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Study on Fuzzy Energy Management Strategy of Parallel Hybrid Vehicle Based on Quantum PSO Algorithm

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Abstract

A fuzzy energy management strategy was designed for the single-axle parallel hybrid electric vehicles, and then the quantitative factor of the fuzzy logic controller was optimized by the quantum PSO algorithm under the Matlab platform based on the equivalent fuel economy. Then a comparison test about the energy management before and after the optimization was carried out based on the secondary development of Advisor which proves that the energy management strategy optimized by the quantum PSO algorithm can improve the SOC of the battery pack by 18% when the VAIL2NREL cycle finished while the power of the vehicles nearly remain the same. What's more, the optimized strategy can make the engine and the motor works in the high efficient area for most of the time which can improve the recycling rate of the energy and reduce the equivalent fuel consumption effectively.

Keywords*: single-axle parallel hybrid, fuzzy energy management, Quantum PSO algorithm*

1. Introduction

As is known to all, Parallel hybrid vehicles generally use two separated driving systems, and it has the advantages of flexible control and high overall efficiency, which can reduce the operating costs of vehicle effectively. Energy management strategy is one of the key directions of hybrid technology. Its main function is to allot the required torque of the vehicle to the engine and the driving motor rationally based on the characteristics of vehicle's driving system and the real-time operating conditions, as well as to get the goal of low emissions and smooth drivability [1-2].

However, the operation mode of the parallel hybrid vehicle is so complicated that the development of control strategy, in general, is not mature enough. Currently, the logic threshold control strategy is used more in the engineering practice, but its parameters' adjustment is mainly rely on the experience or the "trial and error" method. This method can't guarantee the best match of the power system and the maximum fuel economy though it can be realized easily. Literature [6-7] proposed a global optimal energy management strategy based on the classical variational method and the dynamic programming method, but this method requires to know the driving conditions ahead. As a result, it is difficult to apply to the on-line control [6-7]. SALMAN *et al*. proposed an instantaneous optimized energy management strategy based on model predictive control, which using GPS to predict the vehicle's driving conditions in the coming period, and using optimal control theory to obtain the optimal control law which can get the minimum fuel consumption in the next period. But the simplify of the system's mathematical model and the control algorithm of this method are too complicated, as a result of which it's difficult to achieve too [8].

The fuzzy energy management strategy which is based on the fuzzy logic control (FLC), has the advantages of strong robustness, less overshoot and good real-time, and it

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doesn't need the accurate mathematical models. As a result, it has now become used in hybrid electric vehicle's energy management strategy more and more. In this paper, a fuzzy logic controller was designed for a certain type of hybrid tractor, and then the quantitative factor of the controller is optimized based on quantum particle swarm optimization (PSO) algorithm. After that, we embedded the optimized fuzzy logic controller into the ADVISOR environment by the secondary development so as to carry out the simulation experiments. The results of the experiments prove the effectiveness of the controller.

2. The Transmission Structure and Work Mode Analysis of the Parallel Hybrid Tractor

Figure 1 shows the assembly structure of the parallel hybrid tractor, mainly includes: the engine, the disc GM motor, ISG motor, clutch, batteries, inverter, variable displacement hydraulic pump and two hydraulic motors. The engine and GM motor is coaxial, and between them is the electromagnetic clutch. The hybrid tractor has three different driving modes, driven by motor alone, driven by the engine alone and driven by both the engine and the motor. The driving mode will be changed if the clutch turned from combination to separation or from separation to combination.

The engine can drive the ISG motor and the disc GM motor to recharge the battery pack when the starting battery and drive batteries' SOC value is too low. What's more, the GM motor will be worked in the generator mode so as to recovery the braking energy of the tractor when braking.

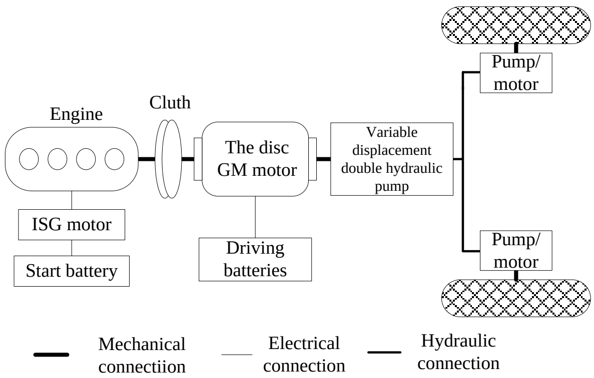


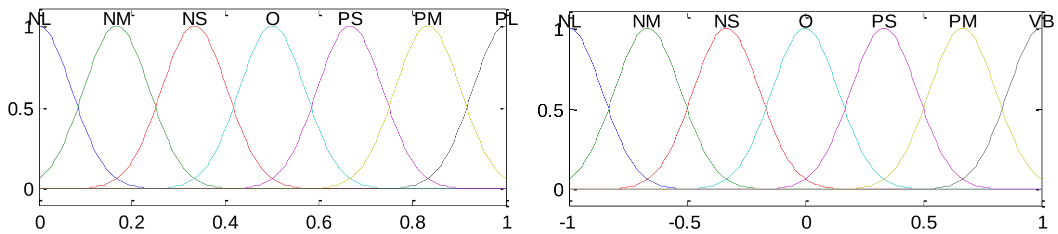
Figure 1. Parallel Hybrid Tractor's Assembly Structure

3. The Fuzzy Logic Energy Management Strategy

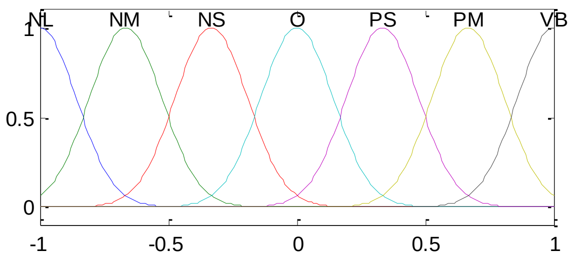
As already noted, the parallel hybrid tractor has two sets of drive system, and the engine and the GM motor have their own high efficient workspace. In order to improve the tractor's fuel economy and reduce the harmful emissions, the energy management strategy must allot the demand torque of the tractor to the engine and the driving motor rationally, what's more, it also neet to optimize the operation point of the engine, motor and the battery pack. Because the hybrid system is a complex nonlinear time-varying system, it is difficult to establish an precise mathematical model. As a result, adopting traditional control method is hard to achieve satisfactory control effection [1-4]. As the fuzzy logic control strategy doesn't depend on the precise mathematical model and has good robustness, it's especially suitable for the optimal control of the hybrid systems [1-5].

According to the specific condition of the hybrid tractor, we established a fuzzy logic controller with two inputs and single output. The estimation of the battery's SOC and the hybrid system's require torque Tr were treated as the inputs. The output torque of the engine Te was treated as the output. When working, the controller fuzzy up the two input signals for first, and then the fuzzy reasoning was carried out based on fuzzy control rules. Finally, the output torque was got by defuzzification. The output torque of the disc GM motor Tm is equal to the difference between the Tr and Te. When the Tm is positive, drive battery output power. On the contrary, when the Tm is negative, the disc GM motor charges the driving batteries.

The membership function of the battery's SOC, system's required torque Tr and the output torque of engine Te were shown in Figure 2. The battery's SOC is in range {0, 1}, and the system's required torque and output torque of the engine were in range {-1, 1}, however, the "0" in the fuzzy domain of the battery's SOC is on behalf of "0.4" in reality and "1" represents "0.9" in reality. The "-1" in the fuzzy domain of Te is on behalf of "0" in reality and "1" represents the maximum output torque in reality, while "0" refers to the optimal torque value which is determined by the optimum torque curve and the engine's speed. As shown in Figure 2, seven fuzzy subsets were defined for all the variables and the Gaussian membership function were adopted. All fuzzy sets are decomposed into seven fuzzy partitions: negative large (NL), negative medium (NM), negative small (NS), zero (O), positive small (PS), positive medium (PM) and positive large (PL).



(a) Membership Functions of Battery SOC (b) Membership Functions of Demand Torque T_r



(c) Membership Functions of Engine Output Torque T_e

Figure 2. Membership Functions of Fuzzy Controller's Inputs and Outputs

The Mamdami type fuzzy reasoning method was used in the FLC. Gravity method is adopted in defuzzification process. Other properties of the FLC design are: and method: min, or method: max, implication: min, aggregation: max. The fuzzy rules represented in the following form,

$$\text{RULE } i\text{: if } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i,$$

$$\text{Then u is } B^i \quad i=1,2,3\ldots$$

In which, RULE *i* refers to the rule number *i*, x_1, x_2 refers to input variables, u refers to output variables. Figure 3 gives an overview of the generated FLC control surface. The surface is a graphical representation of the implemented fuzzy control law.

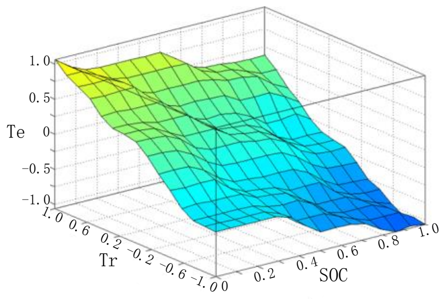


Figure 3. Generated FLC Control Surface

The I/O quantitative factors of the FLC can actual enlarge or reduce the measurement signal and output control, and it can affect the control effect of the system directly. In order to make the energy management strategy of FLC gain better effect, in this paper, we introduce the quantum particle swarm optimization (PSO) algorithm for the setting of FLC's I/O quantitative factor.

4. A Quantum Particle Swarm Optimization Algorithm

4.1 Particle Swarm Optimization Algorithm

Particle swarm optimization algorithm (PSO) is a new optimization algorithm by the simulation of the flock's foraging behavior [9]. It can reach the optimal location by the cooperation of the whole group. Its basic algorithm can be expressed as: in a D dimensions space, equipped with m particles, $X_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,D})$, $(i = 1, 2 \cdots m)$, in which, X_i refers to the D dimensions position vector of the particle i. $v_i = (v_{i,1}, v_{i,2}, v_{i,3} \cdots, v_{i,D})$ refers to the flying speed of particle i. In each iteration, the particles update themselves by tracking two optimal solutions, one is the optimal position of the particle itself p_{best}, namely the individual optimal solution, $p_{i,j} = (p_{i,1}, p_{i,2}, \cdots p_{i,D})$, the other is the optimal position searched by whole group to date, namely the global optimal solution, $g_{i,j} = (g_{i,1}, g_{i,2}, \cdots g_{i,D})$.

The basic PSO algorithm is updated by the following equations [9-11],

$$v_{ij}^{k+1} = wv_{ij}^k + c_1 f_{r1}^k (p_{ij}^k - x_{ij}^k) + c_2 f_{r2}^k (p_{gj}^k - x_{ij}^k) \tag{1}$$

$$x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1} \tag{2}$$

As shown above, type (1) was the velocity updating equation, and type (2) was the position updating equation. Where,

w: The inertia weight.

v_{ij}^k: The velocity of k-th iteration in the j-th dimension of the search space.

c_1, c_2: The coefficients, the balance factors between the effect of self-knowledge and social-knowledge in the test case movement towards the target position.

f_{r1}^k, f_{r2}^k: Refers to the random numbers between 0 and 1, and different at each iteration.

x_{ij}^k: The position of the k-th iteration in the j-th dimension of the search space.

p_{ij}^k: The best position that particle i experienced in the j-th dimension of the search space.

p_{gj}^k : The best position that gBest experienced in the j-th dimension of the search space.

x_{ij}^{k+1} : The position of particle i in (k+1)-th iteration in the j-th dimension of the search space.

However, PSO algorithm also has many disadvantages, for example, its global optimization ability is poor as well as it is easy to fall into local extremums. As a result, this paper introduces the quantum particle swarm optimization algorithm (QPSO). Quantum particle swarm optimization algorithm used the quantum-bit to encode the current position of the particles x_{ij}^k, and the update of the particles' positions are achieved by quantum revolving door. Also the quantum not gate is used to realize the mutation of particles' positions so as to avoid the premature problem of the PSO algorithm and improve the precision of the PSO algorithm.

4.2 Quantum Particle Swarm Optimization

Particles were thought to have quantum behavior in QPSO, when each particle moves in the search space, there is a Pbest centered DELTA potential well [10]. Due to the state of aggregation of the particles were completely different in quantum space, the particles have no certain trajectory, which can make the particles find the global optimal solution in the whole feasible solution space. As a result, QPSO algorithm's global search ability is much better than the classical PSO algorithm. Using quantum bits coding can increase the universality and the ergodicity of the particles, and it can improve the accuracy of the optimization algorithm [12-13].

QPSO algorithm treat the probability amplitude of quantum bit as the encoding of particle's current location. The encoding strateg is as follows,

$$P_i = \begin{bmatrix} \cos\theta_{i1} & \cos\theta_{i2} & \cos\theta_{i3} & \cdots & \cos\theta_{it} \\ \sin\theta_{i1} & \sin\theta_{i2} & \sin\theta_{i3} & \cdots & \sin\theta_{it} \end{bmatrix} \tag{3}$$

Where, $\theta_{ij} = 2\pi * rand()$ and $rand()$ refers to a random number in range [0-1]. i refers to the size of the population, $i = 1, 2, 3 \cdots r$. j refers to the dimensions of the space, $j = 1, 2, 3 \cdots t$.

As shown in type (3), each particle of quantum particle swarm can traversal two position in the solution space at the same time, and the traversal scope is in range[-1,1]. In order to calculate the fitness of each particle, particle position which is represented by probability amplitude of quantum bit in quantum particle swarm needs to be transformed to the solution space $J = [a_j, b_j]$. If the j-th quantum bit of particle p_i is set to $p_{ij} = [\alpha_{ij}, \beta_{ij}]^T$, the variables of corresponding solution space expressed by p_{ij} are as follows.

$$\begin{cases} X_{ijc} = \frac{1}{2}[a_i(1-\alpha_{ij}) + b_i(1+\beta_{ij})] \\ X_{ijs} = \frac{1}{2}[a_i(1-\alpha_{ij}) + b_i(1+\beta_{ij})] \end{cases} \tag{4}$$

According to the coding strategy above, the quantum bit should be updated using quantum revolving door so as to realize the motion of the two position at the same time. The updating equations are as follows,

$$\Delta\theta_{ij}^{k+1} = \omega\theta_{ij}^k + c_1 f_{r1}^k \Delta\theta_p + c_2 f_{r2}^k \Delta\theta_g \tag{5}$$

$$\begin{bmatrix} \cos\theta_{ij}^{k+1} \\ \sin\theta_{ij}^{k+1} \end{bmatrix} = \begin{bmatrix} \cos(\theta_{ij}^k + \Delta\theta_{ij}^{k+1}) \\ \sin(\theta_{ij}^k + \Delta\theta_{ij}^{k+1}) \end{bmatrix}$$

$$=\begin{bmatrix}\cos\Delta\theta_{ij}^{k+1} & -\sin\Delta\theta_{ij}^{k+1}\\ \sin\Delta\theta_{ij}^{k+1} & \cos\Delta\theta_{ij}^{k+1}\end{bmatrix}\begin{bmatrix}\cos\Delta\theta_{ij}^{k}\\ \sin\Delta\theta_{ij}^{k}\end{bmatrix} \tag{6}$$

Where,

$$\Delta\theta_p=\begin{cases}\theta_{pij}-\theta_{ij}+2\pi, & \theta_{pij}-\theta_{ij}\le-\pi\\ \theta_{pij}-\theta_{ij}, & -\pi<\theta_{pij}-\theta_{ij}\le\pi\\ \theta_{pij}-\theta_{ij}-2\pi, & \theta_{pij}-\theta_{ij}>\pi\end{cases} \tag{7}$$

$$\Delta\theta_g=\begin{cases}\theta_{gj}-\theta_{ij}+2\pi, & \theta_{gj}-\theta_{ij}\le-\pi\\ \theta_{gj}-\theta_{ij}, & -\pi<\theta_{gj}-\theta_{ij}\le\pi\\ \theta_{gj}-\theta_{ij}-2\pi, & \theta_{gj}-\theta_{ij}>\pi\end{cases} \tag{8}$$

Type (5) shows the updating equation of the rotation angle and type (6) shows the update equation of the probability amplitude. Type (7) and type (8) were the constraints of the updating equations. θ_{pij} refers to the historical optimal position of the j-th dimension of particle i. θ_{gj} refers to the optimal phase of the j-th dimension of the whole group. θ_{ij} refers to the current phase.

Mutation operation was used to avoid the PSO algorithm falling into the local extremum by the quantum not gate. Firstly, each particle generate a variation factor in the range [0-1] randomly. Secondly, when the variation factor is smaller than the setting mutation probability, the mutate operation of the probability amplitude should be carried out according to type (9).

$$\begin{bmatrix}0 & 1\\ 1 & 0\end{bmatrix}\begin{bmatrix}\cos\theta_{ij}\\ \sin\theta_{ij}\end{bmatrix}=\begin{bmatrix}\cos(\tfrac{1}{2}\pi-\theta_{ij})\\ \sin(\tfrac{1}{2}\pi-\theta_{ij})\end{bmatrix} \tag{9}$$

4.3 Algorithm Flow

The optimization flow of the fuzzy quantitative factor based on QPSO algorithm is as follows,

1) Initialize the quantum particle swarm according to the type (3), and generate the initial population.

2) Mapping the particle position which was expressed as probability amplitude of quantum bit to the solution space according to the type (4). And then calculate the equivalent fuel consumption of the corresponding particles in ADVISOR. If the particle's current location is better than its historical optimal location, the historical optimal location should be replaced with the current position. If the current optimal location is superior to the historical global optimal position, the global optimal position should be replaced with the current optimal position.

3) Update the status of the particles according to the type (5) and type (6).

4) Carry out mutation operation to each particle according to probability based on the type (8).

5) Return to step 2) and carry out circulation calculation until reach the maximum number of cycles or achieve the fitness value. The positions of the quantum particles at this time should be mapped to the solution space, and outputs the optimal value of k_{soc}, k_{te}, k_{tr}. The Figure 4 shows the optimization flow chart of FLC's quantitative factor.

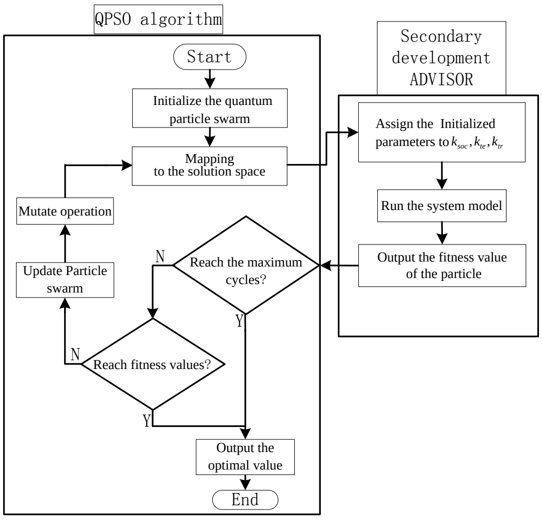


Figure. 4 The Optimization Flow Chart

5. Simulation Experiments and the Analysis

In order to verify the effectiveness of the fuzzy energy management strategy optimized based on QPSO algorithm. A simulation model of parallel hybrid electric tractor was established based on ADVISOR platform, and the optimized fuzzy logic control strategy module was embedded in the simulation model by the secondary development. The simulation parameters of the main components of the tractor are shown in Table 1.

Table 1. Part of the Main Parameters of the Hybrid Tractor

Parameters	Value
The full weight of the vehicle	3000 kg
Axial distance	1300 mm
Windward area	1.6 m^2
The wheel radius	280 mm
Rated capacity of battery	80 AH
Rated voltage of battery	288 V
The initial SOC of battery	0.7

Based on the practical working environment of the hybrid tractor, the VAIL2NREL cycle was chosen to carry out the simulation research, and a comparison test was carried out with the normal fuzzy energy management strategy and the electric assist control strategy.

Figure 5 shows the changes of power battery's SOC value of hybrid tractor under the condition of VAIL2NREL cycle. As can be seen from the diagram, the power battery's SOC under these three kinds of control strategies all can maintain in a reasonable range.

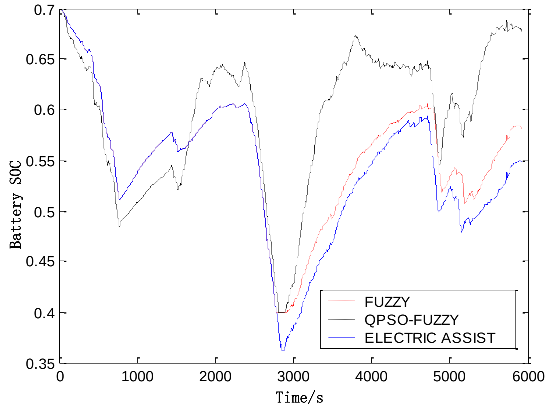


Figure 5. The SOC Changes under VAIL2NREL Cycle

The performance of fuzzy energy management strategy without optimization is slightly better than ADVISOR's own electric assist control strategy. In the cycle, the minimum value of battery SOC is slightly higher than electric assist control strategy, but the slopes of SOC curve nearly the same. That means the braking energy recovery ability and battery energy use ability are basically the same between the fuzzy energy management strategy without optimization and the electric auxiliary energy management strategy. However, the SOC value of the battery used FLC energy management strategy optimized by QPSO algorithm decline faster than the other two methods, which means that the power battery provides more energy on conditions that the SOC is in the reasonable range. As a result, it can reduce the equivalent fuel consumption of the vehicle in the driving stage. In the deceleration phase, battery SOC value also rise more rapidly, which shows that the vehicle recycling more braking energy when the tractor braking. At the end of the cycle, the power battery's SOC value of the tractor used FLC energy management strategy optimized by QPSO algorithm is increased by 18% compared with that without optimization and is increased by 24% compared with electric assist control strategy.

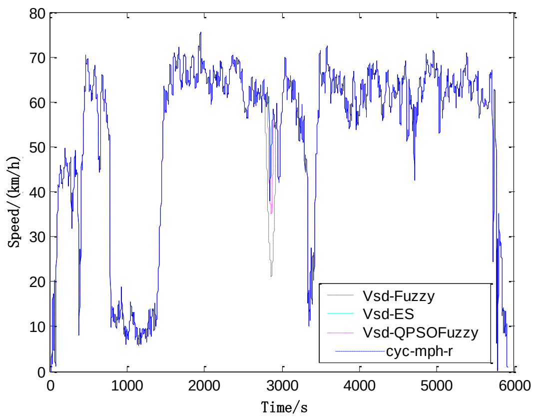


Figure 6. The Dynamic Performance Comparison under VAIL2NREL Cycle

Figure 6 shows the dynamic performance comparison among these three different control strategies under VAIL2NREL cycle. As can be seen from the diagram, under the electric assist control strategy, the actual speed of the vehicle fully meet the requirements of driving cycles. This is because the electric assist control strategy treats adequate performance as main target. The vehicle's dynamic performance under the FLC energy management strategy without optimization can meet the demand in most of the time, but in about 2800s, a short-term power shortfall occurred for road slope is bigger. But when the FLC energy management strategy was optimized with QPSO algorithm, this situation was improved, which shows that the FLC energy management strategy optimized with QPSO algorithm can maximum the braking energy saving to reduce fuel consumption under the premise of meeting the power demand of vehicle.

Figure 7 and Figure 8 show the working points of the disc GM motor under the control of the FLC energy management strategy before and after the optimization with the QPSO algorithm respectively. As can be seen from the diagram, after optimization with the QPSO algorithm, the FLC energy management strategy can make the machine's working points more focused on efficient workspace. In addition, the working points in a state of power is increased which proves that its capability of energy recovery is enhanced effectively.

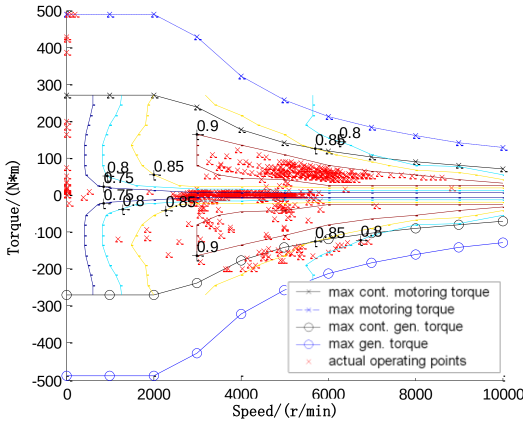


Figure 7. The Working Points Distribution without Optimization

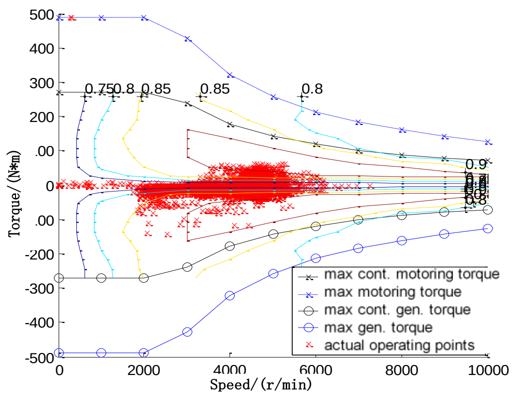


Figure 8. The Working Points Distribution when Optimized with QPSO

Figure 9 and Figure 10 show the engine's working point distribution before and after optimization respectively. As can be seen, the engine's working point after optimization is also more concentrated in high efficient area and the average working efficiency was promoted from 21.7% to 29.8% after the optimization.

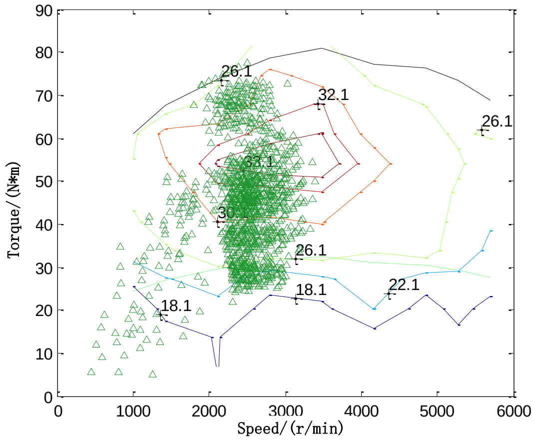


Figure 9. The Engine's Working Point Distribution without Optimization

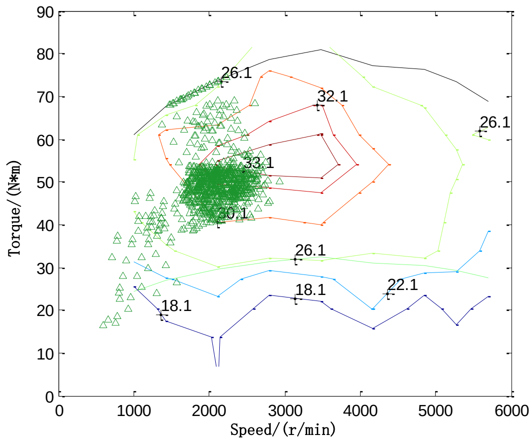


Figure 10. The Engine's Working Points Distribution after Optimization

To verify the tractor's ability to adapt to different road conditions under FLC energy management strategy optimized by QPSO algorithm, two more typical working conditions, UDDS and NEDC was co-opted to carry out simulation experiments. And Table 2 shows comparison of the fuel consumption of the FLC energy management strategy before and after the optimization under the three different cycles. We can find that the optimized management strategy not only has good energy-saving performance under VAIL2NREL conditions, but also has good adaptability for other different cycles. The average fuel efficiency of the fuzzy logic control strategy after optimization is improved by 6.9% compared with the strategy without optimization.

Table 2. The Comparison of Equivalent Fuel Consumption under Several Different Working Cycles

Working cycles	Equivalent fuel consumption(L)		
	FUZZY	QPSO-FUZZY	Bias (%)
VAIL2NREL	8.21	7.60	7.4
CYC_UDDS	0.62	0.58	6.4
CYC_NEDC	0.58	0.54	6.8

6. Conclusions

Energy management strategy is one of the core technologies of the development of hybrid electric vehicle. In this paper, a fuzzy energy management strategy based on fuzzy logic controller was established, and then it was optimized by the QPSO algorithm. After then, the simulation experiments were carried out to verify the effectiveness of the proposed fuzzy energy management strategy optimized by the QPSO algorithm based on the secondary development of ADVISOR under Matlab/simulink environment.

Experimental results show that the strategy can effectively reduce the fluctuating range of the power battery's SOC value in the process of circulation and it also can improve the braking energy's recycling rate under the premise of keeping the vehicle's dynamic performance nearly the same. In addition, the optimized control strategy can obviously improve the working point of engine and GM motor, which can make the two working more in high efficient area, as well as effectively reduce the equivalent fuel consumption and improve the fuel economy of the vehicle.

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