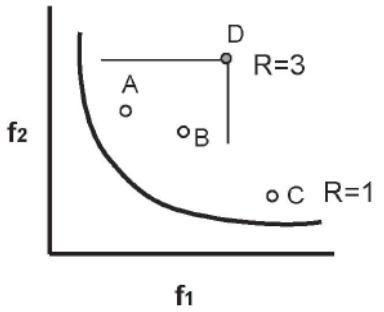


Fig. 6 The concept of Pareto Ranking

4.2. Multi-objective Optimization Methods

MOGA[1]

Fonseca and Fleming [12] proposed a scheme called MOGA, in which the rank of a certain individual corresponds to the number of chromosomes in the current population by which it is dominated. Current position of an individual at generation 't', which is dominated by $p_i^{(t)}$ individuals in the current generation can be given by [12]:

$$rank\left(x_t, t\right) = 1 + p_i^{(t)} \quad (3)$$

All non-dominated individuals are assigned rank 1, while dominated ones are penalized according to the population density of the corresponding region of the

[1] Multi-objective Optimization Genetic Algorithm

trade-off surface. Fitness assignment is performed in the following way [12]:

1. Sort population according to rank.
2. Assign fitness to individuals by interpolating from the best (rank 1) to the worst (rank n < N) in the way proposed by Goldberg, according to some function, usually linear, but not necessarily.
3. Average the fitness of individuals with the same rank, so that all of them will be sampled at the same rate. This procedure keeps the global population fitness constant while maintaining appropriate selective pressure, as defined by the function used.

NSGA-II [2]

Among various multi-objective EAs, those who use an elite-preserving operator are of more interest. No matter how the elitism is introduced, it makes sure that a good solution found early in the run will never be lost unless a better solution is discovered. Moreover, the presence of elites enhances the probability of creating better offspring. Some EAs, like Rudolph's elitist MOEA, use only an elite-preservation strategy, but NSGA-II also uses an explicit diversity-preserving mechanism. In Fig. 7, the procedure of NSGA-II is shown.

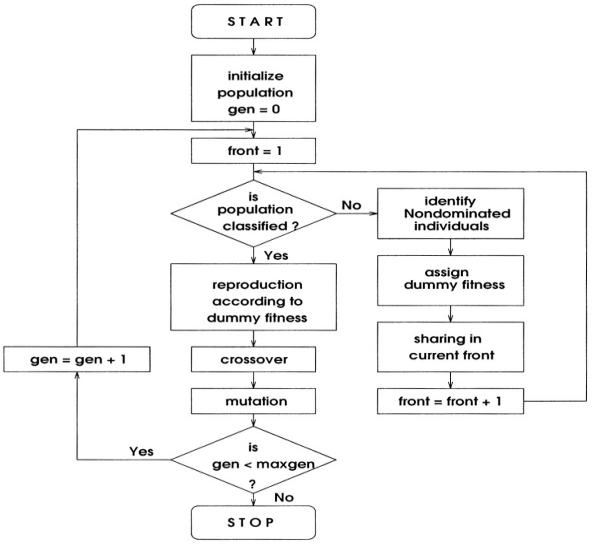


Fig. 7 Schematic of the NSGA-II Procedure[13]

SPEA2+ [3]

SPEA2+ is a new model of a multi-objective genetic algorithm [14] that improves the search performance of SPEA2. SPEA2+ is the same as SPEA2 with the addition of the following mechanisms:

1. Neighborhood crossover to allow crossing over individuals located close to each other in objective space,
2. Mating selection that reflects all good solutions preserved in the archive,
3. Application of two archives to maintain diverse solutions in the objective space and the design variable space.

[2] Non-Dominated Sorting Genetic Algorithms

[3] Strength Pareto Evolutionary Algorithm

It has been indicated in the literature [15] that the main drawback of MOGA is that it performs sharing on the objective value space, which implies that two different vectors with the same objective function values can not exist simultaneously in the population under this scheme. This is apparently undesirable, because these are precisely the kind of solutions that the user normally wants. Other authors [16] report that the NSGA performed quite well in terms of "coverage" of the Pareto front (i.e., it spreads in a more uniform way the population over the Pareto front) when applied to the 0/1 knapsack problem NSGA-II is more efficient (computationally speaking), uses elitism and a crowded comparison operator that keeps diversity without specifying any additional parameters.

In SPEA2+, a new archive (design variable archive) is used to preserve good solutions in the design variable space in addition to the archive (objective archive) that preserves various good solutions in the objective space. Environmental selection [17] of SPEA2 is used to renew the design variable archive. However, when the number of non-dominated solutions exceeds the archive size of the design variable archive, the proximity of the individuals is obtained using the Euclidean distance based on the value of the design variable. Then, the archive truncation method [17] based on proximity is executed in SPEA2, and the number of individual is reduced.

4.2. Comparison Criteria

This part of paper is originally inspired by the work of Hiroyasu et al. [14]. We expect a good breadth of Pareto solutions in Pareto frontier from utilized methods to get engaged with the problem of optimization. Therefore, this is the main criterion for evaluating the suitability of applied algorithm.

In this study, the ratio of non-dominated individuals (RNI) was used to evaluate the accuracy of the obtained solution set. In addition, the cover rate was used to evaluate the breadth and to what extent the obtained solution has an even distribution.

To compare the accuracies of the two methods, their accuracies were evaluated based on the ratio of non-dominated individuals by obtaining the number of solutions that were inferior to the other.

The cover rate is the ratio of the number of divided areas, where each area is the area between the maximum and minimum values divided into arbitrary sizes that have the obtained solution set, to the total number of divided areas [14]. From the cover rate, we can evaluate the breadth of the area covered by the solution and how evenly the solution is distributed against the Pareto-optimal front. The cover ratio $I_{Cover\,k}$ against an objective function f_k can be obtained using equation 5.

$$I_{Cover\,k} = \frac{N_k}{N} \tag{4}$$

Where, N is the number of divisions, and N_k is the number of divided areas covered by the solution set.

Cover ratio, I_{Cover} can be obtained by calculating the average of the cover ratio (equation 5).

$$I_{Cover} = \frac{1}{M}\sum_{k=1}^{M} I_{Cover\,k} \qquad (5)$$

Let M be the number of objective functions. The maximum cover rate is 1 and the minimum value is 0. The closer the value is to the maximum value of 1; the solution set covers a greater area and is more evenly distributed. As the Pareto-optimal front was unknown in this study, the maximum and minimum values in each objective function were used values from experience. In addition, the number of divisions was defined as the number of individuals (Population Size)/2, and as the objective function is expressed by the logarithm, the area was divided by the logarithm ($\log_{10}$).

According to Fig.8, the final results obtained from the optimization procedure show that cover factor is better when we employ the SPEA2+ methodology in front of using NSGA-II and MOGA to the problem of diesel engine. It means that the boundaries for Pareto Front in the objective plane are clearer by using SPEA2+ methodology and the distance between Pareto solutions is lower. This fact can help us to find more appropriate optimum solution for our problem.

Considering NSGA-II and MOGA, it seems that NSGA-II is more powerful method to be used as a multi-objective optimization tool.

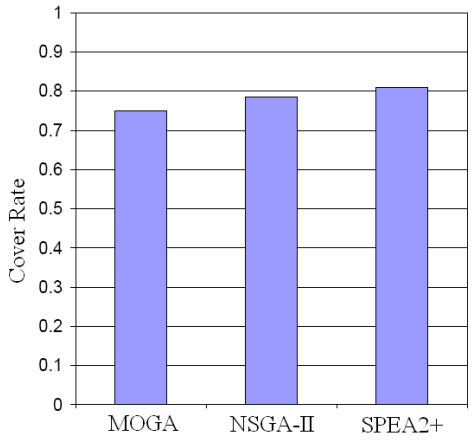


Fig.8 Comparison of MOGA, NSGA-II and SPEA2+ by cover rate.

6. GENETIC ALGORITHM IMPLEMENTATION

We have developed NSGA-II and SPEA2+ codes in Matlab Programming to perform the optimization study of diesel engine. Also, we have used Matlab Multi-objective optimization toolbox (MOGA) to be conducted on our problem. There are two setting parameters to execute the program. Firstly, the number of population should be set, which is chosen 200. It could be noted that the search domain will grow as the population number increases. Therefore, the chance for finding the global minima rises in a certain number of generations. Secondly, generation number –the number of iterations to achieve the global minima- is adjusted to 1000. Input parameters to the computer program are selected from trained neural network outputs and three outputs (objectives) are optimized values of NOx, Soot and Imep.

Optimized quantities of design variables for each set of engine load and speed are determined. In order to reduce the calculation cost and to strengthen the optimization process the results of the trained networks has been applied for optimization instead of the combustion code. According to the weights of the trained networks a fitness function has been introduced and optimized. Using such an optimization algorithm a map of emission and performance can be obtained. In figures 9, 10 and 11 optimized values of AFR, SOI and Injection Duration are plotted for different sets of load and engine speed. These are the results of applying SPEA2+ to the problem by considering minimum quantities of NOx to be the constraints.

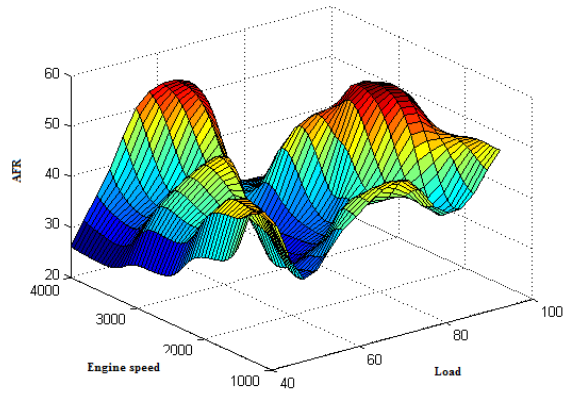


Fig. 9 Optimized value of AFR for sets of load and engine speed resulted from SPEA2+

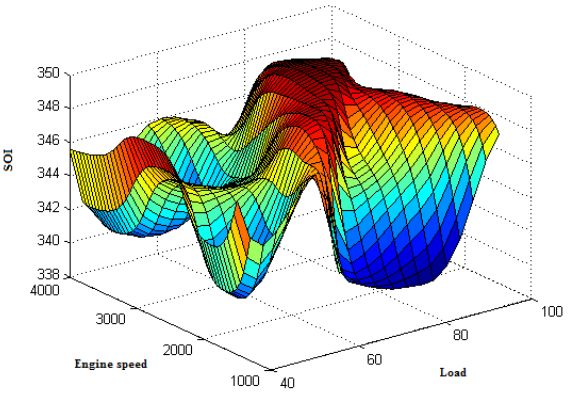


Fig. 10 Optimized value of SOI for sets of load and engine speed resulted from SPEA2+

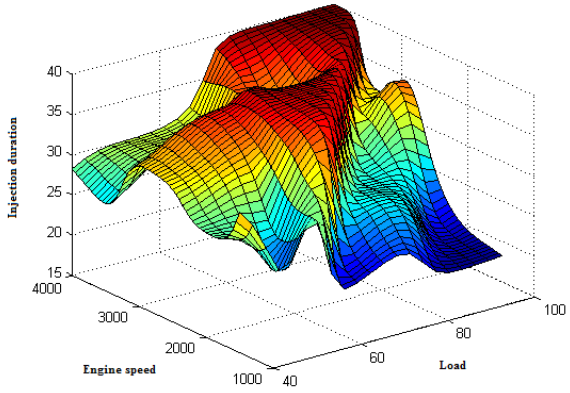


Fig. 11 Optimized value of Injection Duration for sets of load and engine speed resulted from SPEA2+

7. CONCLUSION

In this study, the problem of diesel engine emissions (NOx, soot) and performance (IMEP) optimization was studied. A neural network model of emissions and performance was developed on the basis of a two-zone combustion model of the engine. Results of the ANN model were used for the optimization. A comparison was made between the effectiveness of three well known multi-objective algorithms: MOGA, NSGA-II and SPEA2+. SPEA2+ showed slightly superior solution search ability and was able to obtain a more diverse solution set in the design variable space as compared to MOGA and NSGA-II.

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