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A Dynamic Programming based Fuzzy Logic Energy Management Strategy for Series-parallel Hybrid Electric Vehicles

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Abstract. *The series-parallel hybrid electric vehicles (HEVs) can reduce vehicle fuel consumption and exhaust emissions. In order to give full play to the potential in this aspect, this paper proposes a new method to optimize the control of a Series-parallel hybrid power system. Firstly, through the global optimization algorithm, the energy distribution mode under the optimal fuel economy and emission performance state under different initial conditions is obtained in a specific cycle condition. Then the parameters are extracted from the global optimal results. As a reference, the fuzzy control rules are formulated and the corresponding fuzzy control system is designed. Finally, the fuzzy control, global optimal algorithm and traditional fuzzy control designed in this paper are compared. It shows that the fuzzy control based on the global optimal design has a significant improvement in fuel economy and emissions compared with the traditional fuzzy control. It is closer to the global optimal value. The results show that the fuzzy control system designed in this paper achieves the purpose of optimal control and is easy to implement.*
Keywords: Coaxial dual-motor series-parallel; Dynamic planning; Fuzzy control

1. **Introduction.** In the current world, environmental pollution and energy shortage have become a global problem. Under the background, hybrid electric vehicles, also known as HEV, characterized below oil consumption, low emissions, strong dynamic performance, and long mileage, have become a general research interest of worldwide auto superpowers. In cities, large public buses provide great convenience, but their fuel consumption is high. Thus, it is imperative to improve their fuel economy to increase sustainability of the transportation means. The current market sells HEVs with different structures, which can be generally divided into series, parallel, and series-parallel according to their power transmission routes [1,2].

Compared with series and parallel, series-parallel is an optimized structure, which has a more flexible power transmission route and more working models. These advantages allow series-parallel to efficiently satiate driving demands of public buses under the complex city drive cycles. As shown in Table 1, the series-parallel structure has not only good power but also excellent performance in terms of fuel economy. Hence, it's more convenient to control energy of series-parallel HEVs. The entire driving force is derived from the fuel combustion of the engine for series-parallel HEVs that cannot be externally plugged in.

Table 1. Comparison of three HEV structures

parameter	Fuel economy				dynamic property	
	Idle downtime	braking energy recovery	Efficient workspace control	completed car efficiency	acceleration performance	Continuous high power output performaance
series	○	×	○	○	△	△
parallel	○	○	△	○	○	△
serise-parallel	×	×	×	×	○	○

In order to maximize its fuel economy and emission potential, it is necessary to optimize the control strategy of series-parallel HEVs[3,4].

So far, some researches into energy management strategies mainly focus on two aspects-one on optimization-based management strategies and the other on rule-based energy management strategies. Du et al. [3] study the hydraulic hybrid power system using the rule-based logic threshold method. In their research, the engine map is divided into three areas, and the vehicle working models are divided based on different operating points to realize vehicle control. Pan [4] in order to increase fuel economy of buses, adopt the pedal opening, SOC (State of Charge) of super capacitate, and current vehicle velocity as fuzzy input variables and the engine output torque as the output variable, and then formulated the fuzzy control rule based on engineering experience. The final simulation results show that oil consumption per 100 km increases by 5% as compared with the logic threshold. However, their research fails to consider control of braking conditions. Manzie et al. [5] turns to a new ECMS (Equivalent Consumption Minimization Strate) real-time optimal control approach. They compare charge and discharge, processes the constraint function via weighting, and uses different equivalent factors to greatly improve the fuel economy. However, their research results cannot guarantee global optimum. Lin et. al. [6-7] employs the energy management strategy based on the dynamic programming algorithm to disperse the fixed state of drive cycle into N periods. Then, the motor torque and the transmission gear index are regarded as control variables, while the SOC and the transmission gear as state variables. In this way, the optimal control variables of the HEVs are obtained. Xu and Lin [8] proposed a new hybrid power configuration for hybrid electric vehicles with different control strategies. Hybrid electric vehicles have good performance, when they are equipped with different weight fuel cells and power batteries. Han et. al. [9] a flow chart of parameters matching and optimization of hybrid electric vehicles is proposed. The multi-objective optimization model was established. The parameters matching and optimization of a hybrid vehicle were carried out. The reasonable result of parameter matching was obtained. Chen et. al. [10] based on an electric assist control strategy, the fitness function is defined so as to minimize the vehicle engine fuel consumption and emissions. The driving performance requirements are considered as constraints. And, a new approach is used for the battery control parameters to reduce the number of the decision variables. Mao and Wang [11] presented Fuzzy control method to distribute energy. The system runs well in practice. They improved energy efficiency and realized the reducing tail gas emissions. Zhang [12] combined with the characteristics of genetic algorithm and the advantages of simulated annealing algorithm in avoiding cyclic search. They proposed a hybrid optimization algorithm based on multi-objective genetic algorithm, and optimized the control parameters of the energy management of hybrid electric vehicles. The results show that in multi-objective optimization on HEV control strategy, the hybrid algorithm proposed avoids the defects of premature convergence and random search without direction in traditional genetic algorithm, enhancing the convergence speed and computing efficiency. Lian et.al. [13] take the parallel hybrid electric bus, four typical working condition models are established. The ant colony optimization algorithm is applied to optimize the charge discharge equivalent coefficient of each case under the minimum equivalent fuel consumption control strategy. The relationship between the road slope and the distance regulation of the battery SOC target is analyzed and the corresponding gradient adaptive module is designed. A hybrid vehicle control strategy optimization method based on driving condition identification is proposed. Li et. al. [14] designed a host platform for HEV with the graphic programming software LABVIEW. Aiming at two core issues in the development process of parallel HEV, the engine and motor efficiency point tracking, energy flow animation display and road condition statistics three functions are designed for improving the development efficiency of control strategies. Poeti et. al. [15] proposes a modeling method that makes use of object-oriented modeling principles for the design and development of HEV power train models. Chen et. al. [16-17] proposed a new interpolation and sparse method for fuzzy rules. Zhang et. al. [18] developed a new method to determine the fuzzy boundary of natural language based on big data. Hong et. al. [19] presented new generalizing concept-drift pattern methods for fuzzy association rules.

The authors [20] previously study analyzed the ISG (Integrated Starter Generator) HEV structure and operating models, builds a logic threshold control strategy and then applies it for simulation in Simulink. Results show that the oil economy is improved by 46.2% as compared with that of traditional fuel-driven vehicles. In this paper, a global optimization energy management strategy based on dynamic planning is first built and simulated. Then, simulation results are analyzed for the purpose of extracting design parameters of the fuzzy energy management strategy. Based on the extracted design parameters, the membership function and the fuzzy control rule of variables are formulated to efficiently realize optimal control of series-parallel HEVs.

2. Series-parallel hybrid power system.

Series-parallel hybrid power system structure is shown as Fig.1.This structure is also referred to as a coaxial dual-motor structure just because the engine, ISG, main drive motor, and automatic clutch are installed in same axis. The automatic clutch is set between the drive motor and the ISG. By controlling connection and disconnection of the automatic clutch, the operation mode of HEV can be converted between serial and parallel.

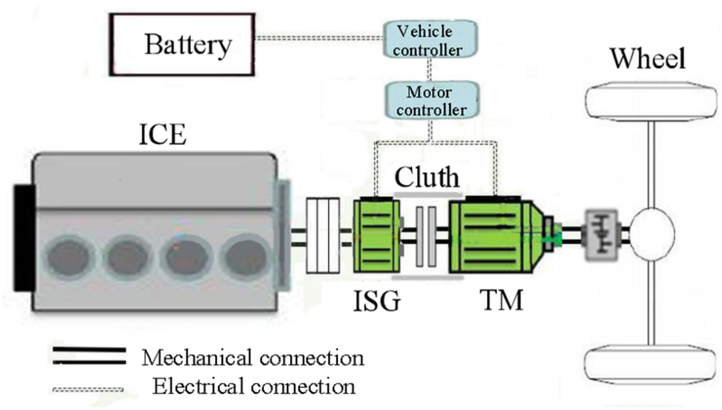


Figure 1. Series-parallel hybrid power system structure

In this system, the ISG motor has both the function of starting and charging. The transmission was cancelled, and coordinating the operation of the engine, ISG motor, and main motor can meet the actual working conditions through rotation characteristics of the main motor. The main deceleration of the reducer is relatively large.

The series-parallel system has three power sources, an engine, an ISG motor, and a drive motor. They are switched by the clutch-controlled system in series-parallel mode of operation. According to the characteristics of the structure, the series-parallel hybrid power system has multiple power modes: pure electric drive, engine quick start, pure engine drive, engine drive and power generation, motor boost, brake recovery and so on. Because this system does not have external charging, all the energy is from the energy released by the fuel of the engine while the vehicle is running. The battery energy consumed by the motor is the power supplied by the engine or converted by the braking energy recovery. The power output of each power source is controlled by the energy management strategy under different working conditions. Different energy management strategies are bound to differ in the fuel economy and emissions of vehicles. Therefore, in order to achieve the maximum reduction of vehicle fuel consumption and air pollution emissions, active optimization control of hybrid buses is required.

2.1. **Dynamic programming based optimization.** Dynamic programming is put forward by Richard Bellman. A dynamic programming algorithm disperses a multi-stage process into a series of single stages, and makes use of the relationship between the single stages to work out solution one by one. Finally, the optimal solution can be obtained. Dynamic programming based optimal control of the series-parallel HEV can be boiled down as: Disperse a given drive cycle into k stages, and introduce certain constraints; choose a series of control variables from the initial state $x(0)$ to the final state $x(k)$ to see which variable can bring down the oil consumption of the whole drive cycle to the minimum.

2.2. **Construction of the dynamic programming based optimization algorithm.** Under the series operation model, the clutch is disconnected, and the system made up of the engine and the engine and the ISG is called the auxiliary power unit (APU), whose power cannot be directly output to the wheel. Hence, the torque required is independently provided by the drive motor. Under the condition, the rotational velocity of the engine (namely the rotational velocity of the ISG) is not influenced by the drive cycle. It can be described by Eq. (1).

Under the parallel operation model, the clutch is disconnected; the engine, ISG and drive motor can directly output their power to the wheel. The torque required by the vehicle can be jointly provided by the engine, ISG and drive motor. The rotational speed of the drive motor and wheels is decided by the vehicle velocity. It can be described by Eq. (2).

According to the operating efficiency characteristics of the engine-generator set, it can be determined that the high-efficiency speed of the engine during power generation in the clutch disengagement state is between 1100 r/min and 1300 r/min.

$$\begin{cases} T_{des} = \eta_0 i_0 T_m + T_{mb} \\ \omega_e = \omega_{isg} \\ T_e = -T_{isg} \\ \omega_m = \frac{v_{i0}}{0.377\gamma_w} \end{cases} \tag{1}$$

$$\begin{cases} T_{des} = \eta_0 i_0 (T_e + T_{isg} + T_m) + T_{mb} \\ \omega_e = \omega_{isg} = \omega_m = \frac{v_{i0}}{0.377\gamma_w} \end{cases} \tag{2}$$

Where, T_{des} is the torque required by the driver; T_{apu} is the output torque of the APU system; T_e and ω_e are the output torque and rotational velocity of the engine, respectively; T_{isg} and ω_{isg} are the output torque and rotational velocity of the ISG; T_m and ω_m are the output torque and rotational velocity of the motor; T_{mb} is the mechanical braking torque; v is the velocity; i_0 denotes the final ratio; r_w represents the radius of the wheel; η_0 is the drive system efficiency.

As mentioned above, when the clutch is disconnected, the rotational velocity of the engine and the ISG cannot be directly identified. When the ISG drives the vehicle separately, the engine will be turned off. When a driving car is charged under the series structure, the rotational speed of the APU system is decided by its work efficiency curve. In this paper, under the China Typical Drive cycle of Bus Cycle (CTDCBC), the dynamic programming model chooses the SOC and the disconnected state, $C_{cl}(t)$, of the clutch as the state variables [See Eq. (3)]; while the engine torque, $T_e(t)$, drive motor torque $T_{TM}(t)$ and the clutch control command, $R_{cl}(t)$, are adopted as control variables. [See Eq. (4)] The clutch state and the control command can be written as Eq. (5) and Eq. (6), respectively:

$$x(t) = (C_{cl}(t), soc(t)) \tag{3}$$

$$u(t) = (R_{cl}(t), T_e(t), T_{tm}(t)) \tag{4}$$

$$C_{cl}(t) = \begin{cases} 0 \ \ (Meaning\ the\ clutch\ is\ disconnected) \\ 1 \ \ (Meaning\ the\ clutch\ is\ connected) \end{cases} \tag{5}$$

$$R_{cl}(t) = \begin{cases} 0 \ \ (Command\ for\ disconnection\ of\ the\ clutch) \\ 1 \ \ (Command\ for\ connection\ of\ the\ clutch) \end{cases} \tag{6}$$

In order to maintain balance of the SOC and work efficiency from the beginning to the end of the drive cycle in the dynamic programming based global optimization performance objective function, the SOC constraints are introduced as shown in Eq. 7. It makes the SOC values at the beginning and end of the cycle condition equal. Meanwhile, state of the clutch and the engine is introduced as the other two constraints [See (8) and Eq. (9), respectively] to prevent problems caused by complicated road circulation conditions. Problems include repeated start and halt of the engine, and the repeated connection and disconnection of the clutch.

$$L_1 = soc(t_f) - soc(0) = 0 \tag{7}$$

$$L_2 = C_{cl}(t_{n+1}) - C_{cl}(t_n) \tag{8}$$

$$L_3 = E_{bs}(t_{n+1}) - E_{bs}(t_n) \tag{9}$$

The CTDCBC operating condition [0, t_f] is stepped in 1s steps and is divided into 1314 stages. Therefore, the objective function J of the dynamic optimization global optimization performance of the coaxial dual-motor hybrid vehicle is as shown in Eq. (10). Eq. (10). It includes four sub-functions. They are in turn oil consumption objective sub-function, SOC correction function, clutch state constraint function, and engine state constraint function.

E_{SW} is the engine switching signal.

$$J = \sum_{k=0}^{t_f} \left\{ \begin{array}{l} \int_{t_k}^{t_{k+1}} Q_e[x(k), u(k-1), t]dt + \alpha \left| C_{cl}(k+1) - C_{cl}(k) \right| + \beta \left| E_{bs}(k+1) - E_{bs}(k) \right| \\ +\varepsilon[soc(t_f) - soc(0)]^2 \end{array} \right\} \tag{10}$$

Where, α, β and ' are the weighting coefficient.

Structures like the motor, engine and battery have their own mechanical constraints and performance constraints. Therefore, the constraint functions, Eq. (11), are introduced to the optimization process. During the solution process, if any control variable or any state variable exceeds the required area of the constraint, the computer will record and store it. The constraints are as below:

$$\begin{cases} soc_{\min} \le soc(k) \le soc_{\max} \\ \omega_{m,\min} \le \omega_m(k) \le \omega_{m,\max}, \quad \omega_{e,\min} \le \omega_e(k) \le \omega_{e,\max}, \quad \omega_{g,\min} \le \omega_g(k) \le \omega_{g,\max} \\ T_{m,\min} \le T_m(k) \le T_{m,\max}, \quad T_{e,\min} \le T_e(k) \le T_{e,\max}, \quad T_{g,\min} \le T_g(k) \le T_{g,\max} \end{cases} \tag{11}$$

2.3. **Operational process.** Gridding is performed of the state variables and the control variables, respectively. The optimal solution is tracked reversely from the final stage, n, to the initial stage of the drive cycle. The operation process is represented in Fig. 2. At the k stage, the grid points of state variables, such as $x_i(k)$ and $x_{i+1}(k)$ corresponding to all allowed control variable points. Then, according to the state transfer function, such as Eq. (12), and the instant cost function, one can solve $x_i(k+1)$, $x_{i+1}(k+1)$, and the instant fuel oil consumption value, $J_i(k+1)$, $J_{i+1}(k+1)$, $x_i(k+1)$ and $x_{i+1}(k+1)$ thus obtained are unlikely to appear on the grid points of the state variables in the next stage. Therefore, the linear interpolation is employed to work out every final cost function. Next, the computer stores the minimum fuel oil consumption function value and the corresponding control variable value of the grid point for the convenience of forward optimum seeking. The operation goes on until the initial stage of the drive cycle.

After the end of the reverse solution, the computer will start from the initial stage of the drive cycle, and use the cost functions and control variable matrices stored by the reverse solution process to find out the optimal solution and the optimal control variable sequence in the whole stage via interpolation.

$$x(k+1) = f[x(k),\ u(k)] \tag{12}$$

where $f[x(k),\ u(k)]$ is the state transfer function.

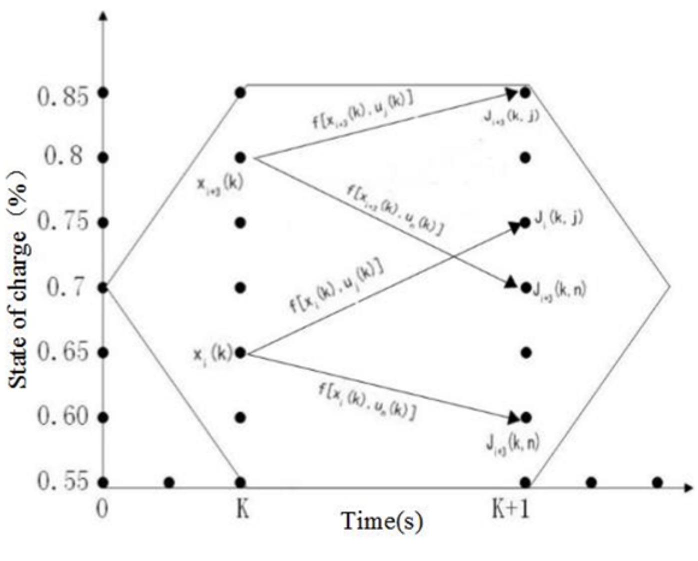


FIGURE 2. Dynamic programming operation process

3. **Fuzzy control strategy.** The vehicle optimal control rule can be obtained through the dynamic programming algorithm. However, the computing quantity is huge, and the algorithm, relying on the already known conditions of the drive cycle, is hardly applicable

to real-time control. Therefore, the dynamic programming algorithm is often applied to offline research. The results thus obtained can serve as reference for design of other energy management strategies or for comparison of advantages and disadvantages of different energy management strategies. The fuzzy energy management strategy has a wide range of applications. Its strong robustness and instantaneity make it highly applicable to the HEV, a complex system with multiple nonlinear, time-varying components. This paper uses the dynamic programming based global optimization algorithm to extract the design parameters. According to the extracted design parameters, the membership function and the fuzzy control rule of the fuzzy logic controller are built. Finally, the fuzzy energy management design of the series-parallel HEV is finished.

3.1. **Establishment of the fuzzy control strategy.** The fuzzy controller usually consists of five parts, including the fuzzification interface, database, rule base, decision-making unit and defuzzification interface. The input variables conduct fuzzification of the accurate signals via the fuzzification interface. The inference engine infers the fuzzy output variables based on the membership function stored in the database and the fuzzy control rule stored in the rule base. Then, the fuzzy variables are output after increasing their precision by going through the defuzzification interface.

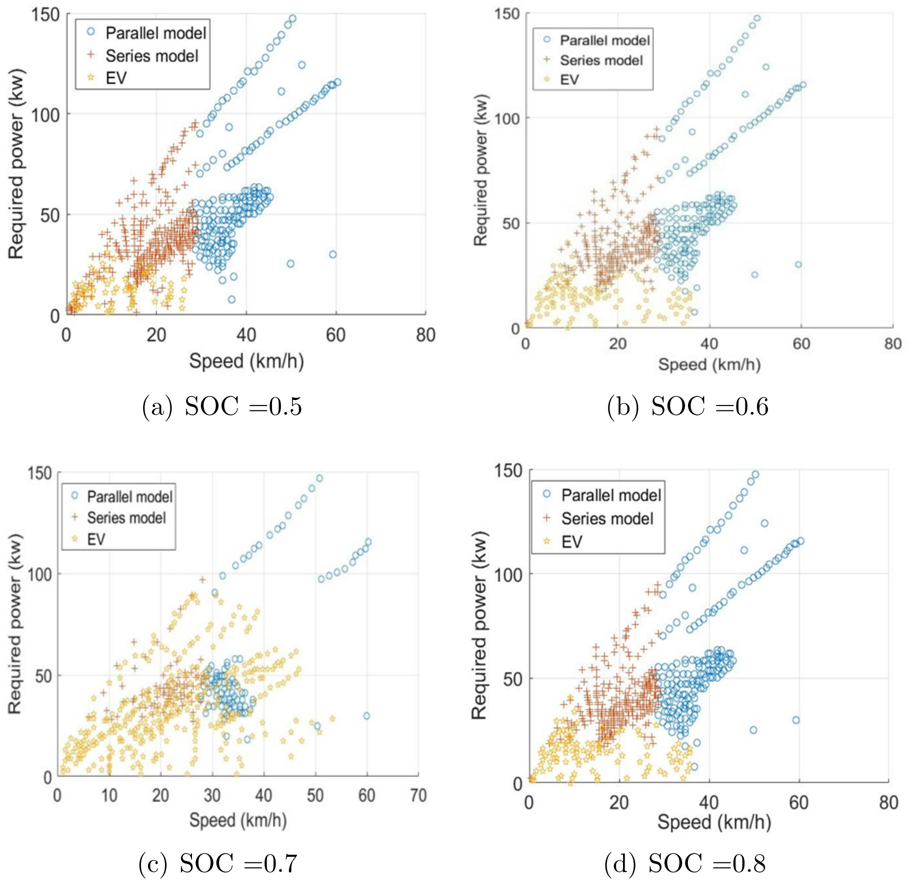
Fig. 3 shows the operation models of the series-parallel HEV using the dynamic programming based global optimization algorithm and at different SOC initial values. From Fig. 3, it can be seen that the series operation model and the parallel operation model do not exchange with each other according to simple control rules. Instead, the parallel operation model can exchange to the series operation model only when the transmission shaft rotational speed, ωt, is higher than 1,000. When the SOC initial value is high, the dynamic programming algorithm might correspondingly increase the purely dynamic drive operation model with a small energy consumption so as to increase the fuel economy.

The SOC of the power battery, vehicle required torque, T_{des}, and the rotational velocity of the drive motor, ω_n, are adopted as input variables of the fuzzy controller, and the torque of the engine, T_e, as the output control variable to build a three-input and one-output fuzzy controller. The vehicle required torque, T_{des}, is set to be a fuzzy set with six elements, namely [HX,LX,X,Z,D,HD]; the drive motor to be a fuzzy set with three elements, namely [X,Z,D]; the battery SOC to be a fuzzy set with four elements, namely [HX,ZX,ZD,HD]. The domain of all variables is set to be [0,1]. The input variable membership function is shown as below:

Fig. 7 show operating points of the engine under the dynamic programming diagram. The engine mainly operates nearby the optimal fuel economy curve. Under the drive cycle with a large demand of power, such as sharp acceleration or climbing, the engine will increase its output power. On the contrary, under the drive cycle with a small demand of power, such as fast cruise, the engine tends to reduce the output power to cut oil consumption. When the battery SOC is too high, the battery should resort to electric discharge. When there is a high demand of power, the engine will deviate from the optimal operation zone to increase power output. Therefore, the membership function of the engine output torque is built as below. The actual output torque of the engine is T_e, a fuzzy set with six elements, namely [HX,LX,Z,D,LD,HD]. See Fig. 8.

3.2. **Fuzzy control rule.** According to the results obtained by the dynamic programming based global optimization algorithm, the control rules are formulated for the fuzzy controller. Some fuzzy control rules are shown as below:

If (T_{des} is D) and (ω_m is D) and (soc is ZD) then (T_e is LD)
If (T_{des} is X) and (ω_m is HX) and (soc is ZX) then (T_e is LX)
If (T_{des} is X) and (ω_m is HX) and (soc is ZD) then (T_e is Z)



(a) SOC =0.5 (b) SOC =0.6

(c) SOC =0.7 (d) SOC =0.8

FIGURE 3. Distribution of operation points at different SOC initial values

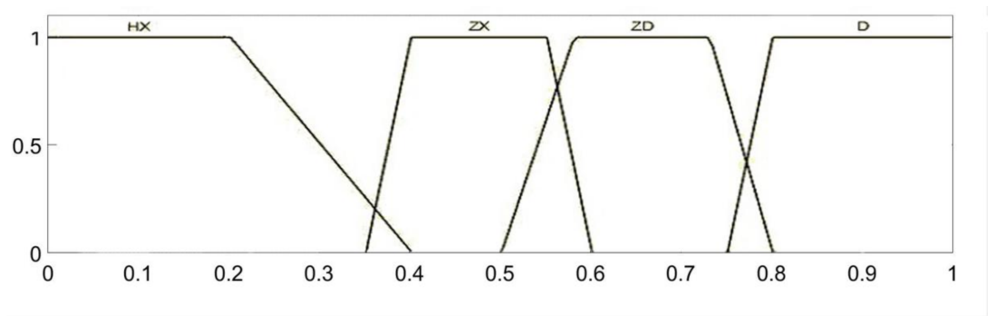


FIGURE 4. Membership function of the battery SOC

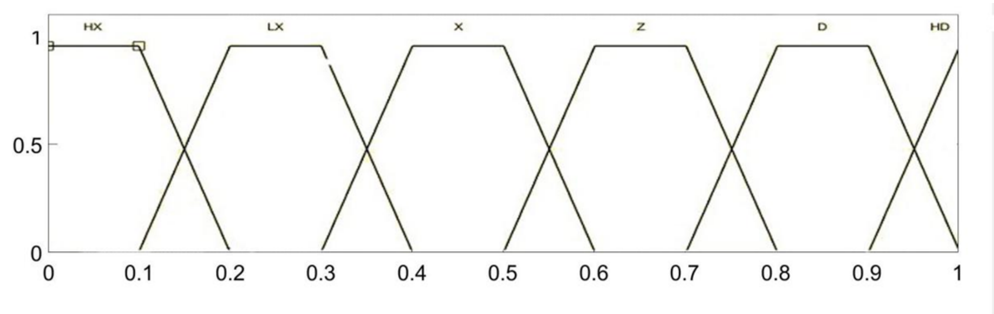


FIGURE 5. Membership function of the vehicle required torque

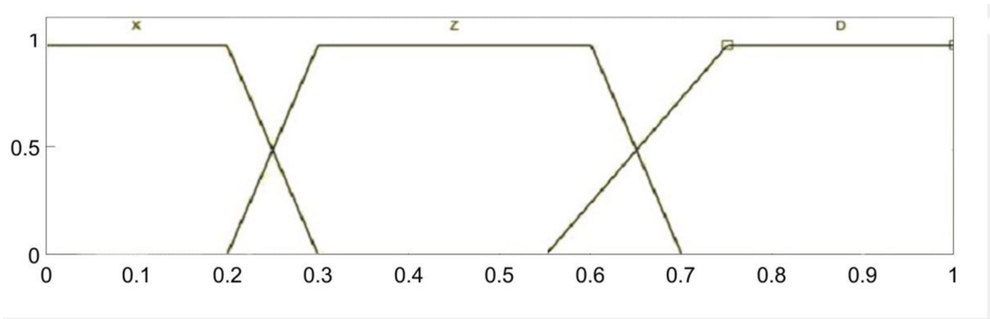


Figure 6. Membership function of the drive motor rotational velocity

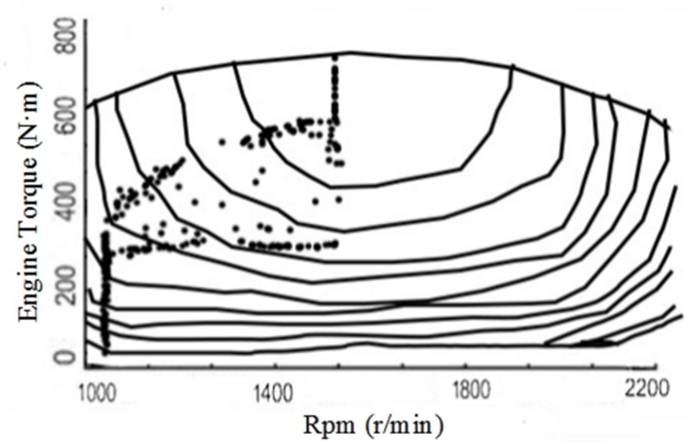


Figure 7. Operating points of the engine under the dynamic programming algorithm

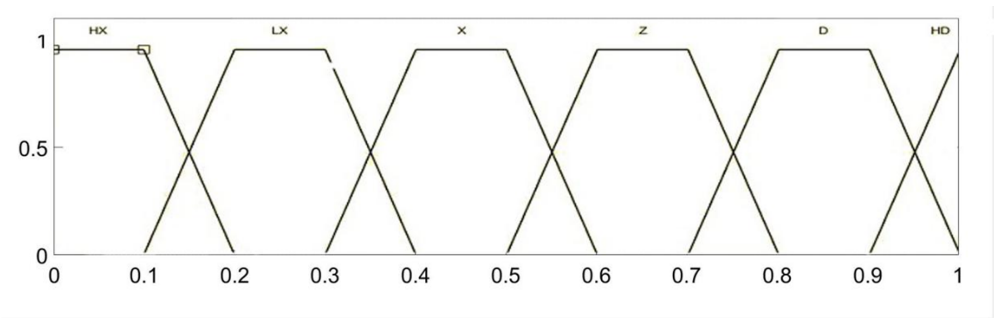


Figure 8. Membership function of the engine torque

If (T_{des} is Z) and (ω_m is HX) and (soc is ZD) then (T_e is Z)
If (T_{des} is D) and (ω_m is Z) and (soc is ZD) then (T_e is LD)
If (T_{des} is D) and (ω_m is D) and (soc is ZD) then (T_e is LD)
If (T_{des} is HD) and (ω_m is D) and (soc is ZD) then (T_e is HD)
......etc.

3.3. **Simulation results.** Major vehicle parameters are presented in Table 2. Matlab/Simulink is used to conduct simulation under the drive cycle of the CTDCBC. The battery SOC initial value is set to be 0.7, and the simulation results are as follows:

From Fig. 9 to 12, it can be seen that, during the whole drive cycle process, the battery SOC value stays at 0.69, which is the SOC value at the end of the balancing process. It

Table 2. Major parameters of the series-parallel HEV

	Parameters	Value
Vehicle	Unladen mass/Gross mass (kg)	12500/17500
	Rolling resistance coefficient	0.012
	Wind resistance coefficient	0.55
	Tire radius (m)	0.526
	Frontal area (m^2)	8.13
Engine	Maximum power (kw)	155
	Highest torque (Nm)	630
Drive motor	Maximum power (kw)	120
	Highest torque (Nm)	500
ISG	Maximum power (kw)	40
	Highest torque (Nm)	300
Power battery	Total capacity (AH)	60

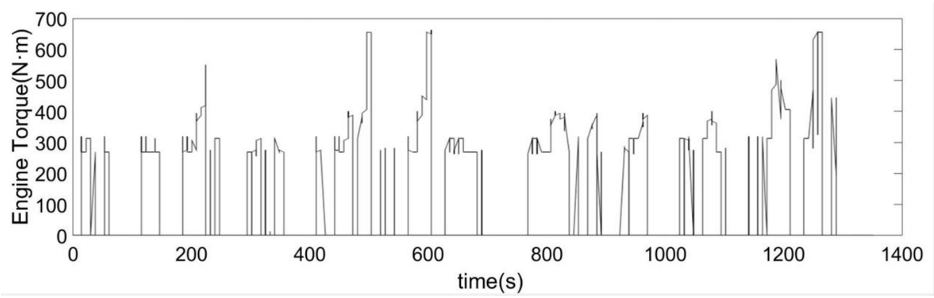


Figure 9. Engine torque

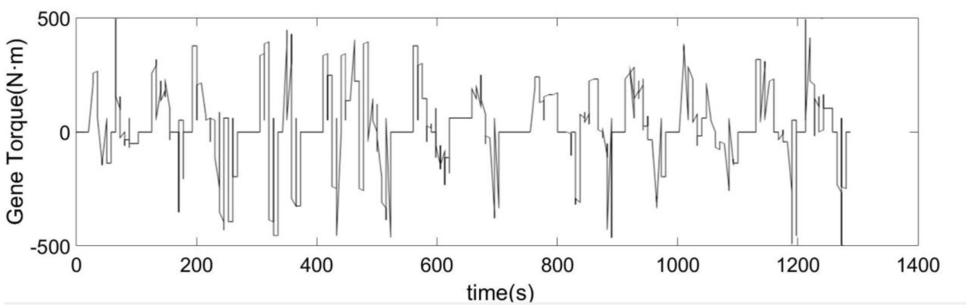


Figure 10. ISG torque

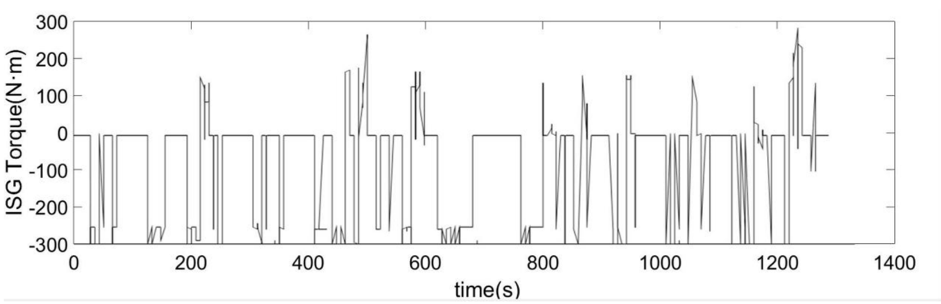


Figure 11. Drive motor torque

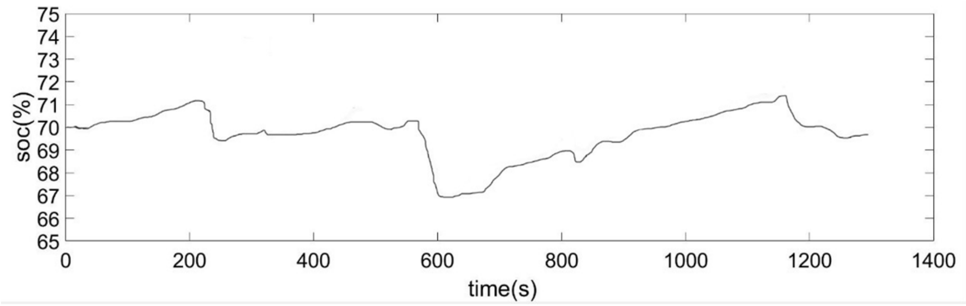


Figure 12. SOC of the battery based on the fuzzy control strategy

is slightly lower than the SOC initial value by 0.1. The engine operates steadily, and the operating points are relatively concentrated. During the whole drive cycle process, the oil consumption per 100 km is 22.1 L under the fuzzy control rule is 22.1 L, and 19.95 L under the dynamic programming algorithm. The gap between the two is 9%. Compared with the oil consumption under the logic threshold control strategy, the oil consumption is reduced by 13% by following the dynamic programming based fuzzy controller put forward in this paper. The comparison results are numerically shown in Table 3. Results of the fuzzy controller are closer to the global optimization results based on the dynamic programming. This suggests the fuzzy control strategy based on dynamic programming outperforms.

Table 3. Comparison of oil consumption simulation results

Control strategies	Oil consumption per 100 km (L/100km)	Improvement (In comparison with the logic threshold)
Logic threshold	25.43	-
Fuzzy control	22.1	13%
Dynamic programming	19.95	21%

4. **Conclusions.**

1. Based on global optimization algorithm, the global optimization objective function with cost function is established under the CTDCBC containing the battery SOC and clutch cost functions. The objective function is then used to solve the optimal control rule to achieve the minimum oil consumption of the series-parallel HEV.
2. The membership function of the engine torque output variables is designed based on distribution of engine operation points under different drive cycles, and according to the dynamic programming results. Next, the corresponding fuzzy control rule is formulated according to distribution of the HEV operation model points at different SOC initial values. Finally, the fuzzy controller aiming at optimizing the engine torque is designed;
3. Based on the Matlab/Simulink platform, the simulation is carried out under typical CTDCBC cycle conditions in China. The globally optimized fuel consumption per 100 km is 19.95 L, and the fuel consumption per 100 km of traditional fuzzy control is 22.1 L. The fuel consumption value based on the globally optimized fuzzy control is 100 km. It is 24.2L. The fuzzy control of the design is 8.6% higher than the traditional fuzzy control, which achieves the improvement of fuel economy and emission. And it illustrates the feasibility and applicability of the scheme.

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