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Research on Genetic-fuzzy Control Strategy for Parallel Hybrid Electric Vehicle

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Abstract

Fuzzy control strategy is developed for the dual-clutch single-axis torque coupling parallel hybrid electric vehicle. In this paper the torque distribution fuzzy controller which has been designed for the hybrid vehicle which is optimized by genetic algorithms. The simulation model of the hybrid vehicle was built upon matlab / simulink and ADVISOR software. Then a fuzzy rules and correspondent membership functions had been established and the input language variable and output language variable use trapeziform and deltoid membership functions. After design of fuzzy logic torque controller, the genetic algorithm was introduced and used it to optimize the fuzzy logic torque controller. Under typical condition NEDC, the fuzzy control strategy is optimized both by genetic algorithms with the constraint condition of economy performance and by integrated constraint conditions of economy performance and emission performance. Optimization results show that when the controller is only optimize fuzzy control strategy for economy performance the fuel consumption decreased by 5.3% but the emission of CO and NO_x both increased, but when the controller both optimize fuzzy control strategy for economy performance and emission performance the fuel consumption decreased by 4.3% with emission quality improved. So the fuzzy control strategy optimize by the genetic algorithm can improve the fuel consumption obvious.

Keywords— Parallel hybrid electric vehicle, genetic algorithm (GA), fuzzy control, optimization

1. Introduction

In order to optimize performance of the engine and electric motor combination, the primary

objectives of the HEV control strategy are the distribution of torque output from both of engine and electric motor and the control of the battery SOC. As a result, we can minimize energy consumption and ensure environmental

friendliness while not compromise on vehicle's performance figures. In recent years, Fuzzy control has been widely applied in HEV control strategies. Distribution of torque can be well managed by using the Fuzzy controller and good control results can be achieved. However, the lack of a well established, systematic model in selection of membership functions and the rules of the fuzzy controller results in the need of professionals and experienced operators in the stage of selecting certain control rules and membership functions.

In this paper, we designed a fuzzy logical torque controller for a certain vehicle model, and then optimized the controller with genetic algorithm. The optimized results are tested and verified to be effectively functional by simulation.

Fig 1 is the diagram for a single-axial, dual-clutch torque coupling parallel hybrid powertrain system. The major components and specifications are shown in table 1. The powertrain system consists: an engine, two clutches, an electric motor/generator, an automatic transmission and a battery.

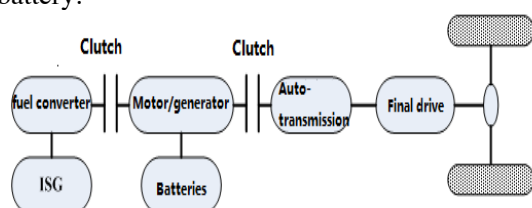


Figure 1: diagram of single-axis dual-clutch torque coupling parallel hybrid powertrain

Table 1: main components and specifications

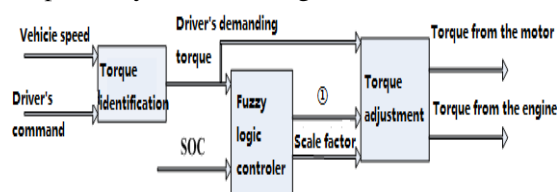
Generator	1.0L EFI Gasoline Engine	50kw/6200rpm
Electric Motor	PMSM	20kw/8000rpm
Storage Battery	Ni-MH Batteries	6.5AH, 144V

1.1 Design of Fuzzy logic Torque Controller

In table 1, it shows that the major power contributor of the parallel hybrid powertrain system is the engine; the power output from the electric motor is considered as compensative power. The design goal of the control system is to make sure that the engine operates according to the optimal performance curve. Only in the scenario when the torque from the electric motor and the battery SOC are either insufficient or overly abundant comparing to vehicle demand, the engine may operate off curve. To ensure that

the engine operates efficiently, the battery SOC should vary within a reasonable interval.

According to engine efficiency and design objective specified above, we define the input variable of the fuzzy torque controller as: the ratio P of the required torque (T_r) divided by the optimal efficient torque under current speed (T_{e_opt}) and the battery SOC. The torque coefficient of the engine (which named as “ r ”) is defined by the output variable of the fuzzy torque controller. The torque output of the engine is defined as the following function: $T_e = r \times T_{e_opt}$. Then, we adjust the engine output torque from the fuzzy controller to satisfy: when $T_e < T_{e_min}$, $T_e = 0$, $T_m = T_r$; When $T_e > T_{e_max}$, $T_e = T_{e_max}$, $T_e + T_m = T_r$ (T_{e_opt} , T_{e_max} , T_{e_min} are the optimal efficient curve, max torque curve, and shut down torque curve of the engine respectively. Shown in Fig 5)



① : Torque coefficient of the engine

Fi

Figure 2: fuzzy torque distribution controller diagram

As shown in the fuzzy torque controller diagram, Fig. 2, we identify the required torque of the vehicle by torque sensing / identification, combined with SOC as inputs. Then we analyze data using fuzzy controller, pass it through the torque adjustment device then obtain optimal engine and electric motor torque.

1.2 Selection of the fuzzy rules

In order for fuzzy logic controller to cover the full range of engine and motor operation, HEV requires various operation modes. Therefore, we categorize the ratio p (T_r/T_{e_opt}) into 5 subclasses: {NB, NS, OK, PS, PB} and define its domain as [-1.5, 1.6]. Similarly, we divide SOC into 5 subclasses according to its range, which are {z1, z2, z3, z4, z5}, and the domain is [0, 1]. We also divided the engine coefficient “ r ” into 5 fuzzy subclasses: {A1, A2, A3, A4, A5} with a domain of [1, 1.6]. The membership function of p , SOC and r are shown in Fig.7 and the input language variable and output language variable use trapeziform and deltoid membership functions. In the fuzzy inferencing, we take the minimum value when running AND operation, and use Mamdani method when running implication operation. Moreover, we employ summation

method to synthesize the conclusion, adopt centroid of area to perform non-structural fuzzy operation, and establish correspondent membership functions and fuzzy rules.

2. Using genetic algorithm to optimize Fuzzy controller

According to the characteristics of the fuzzy controller, the establishment of the fuzzy control membership functions is based on experience and thus, cannot achieve optimal control. Therefore, we use genetic algorithm to optimize the membership functions of the HEV fuzzy controller introduced in the above pages. The optimal design of the parallel HEV powertrain is a nonlinear restriction task, its mathematic model can be stated as follows:

$$\begin{aligned} \min f(x) \\ \text{s.t. } g_j(x) \geq 0, j=1,2,\dots,m \\ x_i^1 \leq x_i \leq x_i^2, i=1,2,\dots,n \end{aligned} \quad (1)$$

Among which, $f(x)$ is the emission and system efficiency objective function, while constraint conditions $g_j(x)$ are a series of nonlinear inequations that stand for the power output of the vehicle. Optimal design variables are represented by control parameter of the HEV torque distribution controller, and the boundary is $[x_i^1, x_i^2]$.

2.1 Generation of the population initialization

In fig.3, we define the fuzzy division of the fuzzy variables and the membership functions of each fuzzy subclass, employing $x_1, \dots, x_7$ to represent each point of the membership functions. Since coding are needed in input and output variable membership functions, a single one dimension decimal matrix of 21 in length is created in sequence to represent the dividing points of p' , SOC' and r' membership functions.

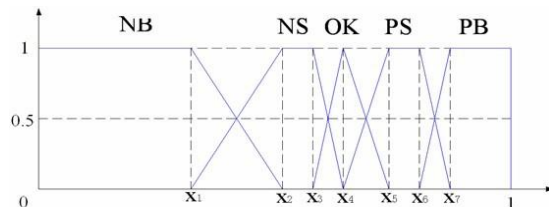


Fig 3 The membership functions for the fuzzy inference engine

The population initialization is consisted of n chromosomes, and each digit of every chromosome is of 0-1 binary notation. When

defining fuzzy functions, we define each dividing point with decimal notation, and make the coding precision of each variable no more than 0.1 to achieve an appropriate coding precision. Meanwhile, we use 5 binary places to represent 1 decimal place. The coding precision of each input/output variable are shown in table.2. Then the length of each chromosome is $21 \times 5 = 105$.

During the operation, we need to convert the population initialization into recognizable data for fuzzy controller, meaning to transform binary notation into decimal notation. Moreover, because each digital of binary notation is randomly created, when switching into decimal notations ($x_1, \dots, x_7, x_8, \dots, x_{14}, x_{15}, \dots, x_{21}$), we cannot assure that the matrix is in ascending order from x_1 to x_7 . As a result, when finishing the conversion from binary to decimal, we should sort the newly-generated numeric string to be in ascending order. x_1 to x_7 , x_8 to x_{14} , and x_{15} to x_{21} respectively represent each dividing points of different input/output membership functions. For each variable has a different domain, we need transform different variable respectively when doing decimal converting.

2.2 Fitness Functions

In this step, we choose objective function of control system as initial fitness function; different objective functions affect the optimized results of the genetic algorithm significantly differently. The fuel consumption and emission in the whole driving cycle are chosen as objective function values^[7-8], and represent optimized objectives in different weight to establish objective functions. Here are the objective functions:

$$ObjV(x) = \frac{1}{w_1 + w_2 + w_3 + w_4} \times \left(w_1 \int_0^{T_{DC}} \frac{FC}{FC} dt + w_2 \int_0^{T_{DC}} \frac{HC}{HC} dt + w_3 \int_0^{T_{DC}} \frac{NOx}{NOx} dt + w_4 \int_0^{T_{DC}} \frac{CO}{CO} dt \right) \quad (2)$$

In which:

X ——the corresponding number of each chromosome;

w_1, w_2, w_3, w_4 ——Weights for FC, HC, NO_x, CO ;

FC, HC, NO_x, CO ——The fuel consumption and emission parameters of the engine;

$\overline{FC}, \overline{HC}, \overline{NO_x}, \overline{CO}$ ——The optimal objective value for each parameter;

T_{DC} ——during the whole driving cycle, each objective value calculated by integral method.

In order to optimize fuzzy control membership functions by the genetic algorithm, we must fix the fitness function in the genetic operation. From the objective functions, it is shown that the smaller the objective function's values, the better optimization results have been achieved. However, in selecting stage of the genetic algorithm, the unit with higher fitness has a better chance to be inherited downwards. So we sort the objective function in order by using "Ranking" (Sheffield University genetic toolbox function) functions to distribute fitness functions to each objective function, making the minimal objective function value correspond with the maximal fitness function value.

2.3 Operation Parameter Setup

In the genetic algorithm, there are several operation parameters that are required to be set up: the length of individual coding (I), the size of colony (M), crossing probability (P_c), mutation rate (P_m), and terminate algebra (n), shown in table.2.

Table 2 The parameters of operation

Length (I)	Size (M)	crossing probability (P_c)	mutation rate (P_m)	terminate algebra (n)
105	80	0.7	0.01	80

2.4 Constraint condition

The genetic algorithm must be constricted in order to perform in a efficient and reliable fashion.

(1) the SOC constraints

In the fitness function, if we take the economical efficiency of the HEV system as the objective of optimization, it only contains fuel consumption parameter when performing fitness value calculation. Because fuel consumption can be determined only after the whole cycle has been completed, if we do not restrict SOC values, the optimized SOC value can be determined as 0 after the cycle is complete. Therefore, we set a limit to the SOC, making the $\Delta SOC \leq 0.03$, between the start and the end of the cycle.

(2) Fuzzy Controller Constraints

After finishing the decimal conversion, the maximal value of $x_1, \dots, x_7, x_8, \dots, x_{14}, x_{15}, \dots, x_{21}$ should be no larger than the maximal value of their corresponding domain, and their minimum values should not be less than the minimal value of the domain.

(3) Power Constraints

In the optimization operation, we set constraint to the power parameter of the vehicle model in order to obtain the optimal power output of the vehicle.

Table 3 The constraint condition of the power performance

Power parameters	Constraint Conditions
Max speed	$\geq 180 \text{ km/h}$
Accelerating Performance	$\leq 11 \text{ s} (0 - 96.6 \text{ km/h})$
Δtrace	$\leq 1 \text{ km/h}$

Δtrace : the different between the actual speed and the demanding speed during the driving cycle in simulation.

3. Analysis of Simulation Results

3.1 optimal calculation for economic in NEDC cycle

When the optimization objective is economic performance only, we define the weight value W_f in the fitness function (function 2) as 1, while the rest are 0. The purpose of such a setup is to monitor the change in fuel consumption when the fuzzy control strategy is changed so that it becomes possible to determine the best fuzzy control strategy to achieve minimum fuel consumption of the HEV system. Then we can determine the operation parameter in genetic algorithm and run simulation in MATLAB/simulink to obtain the results.

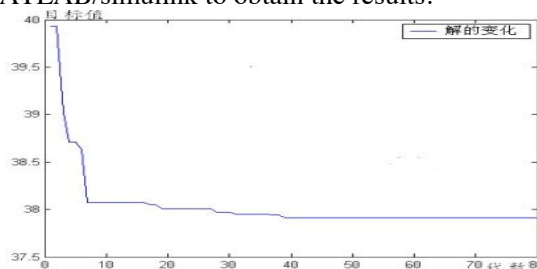


Fig. 4 The convergence curve of the object function

Fig.4 shows the constringency curve of the objective function in the genetic algorithm optimization operation, while the x-axis represents the genetic algebra and the y-axis is the value of objective function. Therefore we obtain the optimal results in the 80th generation and therefore, confirm the optimized fuzzy membership function, as shown in Fig.8.

We put the optimized results in "ADVISOR" and repeat the simulation; obtain the chart figures of each operation parameter in parallel HEV system, and compare them with previous data (before optimization). From the SOC curve in Fig.10 (a),

(b), we can see that the maximum difference of SOC is between ± 0.005 , fitting with the requirement of SOC control. From Fig.11 (a), (b), and 12(a), (b), we can see that the efficiency of the electric motor has been improved and the engine operation point clearly comes close to the expected optimal operation curve of the engine. After a comparison of the Fuzzy control strategy and genetic algorithm economical optimal parameter in Table.4 we can conclude that when using genetic algorithm, the fuel consumption of the parallel HEV powertrain system can be reduced by 5.3% without negatively affecting its power performance. However, the emission of CO and NOx are increased.

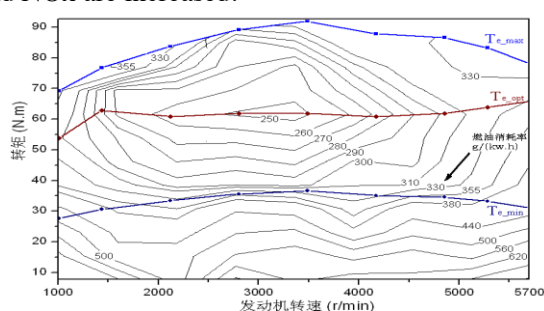


Figure 5 The effect of the engine

3.2 Analysis of Multi-Objective Optimization Results

According to fitness function (2), we set the weights as $w_1=0.25$, $w_2=0.25$, $w_3=0.25$, $w_4=0.25$ when considering both efficiency and emission, and we perform optimization with genetic algorithm in NEDC cycle.

After defining the fitness function, we run simulation in MATLAB/simulink with the genetic algorithm operation parameter (mentioned above) to get the simulation results.

Fig.6 shows the constringency curve of the object function, and the x-axis represents genetic algebra and the y-axis represents objective function's value. The optimized fuzzy membership functions are shown in Fig.9.

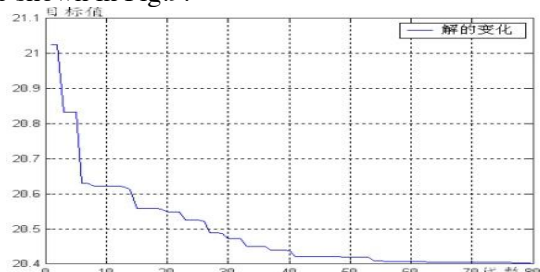


Figure 6 The convergence curve of the object function

We input the optimized results into “ADVISOR” to repeat the simulation, obtaining the chart

figures of each operation parameter in parallel HEV system, and compare them with previous data (before optimization). From Fig. 11(a), (c), and 12(a), (c) we know that the difference between the initial and final value of SOC is satisfied with the control demand. From Fig.11 (a), (c), and 12(a), (c) we can see that the engine operation point clearly moves downwards, and it therefore moves forward to the zone of higher fuel consumption. At the same time, comparing the NEDC testing cycle and SOC curve, shut down the engine in low speed, and the whole vehicle was driven by electric motor; While in middle speed, the vehicle was driven by engine and its operation point came close to the optimal torque curve; In the acceleration and high speed driving circumstance, the vehicle was driven by both engine and electric motor.

Table 4 Compare of the simulation result

Power parameter	Fuzzy control strategy	Optimized genetic algorithm	Multi-objective optimized genetic algorithm
64.4-96.6km/h (s)	6.3	6.5	7.4
Max acceleration (m/s^2)	3.9	3.9	3.7
Fuel consumption(L/100km)	4.6995	4.4845	4.5281
HC (g/km)	0.31626	0.31217	0.31156
CO (g/km)	1.1285	1.1920	1.1047
NOx (g/km)	0.20406	0.21661	0.18814

After we compared the fuzzy control strategy with the Multi-objective optimized genetic algorithm parameter, we know that after optimized by the genetic algorithm, the power output of the parallel HEV powertrain system decreased slightly, but its fuel consumption can be reduced by 4.3%, and the emission parameter HC, CO and NO_x all significantly decrease.

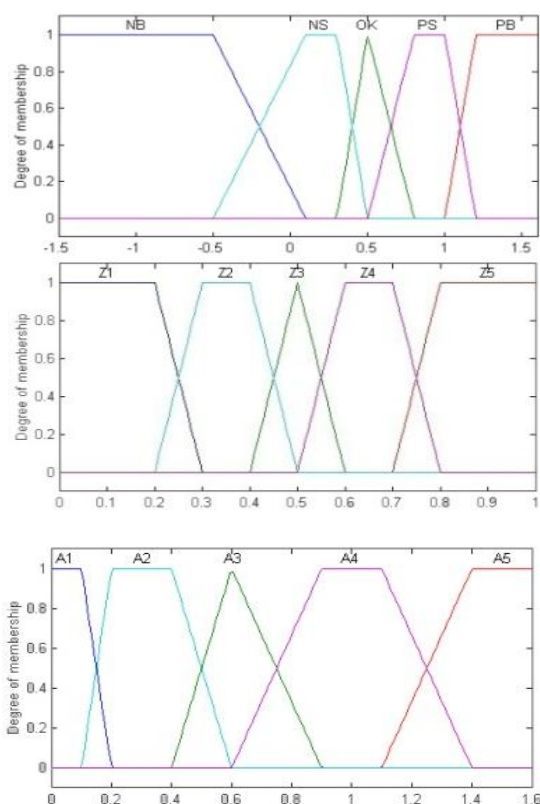


Figure 7 The membership functions of p , SOC and r for the fuzz control strategy

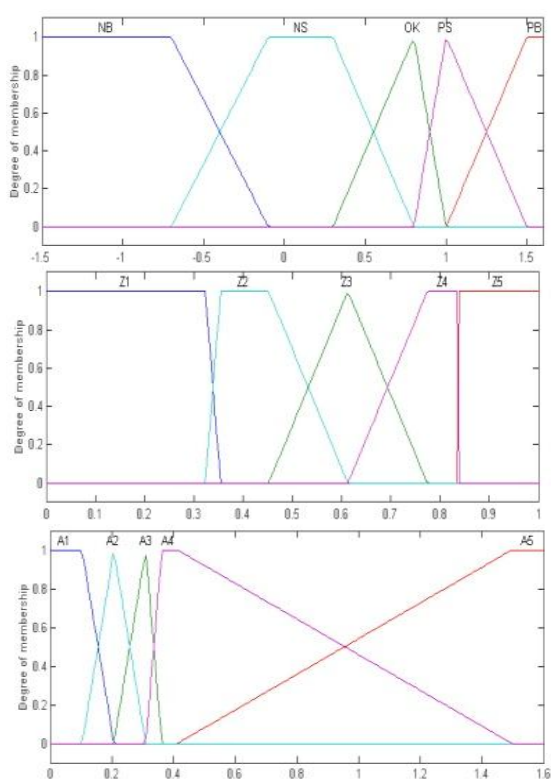


Figure 8 The membership functions of p , SOC and r for the economy optimums with genetic algorithms

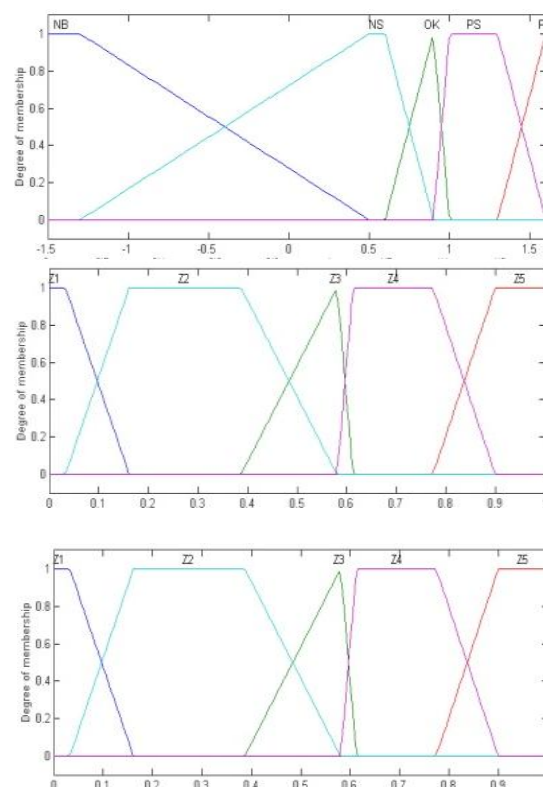


Figure 9 The membership functions of p , SOC and r for the multi-object optimums with genetic algorithms

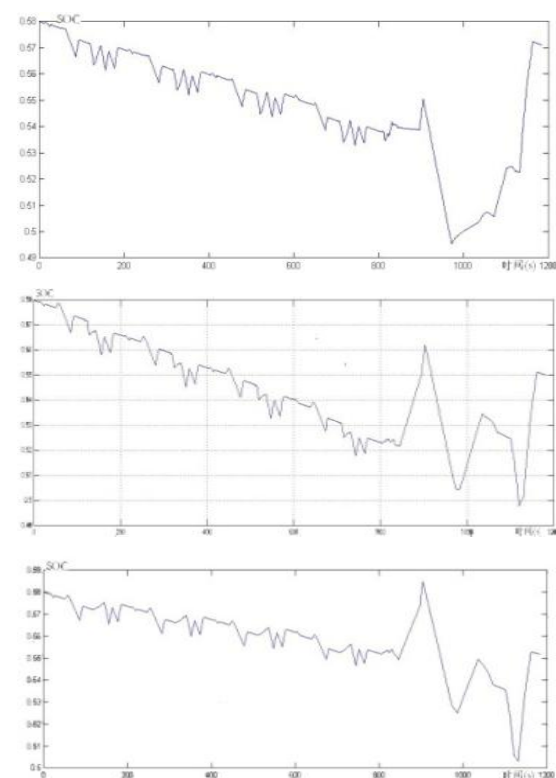


Figure 10 The SOC curve of fuzz control, economy optimized results and multi-object optimized results

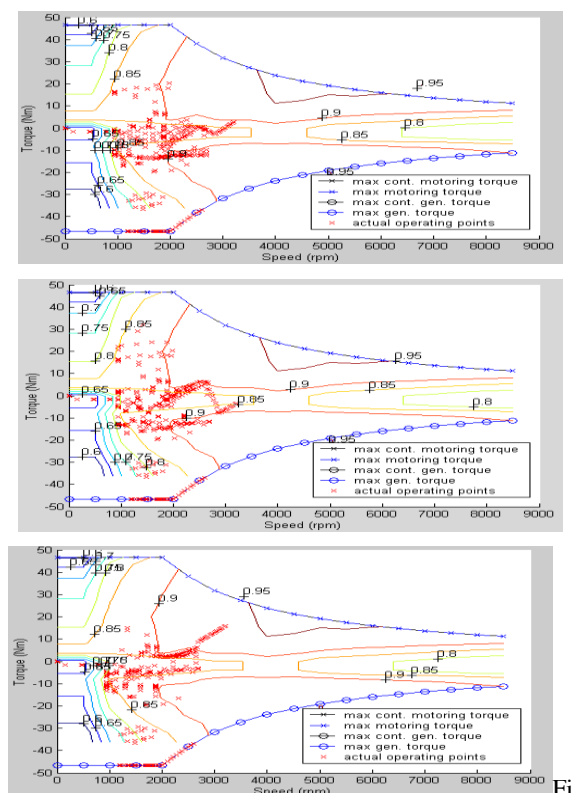


Figure 11 The motor operation area of fuzz control, economy optimized results and multi-object optimized results

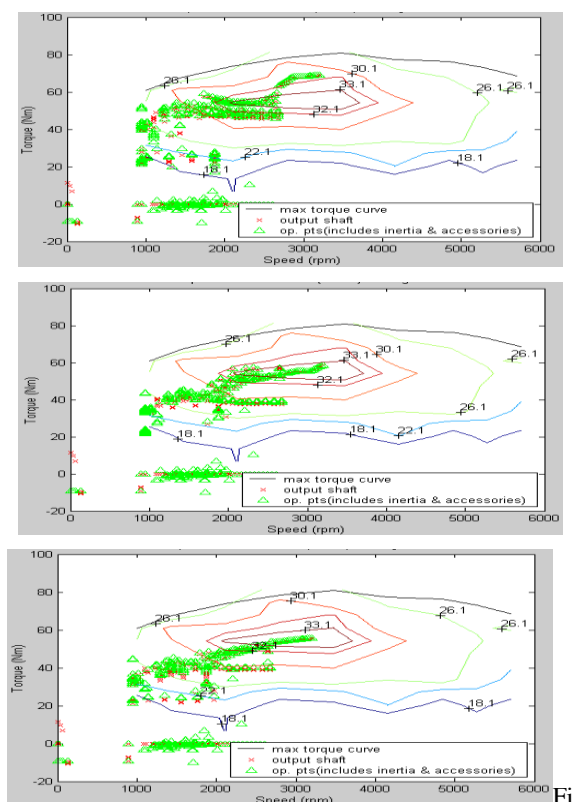


Figure 12 The engine operation area of fuzz control(a), economy optimized results(b) and multi-object optimized results

Conclusion

1) In this paper, we designed single-axis dual-clutch torque coupling parallel hybrid torque distribution fuzzy control strategy, and employed genetic algorithm to optimize the distribution of torque in fuzzy controller, mending the problem that the traditional fuzzy control strategy was based on experience and the optimal control can hardly be achieved.

2) In NEDC cycle, we used genetic algorithm which only optimize fuzzy control strategy for best economy, and the fuel consumption decreased by 5.3% but the emission of CO and NO_x both increased.

3) In NEDC cycle, we used genetic algorithm which optimize fuzzy control strategy for better economy and emission all together, and fuel consumption decreased by 4.3% with emission quality improved.

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