Study and Application of a Constrained Multi-objective Optimization Algorithm

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Abstract - It is well known that the PID regulator has been very sucessful and widely accepted for controlling systems where one objective function is the performance criterion. But when the objective functions are more than one, to select the parameters of the controller is very difficulty. Especially for modern nonlinear robust controllers, it is almost impossible to tune these parameters. This paper introduces the multiobjective fuzzy genetic optimization algorithm, which provide an effective, efficient and intuitive framework for selecting these parameters. This can be used to design complex controllers in developing the diesel engine.

I. INTRODUCTION

In general, the design of a control system for a nonlinear multivariable system with a number of constraints and competing objectives. To obtain an satisfy solution (a tradeoff between the stated objectives), a formal mathematical method for decision-making is required.

In a typical control system design , the constraints are usually mixed. In order to generate flexible and robust solutions for multiobjective optimization, the concept of fuzzy sets must be employed to represent the vast amount of vagueness that exists in both the objective and constraint function. The concept of multiobjective fuzzy optimization has been used in [1-4].

A new framework is represented for selecting control parameters of an input-output linearising controller for the control system of the diesel engine. This uses the concept of multiobjective fuzzy genetic algorithm(GA) optimization[5].

The main objective for electronic diesel controls is to provide the required engine torque with minimal fuel consumption under the constraint of meeting the given exhaust gas And noise emission laws. This requires an "optimal" coordination of injection, turbocharger, and EGR system under stationary and dynamic operation.

From a controls point of view there are three important paths, which have to be considered [6,7,8,9,10], namely:

. the fuel path
. the air path
. the EGR path

Every path of above paths can be controlled in a closed loop. But the needs of the objective functions and objectives are often contrary to each other, and the more functions and parameters are considered, the more complex the work will become and the more difficult it will be to satisfy different objectives, so it is very difficult to get a macrocosmic optimum solution. Aiming at this problem, this paper introduces a method based on fuzzy genetic algorithm to optimize diesel's characteristics.

II. MULTIOBJECTIVE FUZZY OPTIMIZATION

The general multiobject fuzzy optimization problem can be stated as follow [1][2]:

Minimizes f(X)

Such that $g_j \underset{*}{\in} b_j$ (2)

Where,

$f(X) = [f_1(X), f_2(X), \cdots, f_k(X)]$ is a vector objective function and $g_j(X)$ are constraints , with the "*" symbol indicating that the constraints contain fuzzy information.

The first stage is to fuzzify the objective functions and fuzzy constraints. The membership function for the fuzzy objective function is

$$\mu_{f_i} = \begin{cases} 0 & if\ f_i(X) > f_i^{\max} \\ \dfrac{-f_i(X) + f_i^{\max}(X)}{f_i^{\max} - f_i^{\min}} & if\ f_i^{\min} < f_i(X) \le f_i^{\max} \\ 1 & if\ f_i(X) \le f_i^{\min} \end{cases} \quad (3)$$

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where $\mu_{fi}(X): R^n \rightarrow [0,1]$ and $\mu_{fi}(X)$ is a mapping from the real number set R^n to the closed interval [0,1] ,which is a measure of the degree of satisfaction for any $X \in R^n$ in the ith fuzzy objective function. $f_i^{\min}$ and $f_i^{\max}$ represent the minimum and maximum values for the objective function, respectively and are defined as

$$f_i^{\min} = \min_i f_i(X^*) \qquad (4)$$

$$f_i^{\max} = \max_i f_i(X^*) \qquad (5)$$

where X^* is the solution for each of the objective functions in the crisp domain.

The fuzzy constraints membershipp function is defined as

$$\mu_{gj}(X) = \begin{cases} 0 & \text{if } g_j(X) > b_j + d_j \\ 1 - \dfrac{g_i(X) - b_j}{d_j} & \text{if } b_j \le g_j(X) \le b_j + d_j \\ 1 & \text{if } g_j(X) \le b_j \end{cases} \qquad (6)$$

where $\mu_{gj}(X): R^n \rightarrow [0,1]$ and $\mu_{gj}(X)$ is the mapping from the real number set R^n to the closed interval [0,1] ,which is an indication of the degree of satisfaction for any $X \in R^n$ in the jth fuzzy constraint. $\mu_{gj}(\ ) = 1$ represents complete satisfaction, $\mu_{gj}(X) = 0$ is not satisfaction and values between 0 and 1 represent the degree of satisfaction of jth constraint. The allowable tolerances for each fuzzy constraint are given by d_j.

The objective functions and constraints have been defined as fuzzy subsets in the space of alternatives using linear membership functions $\mu_{fi}(X)$ and $\mu_{gj}(X)$, respectively. The optimal decision is made by selecting the best alternative from the fuzzy decision space D characterised by the membership function μ_D .In other words, find the optimum X^* which maximizes μ_D (where $\mu_D \in [0,1]$).

The fuzzy decision can be made by employing the convex decision [3] . At last, the original multiobjective fuzzy optimization problem can be transformed into the following single objective nonfuzzy optimization problem[1]:

$$\max\ \mu_D(X) = \sum_{i=1}^{k} \alpha_i \mu_{fi}(X) + \sum_{j=1}^{m} \beta_j \mu_{gj}(X) \qquad (7)$$

This problem can be solved using any standard optimization technique.

Where weights α_i and β_j are given so that a linear weighted sum can be obtained[1].

III. MULTIOBJECTIVE FUZZY GA OPTIMIZATION

Fig. 1 shows a flow chart of the design procedure for the multiobjective fuzzy GA optimization technique.

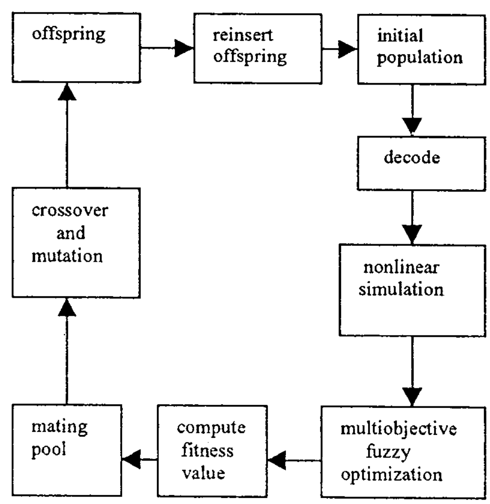

Fig. 1 Flow chart of the design procedure for multiobjective fuzzy GA optimization

A brief description of each step is given below:

(1) Initial population

At the beginning of a cycles, randomly select a population P(0) of N individuals, each of length L.

(2) Evaluation of multiobjective fuzzy optimization function

The results of the simulation are passed to the multiobjective fuzzy optimization to evaluate the degree of satisfaction and to check whether any of the constraints have been exceeded. The number of constraints exceeded and the degree of satisfaction values for each individual are passed to the fitness function.

(3) Fitness

Fitness is a metric used to assess the performance of individual members of a population relative to the rest of the population.

(4) Reproduction

Reproduction is the process whereby a mating pool is generated. Although the initial population p(0) can be generated randomly, the next generation is chosen from the previous generation members using a probabilistic selection process. This ensures that individuals with large fitness values have a greater probability of contributing offspprings to the new population. The concept of generation gap is employed in this work.

(5) Crossover

Crossover utillses probabilistic decisions to exchange systematic information between two randomly selected individuals from the mating pool, to produce new individuals. The process involves the uniform random selection of a crossover point between the two individuals, followed by the exchange of all characters either to the right or left of this point. Two new individuals are generated after crossover.

(6) Mutation

Mutation generates new individuals by simply modifying one or more of the gene values of an individual offspring after crossover. Mutation therefore provides a framework to ensure that a critical piece of information can always be reinstated or removed from a population.

(7) Reinsert offspring

Since a generation gap is used, the number of offspring is less than the size of the initial population. The offspring population is then inserted into the initial population to generate a new population.

Finally, steps (1) to (7) are repeated until P(maxgen)=maximum number of generations(maxgen).

IV. CONCLUSION

We can simulate this method using the Genetic Algorithm Toolbox in MATLAB.
It is easy to select the parameters of complexed and nonlinear controllers with this method.

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