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Fuzzy energy management strategy for parallel HEV based on pigeon-inspired optimization algorithm

PEI JiaZheng, SU YiXin & ZHANG DanHong*

School of Automation, Wuhan University of Technology, Wuhan 430070, China

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Improvements in fuel consumption and emissions of hybrid electric vehicle (HEV) heavily depend upon an efficient energy management strategy (EMS). This paper presents an optimizing fuzzy control strategy of parallel hybrid electric vehicle employing a quantum chaotic pigeon-inspired optimization (QCPIO) algorithm. In this approach, the torque of the engine and the motor is assigned by a fuzzy torque distribution controller which is based on the battery state of charge (SoC) and the required torque of the hybrid powertrain. The rules and membership functions of the fuzzy torque distribution controller are optimized simultaneously through the use of QCPIO algorithm. The simulation ground on ADVISOR demonstrates that this EMS improves fuel economy more effectually than original fuzzy and PSO_Fuzzy EMS.

parallel hybrid electric vehicles (parallel HEV), energy management strategy (EMS), fuzzy controller, pigeon-inspired optimization (PIO) algorithm, quantum evolution, chaotic search

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1 Introduction

A hybrid electric vehicle (HEV) is a vehicle that uses mechanical energy obtained from at least an internal combustion engine (ICE) and an electric motor (EM). On the basis of traditional system configuration and composition, a hybrid electric vehicle can be classified into the series, parallel or mix three sorts. Different hybrid powertrain styles have different flexibilities for the control strategy. In this respect, parallel hybrid drive is a kind of very promising structure with special advantages and a good developing future.

Nevertheless, the energy management strategy (EMS) of parallel HEV is insufficient for the complex driving cycle of parallel HEV. The logic threshold control strategy is generally used to preset a set of threshold parameters mainly depending on traditional engineering experience so that it cannot guarantee an optimal result in all situations [1]. An instantaneous optimization control strategy was developed by Park [2] based on the equivalent fuel consumption minimization method, but it is difficult to implement because it requires complex computation and precious vehicle model. Later, a series of optimization-based methods be used for EMS to determine the power distribution among power sources. Patil et al. [3] proposed supervisory control strategies for plug-in hybrid electric vehicle powertrains by using deterministic dynamic programming (DDP) method. Ref. [4] has compared dynamic programming and Pontryagin's minimum principle (PMP) on energy management for a parallel hybrid electric vehicle. The optimal results demonstrated the total fuel consumptions in PMP are very close to DDP, but the former has less time-consuming than the latter. Borhan et al. [5] utilized model predictive control (MPC) strategies to obtain the power distributions. Xia and Zhang [6] firstly adopted linear quadratic optimal control theory to

*Corresponding author (email: zhangdh@whut.edu.cn)

solve the power distribution problem of HEV. However, both of the two methods need accurate model and complex computations.

Few researchers have proposed fuzzy logic for EMS, which is tolerant of imprecise mathematical model or data and has good flexibility and strong robustness [7,8]. However, the fuzzy controller is built on top of human expertise and thus it cannot find the optimal solution [3,4]. In an attempt to obtain the optimal solution for fuzzy control parameters, many metaheuristic population-based intelligence algorithms were implemented to overcome these deficiencies. Xing et al. [9] introduced genetic algorithm (GA) and applied it for optimizing fuzzy membership function parameters. A similar optimized application was described by Zhou et al. [10], and the results indicated that the proposed strategy could reduce fuel consumption and exhaust emissions to 43.84%. In ref. [11], the study also optimized the fuzzy control rules as one of technic parameters by using particle swarm optimization (PSO) algorithm [12]. Some machine learning algorithms are used in a mixed-fuzzy controller, such as learning vector quantization (LVQ) neural network [11], machine learning optimal power sources (MLOPS) [13] and continuous state Markov decision process (MDP) [14]. However, there is opportunity to improve them in convergence performance and time.

In this paper, a fuzzy EMS based on quantum chaotic pigeon-inspired optimization (QCPIO) algorithm is proposed to improve the fuel economy of parallel HEV. The simulation results show that the QCPIO_Fuzzy EMS can effectively reduce the fuel consumption substantially compared with other kinds of fuzzy EMSes.

2 Fuzzy control for parallel HEV

2.1 Parallel HEV control strategies

A parallel style powertrain is used in this study for a parallel HEV and the configuration is shown schematically in Figure 1. The internal combustion engine and the electric motor are combined together through a torque combination device. Both the engine and the motor can supply driving torque to propel the vehicle. In addition, the motor can also act in reverse as a generator for braking and charging the batteries [15]. The ICE can drive the EM as a generator to charge the battery. The EM also acts as assistant role of the ICE in supplying the required energy.

The electric assist control strategy (EACS) was adopted in this study. By means of EACS, the main power provider of EMS is the ICE, and the EM is additional assistance for ICE. The EACS of the parallel HEV can be haply categorized into five classes as follows.

(1) If the vehicle speed is less than a certain minimum value or the required torque is below a certain value, the ICE can turn off and the vehicle will operate as a zero emissions.

(2) The engine will produce the required torque to propel the vehicle alone when the engine runs efficiently with the required driving torque at a given speed.

(3) When the required torque is greater than the maximum that can be produced from the engine, the motor and ICE collectively impel the vehicle.

(4) If the battery state of charge (SoC) is below the lowest desired battery state of charge, the ICE will supply additional driving torque, which is required from the engine to charge the battery in accordance with specific battery state of charge; otherwise, the engine is turned off.

(5) When the battery SoC is lower than the highest desired value, the motor charges the batteries by regenerative braking.

The basic principle of energy management strategy based on torque distribution as follows: the torque identification module of vehicle converts accelerator pedal, the brake pedal signal, speed signal and gear shift signal to vehicle required torque T_r then comprehensively considering battery state of charge can determine to the aforementioned operating mode so that output torque T_e be obtained. Since the power of the vehicle required torque T_r come from motor and engine, the output torque of the motor T_m is a difference between required torque T_r and engine output torque T_e. The equations can be written as:

$$T_m = T_r - T_e. \tag{1}$$

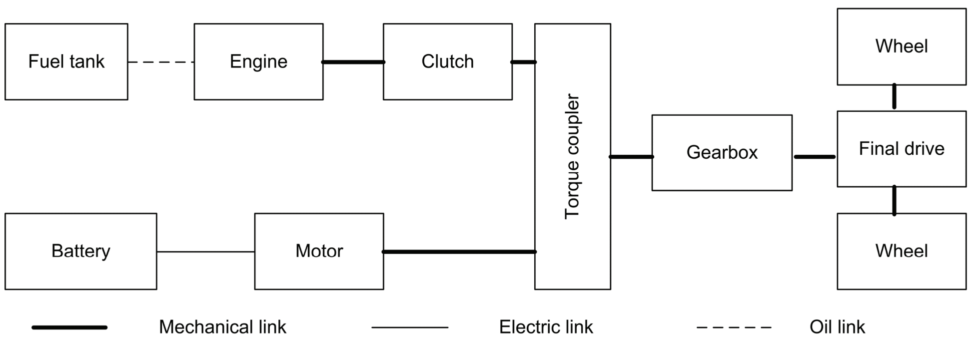

Figure 1 Parallel HEV configuration [15].

In the operating mode (5), the torque request of vehicle hybrid powertrain T_r less than zero hence the energy management strategy is not complex. In addition to this, T_r is equal or greater than zero.

In this case, the optimum combination of the engine and the motor torque value must be selected by the EMS of a parallel HEV in accordance with the T_r, SoC and control rules at the same time the battery charge is maintained.

2.2 Fuzzy logic controller

In terms of the controlling of a parallel hybrid electric vehicle (HEV), to decrease emissions of HEV, the ICE operation must be set in peak efficiency region in the light of road-load and the battery state of charge.

Nevertheless the parameters of the electric assist control strategy is static threshold parameter expression, some of hybrid electric vehicle energy management control rules are difficult to precise quantitative expression. In fact EACS has poor ability to adapt to the change and parameters drift of driving cycles so that it is hard to achieve a sufficient control effect.

In the energy management strategy of fuzzy logic, fuzzy logic instead of Boolean logic, the multi-valued logic instead of binary logic, the fuzzy parameters instead of static parameters, hence it has higher refine level of control rules than EACS. Plus, in consideration of nonlinear time-varying characteristics of the system, a fuzzy logic controller (FLC) based on EACS will be introduced in the energy management system.

2.2.1 Fuzzification of fuzzy logic controller

In this paper there are two inputs which are respectively the required torque T_r and the battery pack SoC in the FLC. Ground on the two inputs, the output is the engine torque T_e.

The inputs crisp value is converted into fuzzy values by fuzzification process. First step is determining fuzzy domain of two inputs and one output of the established hybrid system. To be specific, basic domain of system requirements torque T_r the battery SoC and engine torque T_e respectively are [0, T_{rmax}], [0.4, 0.9] and [0, T_{emax}], then quantify them to the continuous change range from zero to ten. The domain of T_e corresponds to the [0, T_{emax}], where zero represents the 0, ten represents the maximum engine torque T_{emax} and the other values to the torque by linear interpolation. For the domain of the battery SoC, zero corresponds to 0.4, ten to the maximum value, 0.9.

Fuzzy segmentation is to determine fuzzy sets name and number to each linguistic variable. The hybrid system of two input torque T_r and SoC are divided into seven fuzzy subsets {VS, S, TS, M, TB, B, VB}. The output T_e is classified as nine fuzzy sets {VS, S, TS, MS, M, MB, TB, B, VB}, where VS means very small, TS is a little small, M is middle, MS represents a value between TS and M. The number of fuzzy subset is a moderate size in this article.

2.2.2 Membership functions and the rules for the FLC

To determine the membership functions (MFs) and control rules for the FLC is a very important step. This paper adopts the overlapping symmetrical triangular and trapezoidal membership function, for instance, the shape of S, TS, M, TB, B is triangular，the shape of VS and VB is trapezoidal in input membership functions. Two edges of domain form saturation shape. The output fuzzy domain added two triangles respectively corresponded to MS and MB. Figure 2 presents the design of inputs and outputs membership functions.

The fuzzy control rules are shown in Table 1. It is the fuzzy rules description of the control strategy which is depends on EACS. For the double inputs and single output system, the article employs Mamdani method for fuzzy inference according to this rule form: if x is A and y is B then z is C.

2.2.3 Output of the FLC

In the end, we should give the output of the FLC. The process of defuzzification, according to the MFs, the fuzzy rulers and the control strategies, choose the center of area (COA) to get the optimal output torque. The built fuzzy logic is shown as Figure 3.

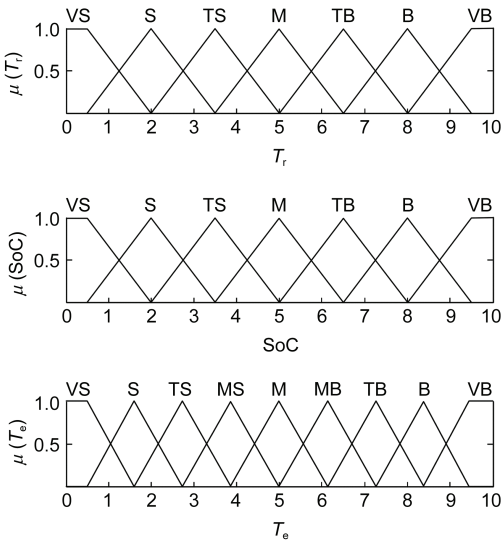

Figure 2 Membership functions for fuzzy.

Table 1 Fuzzy control rules

T_r	SoC						
	VS	S	TS	M	TB	B	VB
VS	MS	TS	TS	S	VS	VS	VS
S	M	MS	TS	TS	S	S	VS
TS	M	M	MS	TS	TS	S	S
M	MB	M	M	MS	MS	TS	TS
TB	TB	MB	MB	M	M	MS	MS
B	B	TB	TB	MB	MB	M	M
VB	VB	VB	B	B	TB	TB	MB

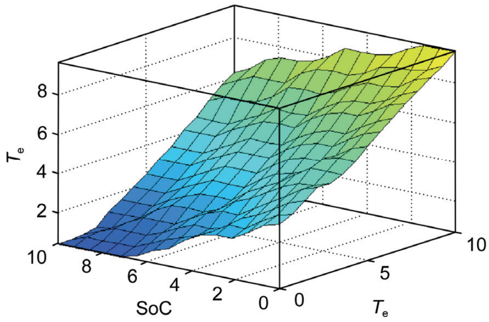

Figure 3 (Color online) The output surface of fuzzy logic.

3 Pigeon-inspired optimization algorithm and improvement

The PIO (pigeon-inspired optimization algorithm) is devised by Duan in 2014 for the first time. Duan and Qiao [16] compared the results of PIO with standard differential evolution (DE) algorithm for solving air robot path planning problems and they proved it is a feasible and effective algorithm. The PIO algorithm was inspired by special homing behaviors of pigeons, which is similar with the process of searching optimal solution.

3.1 Natural pigeon behavior profile

For thousands of years, due to pigeons have a strong homing ability, they were once widely applied in the communication and military field. Through lots of studies [17,18] it has been found that pigeons probably have different navigational techniques to discriminately handle different sections in their journey.

Once pigeons start their trip, they will prior select compass-like directivity methods. And specifically, when they started flying, they use iron crystals in their beaks which can give birds a nose for north to feel and detect different magnetic field. In addition to their perception of the magnetic field, sun is also concerned in pigeon navigation. Studies show that the pigeons seem to have a method to distinguish discrepancies in altitude between the sun at the start point and at the end point. It is because the pigeons have outstanding perception of magnetic field and the altitude of the sun, they can determine the general direction of flight.

On the other hand, when the pigeons place the middle of journey, they change navigation skills to focus to landmarks or waypoints, such as mainland, lakes, highroads and rivers, for making any necessary corrections and reassessing again until successful reached destination.

It is based on the above analysis of homing behaviors of pigeons, the pigeon-inspired optimization algorithm is obtained and closes to the optimization process.

3.2 Description of pigeon inspired optimization algorithm

Through the abstraction of the homing characteristics of pigeons, we use two operators which are compass-like operator and landmark operator to indicate this algorithm. The compass-like operator is rendered according to the changing of solar altitude and magnetic field, while landmark operator is presented in the light of landmarks [16]. As mentioned above, with the gradually close to the destination, pigeons will depend less on compass-like operator and more on landmark operator.

3.2.1 Compass-like operator

The PIO algorithm begins by generating a number of virtual individuals in pigeon colony. The compass-like operator is used to update two D-dimensional vectors, the positions and velocities of virtual pigeons, in each iteration process. Specifically, pigeons update positions and velocities by following equations:

$$V_i(t) = V_i(t-1)\cdot \mathrm{e}^{-Rt} + \mathrm{rand}\cdot (X_g - X_i(t-1)), \tag{2}$$

$$X_i(t) = X_i(t-1) + V_i(t), \tag{3}$$

where X and V mean positions and velocities of virtual pigeons; rand is a random real number and R is the navigation or compass factor; i and t being the individual indexes and the number of iterations, respectively. X_g is the best known position, which can be procured by comparing all the current pigeon positions in whole pigeon swarms. The meaning of that part $V_i(t-1)$ is the former flying direction of current pigeon. And apparently, a new direction of travel is affected by its former flying direction and the current global best position.

3.2.2 Landmark operator

In the Landmark Operator, the first thing we need to calculate the fitness value of each virtual pigeon current position by following expression:

$$\mathrm{fitness}(X_i(t)) = \frac{1}{f_{\min}(X_i(t)) + \varepsilon}. \tag{4}$$

Then according to rank of fitness values, half of the individuals will be abandoned. Let average value of the remaining part stand by the center pigeon $X_c(t)$ at the t-th iteration. This optimal position is considered the most familiar individuals for landmark. Others will follow the one fly to their destination. The new position of other birds can be given through following formulas:

$$X_c(t) = \frac{\sum X_i(t)\cdot \mathrm{fitness}(X_i(t))}{N_p \sum \mathrm{fitness}(X_i(t))}, \tag{5}$$

$$X_i(t) = X_i(t-1) + \mathrm{rand}\cdot (X_c(\mathrm{t}) - X_i(t-1)), \tag{6}$$

where N_p is the number of individuals in pigeons.

3.3 Improvements on pigeon-inspired optimization algorithm

The pigeon-inspired optimization algorithm is same as other metaheuristic algorithm, which still has a problem named "trapping in local optimum". Hence, quantum evolution and chaotic strategy are usually used to solve premature convergence problem.

3.3.1 Quantum evolution

Quantum evolution emerged in many swarm intelligent optimization algorithms for improving random search capacity [19]. In quantum evolution algorithm, quantum rotation gate is a key concept which can be described as:

$$U(\Delta\theta_i)=\begin{bmatrix}\cos\Delta\theta_i & -\sin\Delta\theta_i\\ \sin\Delta\theta_i & \cos\Delta\theta_i\end{bmatrix}, \tag{7}$$

$$\begin{bmatrix}\alpha_i'\\ \beta_i'\end{bmatrix}=\begin{bmatrix}\cos(\theta_i+\Delta\theta_i)\\ \sin(\theta_i+\Delta\theta_i)\end{bmatrix}, \tag{8}$$

where θ_i is the quantum rotations angle of each quantum bit; $U(\Delta\theta_i)$ is the quantum rotation gate. The detailed update process is shown as follows:

$$\begin{bmatrix}\alpha_i'\\ \beta_i'\end{bmatrix}=U(\Delta\theta_i)\cdot\begin{bmatrix}\cos(\theta_i+\Delta\theta_i)\\ \sin(\theta_i+\Delta\theta_i)\end{bmatrix}. \tag{9}$$

Each update, the angle of a quantum bit should be changed and have a certain direction for the best position of virtual pigeon, which is an advantage compared with conventional random conversion. To determine values and directions of θ_i, here a table is listed in Table 2.

In order to using quantum bit to express an individual of the population, quantum bit string consisting of a number of quantum bit is introduced [20]. The quantum bit string is a block matrix which each column is a quantum bit as shown below:

$$q=\left[\begin{matrix}\alpha_1\\ \beta_1\end{matrix}\middle|\begin{matrix}\alpha_1\\ \beta_1\end{matrix}\middle|,\mathrm{K}\ ,\begin{matrix}\alpha_n\\ \beta_n\end{matrix}\middle|\begin{matrix}\alpha_{n+1}\\ \beta_{n+1}\end{matrix}\middle|,\mathrm{K}\ ,\begin{matrix}\alpha_{D+1}\\ \beta_{D+1}\end{matrix}\middle|\right]. \tag{10}$$

The range of *i*-th dimension vector is randomly spread between the prespecified $U_{\min}$ and $U_{\max}$. Then the value of the *i*-th dimension can be calculated as follows:

$$x_i=U_i^{\min}+\left(\sum_{i=1}^{n}b_i\cdot 2^{i-1}\right)\cdot\frac{U_i^{\max}-U_i^{\min}}{2^n-1}. \tag{11}$$

Do the same actions with each dimension of the problem, we can get the pigeon individual $X=(x_1,x_2,\ldots,x_D)$.

Table 2 Rotation angle

x_i	Best_i	$f(x)>f(\mathrm{best})$	θ_i: $\alpha_i\beta_i>0$	$\alpha_i\beta_i<0$	$\alpha_i=0$	$\beta_i=0$
0	0	False	0	0	0	0
0	0	True	0	0	0	0
0	1	False	0	0	0	0
0	1	True	−0.05π	0.05π	±0.05π	0
1	0	False	−0.05π	0.05π	±0.05π	0
1	0	True	0.05π	−0.05π	0	±0.05π
1	1	False	0.05π	−0.05π	0	±0.05π
1	1	True	0.05π	−0.05π	0	±0.05π

3.3.2 Chaotic local search

The essence of chaos theory is a slight change of initial conditions can lead to extremely enormous distinction after a long time [21]. Therefore to avoid the problem named premature convergence, chaotic search technique is carried out in the metaheuristic algorithm. After chaotic search process, swarm intelligent algorithm reduces possibility of trapping in local optimum. Meanwhile it can decrease convergence time of system.

In this paper, we will generate some new individuals with Chebyshev map [22] to replace those lower fitness values of individuals. The Chebyshev map is a classical chaotic model and incrementally iterates by the following formula:

$$z_m^{t+1}=\cos(k\cdot\cos^{-1}z_m^t),\ t=0,1,2,..., \tag{12}$$

where k is a control parameter and here k=2 and $z_m^t\in(-1,1)$; then substituted all of the parameters into eq. (12), we can get the chaotic sequence that reflects the dynamic characteristic [23]. In PIO algorithm, the target of chaotic local search is to search a better position around the X_{best} by introducing Chebyshev map. The detailed procedure of Chebyshev chaotic search is described as follows.

Step 1: Set the number of iterations N_c and create a random number $z_m^0\in(-1,1)$ to form a Chebyshev sequence.

Step 2: The following equations express relationship between iteration numbers i and control parameter k.

$$k=\frac{N_e+1-i}{N_e}. \tag{13}$$

Step 3: Generate new individuals by following equation:

$$V=(1-k)\cdot X_p+k\cdot X_{\mathrm{new}}. \tag{14}$$

Step 4: Calculate fitness of new individuals and record the best one to X_p.

Step 5: When current iteration times i is equal to the total of iterations N_c, the chaotic local search should be stop. Otherwise, keep searching.

4 Implementation of the QCPIO for FLC

4.1 Fuzzy controller based on QCPIO

Traditionally, the determination of membership functions, different of experts, has different result from different subjective experience. Thus the control accuracy and global optimization result cannot be guaranteed. The metaheuristic algorithms to obtain the optimal solution have a wide range of applications and good effect. Among them, the PIO algorithm has certain advantages in problem representation, solving ability and parameter adjustment.

In PIO, a pigeon colony is flown in search space to explore a homing position that could be an optimum solution. PIO has a simple structure and good convergence ability.

Therefore, in an attempt to obtain the best running performance of hybrid electric vehicle, the PIO is implemented to optimize membership functions and fuzzy control rules. Afterwards, the PIO selects a set of optimal control parameters for the fuzzy torque distribution controller according to fitness value of the objective function.

It is important that code optimized parameters of membership functions and fuzzy control rules of FLC. There are two parts of the optimized parameters and variables: membership function parameters and fuzzy control rules variables. In the part of membership function parameters, taken T_{r} as an example here, Figure 4 shows four real numbers v1, v2, v3 and v4 in interval [0, 4]. As these parameters change, the coordinates of the triangle and the trapezoid are ascertained, thus influenced fuzzy torque distribution controller efficiency. The means of determine the MFs of the SoC and T_{e} are analogous to T_{r} and both of parameters number are three. Thus here are ten membership function parameters will need to be determined.

For the fuzzy control rules variables, as shown in Table 1, if fuzzy sets of input variables are decided, corresponding output variables will be determine. We encode 49 integral output variables in interval [1, 9]. Therefore, a total of 59 parameters will be optimized by the QCPIO algorithm. The number of parameters equals to dimension of the search space.

4.2 Procedure of the proposed QCPIO algorithm for FLC

To fully explore advantages of hybrid power system, the optimization objective of control strategy is minimize fuel consumption and emissions of hybrid electric vehicle by optimized variables of the fuzzy torque distribution controller. Through calculation by means of ADVISOR simulation, evaluations values of the objective are obtain for the given drive cycle.

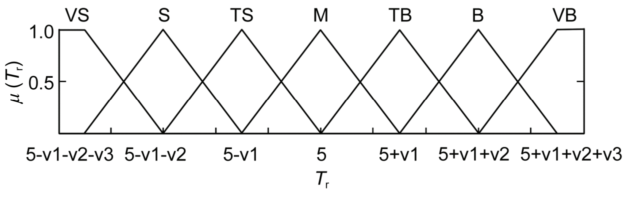

Figure 4 Optimized parameters of the input membership function.

The optimization step of fuzzy torque controller of parallel hybrid electric vehicle employing a quantum chaotic pigeon-inspired optimization algorithm can be stated as follows.

Step 1: Preset the parameters of the QCPIO include number of individuals N_p, dimension of the search space D, the map and compass factor R, the borders of the search space, maximum number of generations that the compass-like and landmark operation is carried out.

Step 2: Initialize the quantum bit sting angle of potential homing positions which represents the optimization variable in the fuzzy torque distribution controller.

Step 3: Evaluate the objective functions for the given driving cycle of each potential dovecote in the space by combining the QCPIO algorithm and the ADVISOR software. Then choose the one with better fitness and update X_p and X_g.

Step 4: Enter chaotic local search. The detailed steps are described in Section 3.3.2.

Step 5: Update all quantum bits by employing the quantum rotation gate.

Step 6: When iteration times N_c equals to $N_{c2\max}$, stop the iteration and output the optimal parameters of fuzzy membership function and control rules.

The Flow chart of the QCPIO for FLC is shown in Figure 5.

The parameters membership functions and control rules are optimized to make fuzzy torque distribution controller can accomplish optimal power allocation between engine and electric motor so that meet necessity of HEV energy management.

5 Experimental results and comparative performances

This paper implements the all of the algorithms in Matlab R2012a on a notebook personal computer with 1.7 GHz CPU, 4GB RAM running Windows 8.1 system. The original pigeon-inspired optimization (PIO) Algorithm programs are revised from ones given by the homepage of pigeon-inspired optimization algorithm [16].

This section build fuzzy control simulation model of the parallel hybrid electric vehicle on vehicle simulation software platform ADVISOR2002. Then energy management strategy based on fuzzy control model was set up (Figure 6) and embedded in the ADVISOR to realize an energy management system based on torque distribution.

The Chebyshev map chaotic and quantum modification were combined with pigeon-inspired optimization algorithm to optimize the fuzzy controller. To test and verify the effectiveness of the algorithm, the simulation is carried out under the three typical driving cycles so that obtained the optimal working point of engine under different working

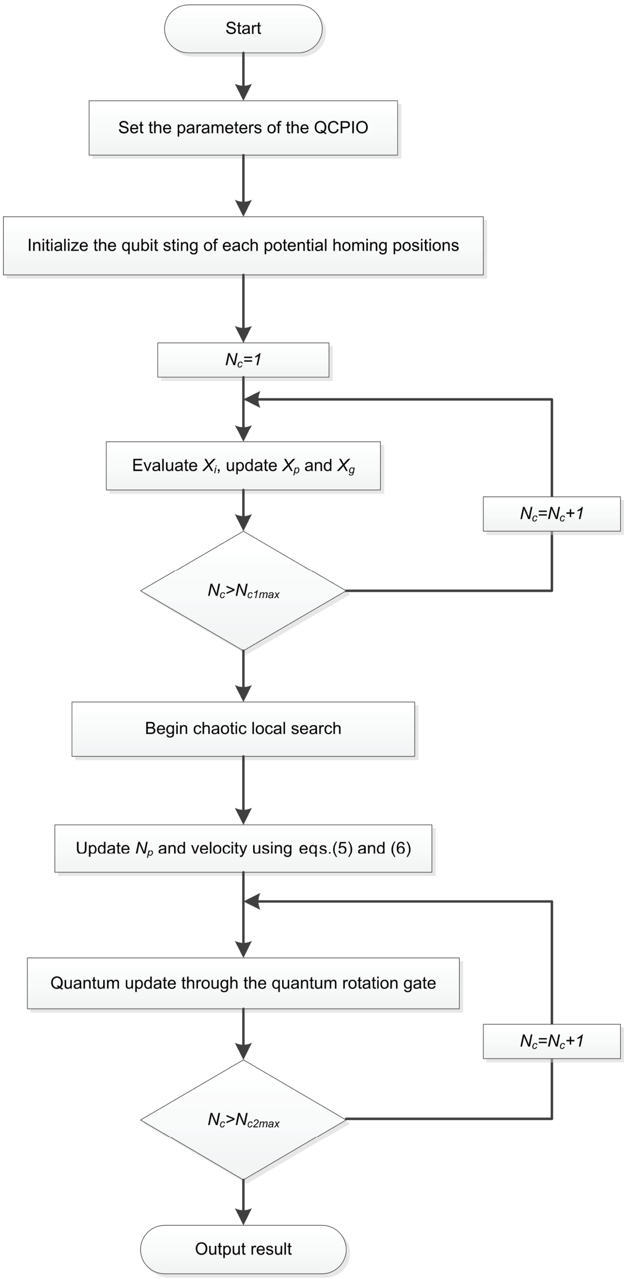

Figure 5 Flow chart of the QCPIO for FLC.

conditions. Finally, the simulation of the EMS is conducted for the CYC_NEDC, CYC_UDDS, and CYC_1015 driving cycles based on ADVISOR. In order to compare the results of different types of fuzzy controller, original fuzzy EMS without optimization and PSO fuzzy EMS are treated as comparison objects. In simulation experiment, parameters of the main vehicle components are listed in Table 3.

The optimized fuzzy controller is compared with the established fuzzy controller of energy management strategy for three standard driving cycles is presented in Table 4. The results of simulation show that fuzzy control strategy based on QCPIO algorithm optimization can effectively reduce the vehicle emissions, meet the demand of vehicle dynamic performance and improve fuel economy of vehicles meanwhile.

Figure 7 shows the comparison of the SoC value for the traditional fuzzy EMS and the optimized fuzzy EMS for the UDDS which is a typically urban dynamometer driving cycle. It can be seen from the Figure 7 that the initial value of the battery SoC are 0.65, the original fuzzy control strategy at the end of the cycle battery SoC is 0.509, then after PSO and QCPIO optimization the value is 0.532 and 0.557, respectively. Thus the optimized fuzzy EMS can more effectively to ensure the balance of the charged state battery and improve the efficiency of the battery charge and discharge.

Figure 8 illustrates the optimization process history for UDDS and NEDS driving cycles. System initial emissions total are 2.995 and 2.9018 for UDDS and NEDS respectively. With the improved quantum chaotic pigeon-inspired

Table 3 Basic parameters of the hybrid electric vehicle

Component	Parameter	Value
Vehicle	Mass m (kg)	1350
	Frontal projection area A (m^2)	0.62
Engine	Displacement Q (L)	1.0
	Maximum power P_{max} (kW)	41
Motor	Type	AC
	Maximum Power P_{max} (kW)	75
Battery	Type	PbA
	Capacity C (Ah)	60
	Voltage U (V)	312

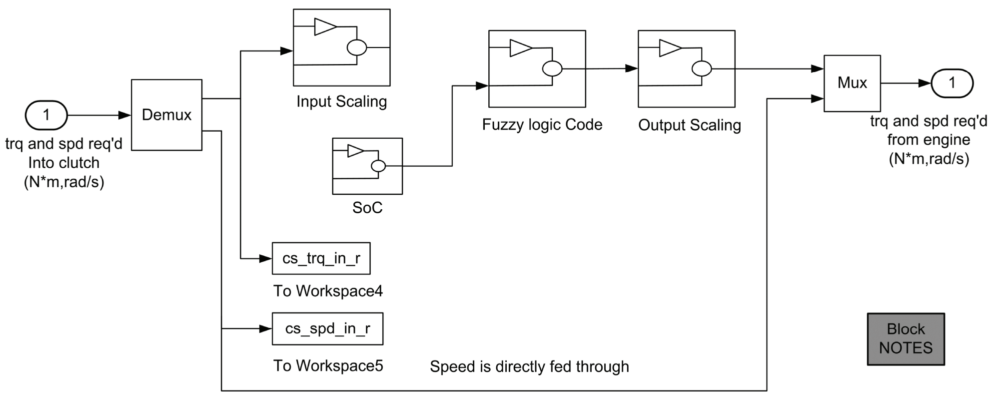

Figure 6 Fuzzy controller.

Table 4 Fuel consumption and emission of different EMS

Driving cycle	EMS	Emission CO (g/km)	Emission HC (g/km)	Emission NO*x* (g/km)	FC (L/100 km)
UDDS	Fuzzy	2.134	0.543	0.243	4.742
	PSO_Fuzzy	2.102	0.511	0.187	4.156
	QCPIO_Fuzzy	2.073	0.487	0.135	4.086
NEDS	Fuzzy	2.102	0.464	0.253	5.080
	PSO_Fuzzy	2.067	0.433	0.190	4.246
	QCPIO_Fuzzy	2.013	0.408	0.112	3.884
1015×3	Fuzzy	5.380	1.094	0.288	4.134
	PSO_Fuzzy	5.324	1.033	0.217	3.528
	QCPIO_Fuzzy	5.271	1.002	0.184	3.107

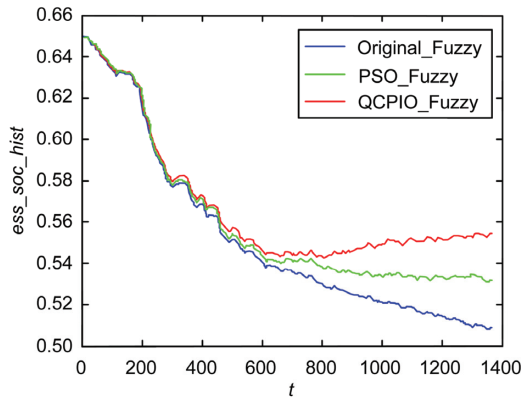

Figure 7 (Color online) SoC value of the two fuzzy EMS.

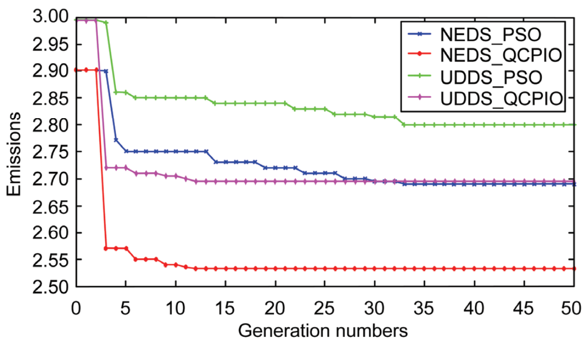

Figure 8 (Color online) Optimization process for UDDS and NEDS.

optimization, exhaust emission was respectively reduced by 10.01% and 12.71%. Meanwhile, the iterations were 12 times when it achieves the optimal solution, which to ensure the convergence of the algorithm. The curves are demonstrated that convergence ability of QCPIO is better than PSO algorithm.

Figure 9 reveals the comparison of the distribution of engine working point for the usual fuzzy EMS and the optimized fuzzy EMS for the UDDS. Revelation in the figure, the working points of the engine using PSO optimization has focused on the low efficiency of the low load area, while using QCPIO method optimized engine working points are mainly distributed in the region of the high

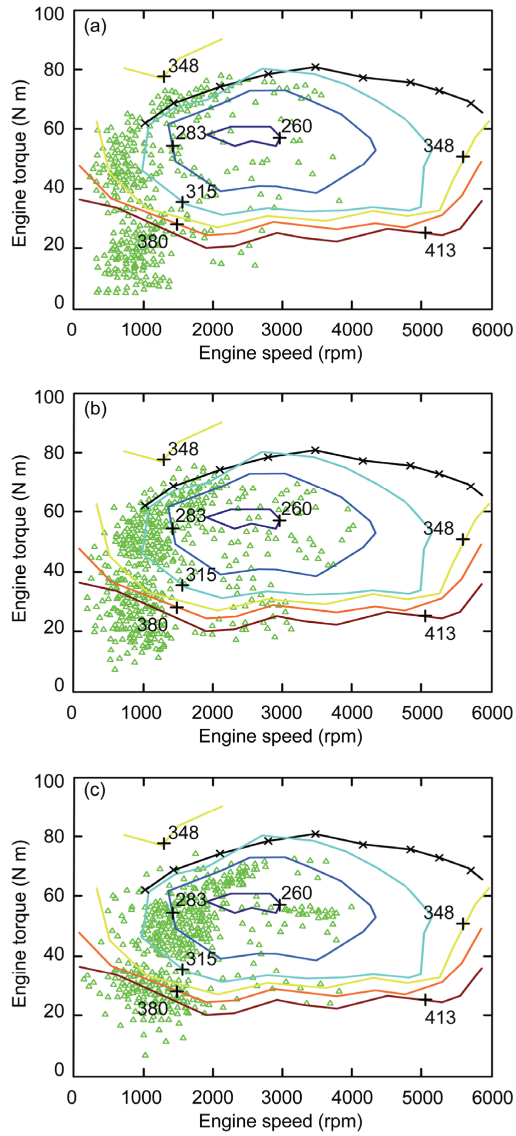

Figure 9 (Color online) Engine working point curves. (a) The original fuzzy without optimization; (b) the result of FLC adopt PSO; (c) the result of FLC adopt QCPIO.

efficiency of high load. This suggests that the QCPIO optimized fuzzy energy management strategy can be more reasonable distribution of the engine and motor torque and then improve the working efficiency of the engine.

Through the above analysis, comparing to established fuzzy EMS, QCPIO has a better balance efficiency of the battery charge and discharge, better convergence ability and more reasonable torque distribution.

6 Conclusion

Due to the complexity of the vehicle configuration combining driving cycle and the variability and robustness of fuzzy logic, a fuzzy EMS based on an improved PIO algorithm enhance the global search ability is proposed in this paper. It is demonstrated that the pigeon fuzzy EMS can decrease fuel consumption and emissions more effectively than traditional fuzzy energy management strategies.

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