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Original scientific paper

An Optimization Approach for Energy Management of Hybrid Vehicles Based on Dynamic Programming and Cuckoo Search

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Abstract: This paper proposes optimization models integrating dynamic programming and cuckoo search algorithms for energy management and saving in hybrid electric vehicles (HEV). An energy management strategy based on dynamic programming is designed to allocate power across engine, motor and battery. A cuckoo search-based model tunes the electronic throttle controller to improve fuel economy. Experiments validated the efficacy of the models. The dynamic programming strategy reduced fuel consumption by 4.31 L/100 km and stabilized battery state of charge compared to rule-based methods. The cuckoo search algorithm tuned controller decreased system response time to 0.0132 s and tracking error to zero. The models provide an effective optimization framework for HEV energy management and fuel saving. However, considerations like exhaust emissions were not included. Further research should evaluate the models on real HEV test data and incorporate additional objectives like emissions. In conclusion, this paper proposed and validated optimization models integrating dynamic programming and cuckoo search algorithms to address hybrid electric vehicle energy management and fuel economy.

Keywords: Cuckoo search algorithm; dynamic programming; energy management; energy saving optimization; hybrid system

1 INTRODUCTION

The rapid progress of technology and economy has led to increasingly serious environmental pollution problems. Therefore, as a new energy vehicle, hybrid electric vehicles (HEV) are receiving more and more attention. Comprehensive energy efficiency optimization of the power system, energy recovery, and elimination of idle speed can improve fuel consumption and reduce emissions. This is an important technical means for energy conservation and emission reduction in the automotive industry [1]. Hybrid vehicles combine the benefits of traditional internal combustion engines and electric motors to reduce fuel consumption and emissions. However, they require coordinated management of multiple energy sources, including internal combustion engines and electric motors. The complexity of energy management systems is high, requiring more intelligent algorithms and control strategies [2]. Optimizing energy management in hybrid systems and improving the dynamic response characteristics of electronic throttle valves can enhance energy efficiency, optimize power performance, and reduce emissions. Selecting an appropriate energy management strategy (EMS) can allow the vehicle to distribute power to various power sources based on different driving situations, resulting in optimal energy utilization efficiency and performance. This is of great significance for improving the driving and environmental performance of hybrid vehicles, and has become a key research direction for hybrid vehicles. The dynamic response characteristics of the electronic throttle refer to its ability to respond rapidly and perform dynamically when receiving control signals [3, 4]. Improving the dynamic response characteristics of electronic throttle can improve the fuel economy and emission performance of the entire vehicle. The hybrid power system (HPS) involves converting and managing multiple energy sources. However, the current energy management system cannot accurately predict and control energy demand and distribution [5]. This results in low energy utilization efficiency and slow response speed of electronic throttle valves, which affects the overall performance of the HPS. To further optimize the power distribution of the power source, improve the response speed of the throttle valve, thereby improving fuel utilization and reducing emissions, this study established a hybrid-power EMS model based on dynamic programming algorithm (DPA). The gain fractional order Process Identification (PID) control strategy is adopted, and the Cuckoo Search (CS) algorithm was introduced to tune the control parameters. Finally, an EMS optimization model for HPSs is established based on optimization algorithms and dynamic programming. There are two main innovations in this study. The first point is to study the EMS of parallel HEV using DPA. The second point is to design a controller based on the CS algorithm that can adaptively optimize the gain fractional PID parameters. The context has four parts. Part 1 is an analysis of the current research status. Part 2 designs an EMS for hybrid systems on the basis of DPA, and builds an energy-saving optimization (ESO) model for HEV based on CS algorithm. Part 3 is to analyze the application effect of the designed model. Part 4 is a summary of the entire study. Dynamic programming is a global optimization algorithm that can decompose complex decision-making processes into sub-stage decisions, thereby solving the optimization of the decision-making process. Liu D. et al. reviewed the latest developments in adaptive dynamic programming and its applications in control. And through comprehensive and complete research on the application of this intelligent control method in many existing fields, they have fully demonstrated the prospects of adaptive dynamic programming intelligent control in the current era of artificial intelligence [6]. Alzubi O. A. et al. introduced and studied in detail a new ensemble design algorithm based on dynamic programming to address the issue of how classifier ensemble technology can be combined with machine learning to improve ensemble accuracy. The proposed algorithm outperformed classical ensemble in terms of accuracy and ensemble size on all datasets, with reliability, stability, and effectiveness [7]. Yang Y. et al. proposed a policy evaluation and improvement process based on continuous feedback and an intermittent policy executing process. They studied the impact of aperiodic sampling on the communication bandwidth and control performance of intermittent adaptive DPA using a model-based hybrid adaptive dynamic programming framework. The proposed framework had high efficiency [8]. Demirović E. et al. proposed a new algorithm for learning the optimal classification tree based on dynamic programming and search to address the problem of traditional optimal decision-making and heuristic algorithms being prone to falling into local optima. This method could handle a dataset of tens of thousands of instances, providing several orders of magnitude of improvement, and has certain feasibility and effectiveness [9]. Kong L. et al. introduced an auxiliary system to optimize the tracking control of robots and improve robustness under the influence of unknown nonlinear disturbances. Its optimal control could be seen as the approximate optimal control of the robot. Under the framework of adaptive dynamic programming, a neural network was used to approximate the Hamilton Jacobi Isacs equation. The system had a certain degree of effectiveness [10]. Din AFU. et al. have proposed unique intelligent control architecture to maximize the gliding distance of experimental drones with unconventional control, and an improved DPA based on reinforcement learning. This algorithm could dynamically adapt to constantly changing environments, making it suitable for unmanned aerial vehicle applications and had certain effectiveness [11]. Energy management is the general term for organization, scientific planning, control, inspection, and supervision of the entire process of energy distribution, consumption, conversion, and production. It can effectively coordinate energy sharing and trading among all available energy sources. Rathor S. K. et al. reviewed research on various aspects of energy management systems in response to the challenges they currently face. They conducted a comprehensive analysis of various stakeholders, and also critically analyzed the main optimization techniques that meet multiple constraints for different energy management system objectives simultaneously [12]. Yu L. et al. stated that the growth of new intelligent building energy management technologies is of important and urgent significance for promoting energy-saving and green buildings. They also pointed out five challenges in developing efficient energy management technologies and conducted a comprehensive review of deep reinforcement learning in intelligent building energy management from a system scale perspective [13]. Wang Y. et al. stated that efficient energy management is essential for perfecting the performance of solar steam power generation. By carefully designing the configuration of photo-thermal materials and warm and cold evaporation surfaces, the solar evaporation performance has been greatly improved. This was of great significance for seawater desalination and wastewater treatment, and could also generate certain economic benefits [14]. Yin L. et al. discussed the use of artificial intelligence and advanced algorithms to achieve accurate and intelligent energy budgeting and regulation for rapidly changing dynamic data-driven predictions of electricity supply and demand. This provided broad prospects for the application and development of more efficient and sustainable wearable micro-grids with higher power [15]. Xu X. et al. proposed a new family energy management framework based on reinforcement learning for efficient household needs. This framework formulated the energy consumption scheduling problem before the hour as a finite Markov decision process with discrete time steps. The results indicated that the proposed data-driven household energy management framework has certain effectiveness [16]. Li P. et al. stated that the energy crisis and the increasing attention of modern society to the environment have promoted in developing integrated energy systems in smart grids. They also proposed an EMS based on Lyapunov optimization for energy hubs with energy routers. It described the configuration of an energy hub and set up the basic working principle of the energy router. It is indicated that this strategy has certain effectiveness and feasibility [17, 18]. In summary, many previous experts and scholars have conducted extensive research on energy management. Although DPA is often utilized to deal with the optimal decisions, there are still relatively little studies about the optimization of EMS for HPS that combine CS algorithms with dynamic programming. Therefore, the constructed model has important practical application value and prospects for the HEV development.

2 ENERGY MANAGEMENT AND ESO OF HYBRID POWER SYSTEMS BASED ON DPA AND CS ALGORITHM

Under the oil crisis, hybrid vehicles have attracted attention of many researchers as a new energy vehicle. A dynamic programming based EMS for HPS in automobiles has been studied and designed to address the issue of energy management in HPS. On this basis, the dynamic response characteristics of the electronic throttle were strengthened, and a HEV-ESO model built on CS algorithm was established. The purpose is to further improve the fuel economy and emission performance of the entire vehicle.

2.1 EMS for HPS Based on Dynamic Programming

The power system of a parallel HEV consists of multiple power sources. By improving the energy distribution between various power sources through EMS, the fuel economy of a car can be improved to a certain extent. The EMS mainly focuses on the fuel economy and power performance of parallel hybrid vehicles.

Table 1 Parameters of Parallel HEV

-	Parameter	Numerical value
Vehicle system parameters	Air resistance coefficient	0.29
	Vehicle mass	1870 kg
	Windward area	2.362 m^2
	Air density	1.225 kg/m^3
	Wheel radius	0.325 m
Engine parameters	Maximum speed	5000 rad/min
	Maximum power	81 KW
	Maximum torque	140 N×m
	Displacement	1.5 L
Motor parameters	Maximum power	25 KW
	Maximum torque	260 N×m
	Maximum speed	5000 rad/min
Gear ratio of transmission system	Transmission 1	3.76
	Transmission 2	2.64
	Transmission 3	2.15
	Transmission 4	1.52
	Transmission 5	0.98
	Transmission 6	0.83
	Main reducer transmission ratio	3.52

This study selects a P2 configuration parallel HEV as the research object. The power source is a four stroke gasoline engine, permanent magnet synchronous motor, and lithium-ion battery. Traditional systems choose friction clutches and electronically controlled automatic transmissions. Tab. 1 lists the specific details of each component.

DPA is often used to address issues with optimal properties. It decomposes complex decision-making processes into sub-stage decisions, thereby optimizing the decision-making process. The DPA can consider multiple factors and constraints comprehensively, adjust in real-time to environmental changes and power requirements, and calculate the optimal energy allocation strategy. This allows the HPS to use multiple energy sources, such as internal combustion engines and electric motors, in the best way possible under different working conditions, thereby improving overall energy utilization efficiency. Therefore, this study utilizes DPA for energy management of HPS. Considering the impact of changes in electronic throttle opening on engine output torque (EOT) and fuel consumption, to improve the fuel economy of the entire vehicle (FEoEV), this study puts forward an EMS based on DPA. Dynamic programming is a mathematical idea of solving decision problems in stages. It makes decisions by decomposing the original problem into simple sub problems. Generally, it is used to solve optimal problems, and problems applicable to dynamic programming must meet the principles of optimization and have no aftereffects. For parallel HEV, DPAs are applied to EMS under certain operating conditions. It divides the multi-stage optimization problem into multiple single stages, and uses the best solution of the single-stage to calculate the global optimal solution. The DPA is divided into forward solving and inverse solving, and the discrete system for setting a certain optimization problem is shown in Eq. (1).

$$\begin{cases} x(k+1) = f\left(x(k), u(k), k\right) \\ x(0) = x_0 \\ k = 0, 1, ..., N-1 \end{cases} \tag{1}$$

In Eq. (1), $x(k + 1)$ and $x(k)$ are the state of the system at moment k + 1 and k. f is the system transfer function. N represents the step size. The function for finding the optimal control sequence is Eq. (2).

$$J = \min\left\{J_{k+1}\left(x(k+1), u(k+1)\right) + L_k\left(x(k), u(k)\right)\right\} \tag{2}$$

In Eq. (2), L represents the cost function. In the inverse solving process, it is necessary to reverse from stage N to stage 1, and sequentially calculate the minimum value accumulation of the objective function from the current stage to the previous stage. The expression for stage N is Eq. (3).

$$J_N\left(x(N), N\right) = \min\left[L\left(x(N), u(N)\right)\right] \tag{3}$$

The expression for stage k is Eq. (4).

$$J_k\left(x(k), k\right) = \min\begin{bmatrix} J_{k+1}\left(x(k+1), k+1\right) + \\ +L_k\left(x(k), u(k)\right) \end{bmatrix} \tag{4}$$

In Eq. (4), L_k represents the compensation required for the system to transition from $x(k)$ to $x(k + 1)$ using $u(k)$. The relationship between the required torque of the entire vehicle and the output torque of the power source at any stage is Eq. (5).

$$T_{re}(k) = T_{Eng}(k) + T_{Em}(k) \tag{5}$$

In Eq. (5), $T_{re}(k)$ represents the required torque of the entire vehicle. $T_{Eng}(k)$ represents the EOT. $T_{Em}(k)$ represents the output torque of the motor. The cost function includes the fuel consumption and State of Charge (SOC) value of the entire vehicle, as shown in Eq. (6).

$$L_k\left(x(k), u(k)\right) = L_{fuel}(k) + L_{SOC}(k) \tag{6}$$

To ensure stable changes in the power battery level and reduce excessive battery charging and discharging of the motor, this study uses the SOC value as a cost function, as shown in Eq. (7).

$$L_{SOC}(k) = \varsigma\left(SOC(k) - SOC_{end}\right)^2 \tag{7}$$

In Eq. (7), ς represents the dynamic adjustment factor. SOC_{end} represents the expected SOC value at the end of the working condition. After determining the throttle opening, the output torque and fuel consumption are determined based on engine experiments to ensure the FEoEV. The variance value of throttle opening is Eq. (8).

$$L_{jk}(k) = \frac{\tau}{k}\begin{bmatrix} \left(S_{jk}(1) - \overline{S_{jk}}\right)^2 + \left(S_{jk}(2) - \overline{S_{jk}}\right)^2 + ... \\ ... + \left(S_{jk}(k) - \overline{S_{jk}}\right)^2 \end{bmatrix} \tag{8}$$

In Eq. (8), τ represents the dynamic adjustment coefficient. $\overline{S}_{jk}$ represents the average opening of the throttle valve. The objective function of EMS based on DPA is Eq. (9).

$$\begin{aligned} & J_k\left[x(k), u(k)\right] = \\ & = \begin{cases} \min\begin{bmatrix} J_{k+1}\left(x(k+1), u(k+1)\right) + \\ +L_k\left(x(k), u(k)\right) \end{bmatrix}, 0 < k < N \\ 0, k = N \end{cases} \end{aligned} \tag{9}$$

The inverse solution process of the DPA is shown in Fig. 1.

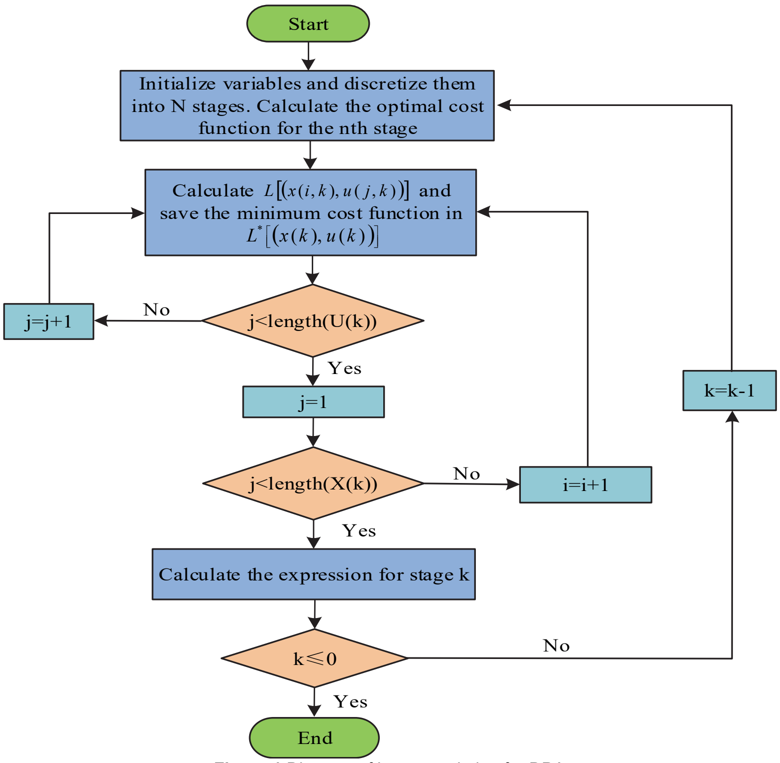


Figure 1 Diagram of inverse solution for DPA

2.2 Building an ESO Model for HEV Based on CS Algorithm

The engine is one of the important factors affecting the fuel economy of HEV. The electronic throttle system is a nonlinear system. The different opening angles of the electronic throttle greatly affect the engine's operation, thereby achieving accurate control of the electronic throttle importantly. When designing the corresponding controller, it is necessary to consider the ability to eliminate or reduce the influence of nonlinear factors on system control, as well as ensuring that the electronic throttle meets both response and following characteristics. Response characteristics are evaluated based on response time, which indicates the time it takes for the electronic throttle to rotate from the static balance position to the desired position. The following characteristics are evaluated by steady-state error and overshoot [19]. The working principle of the electronic throttle control system for parallel HEV is Fig. 2.

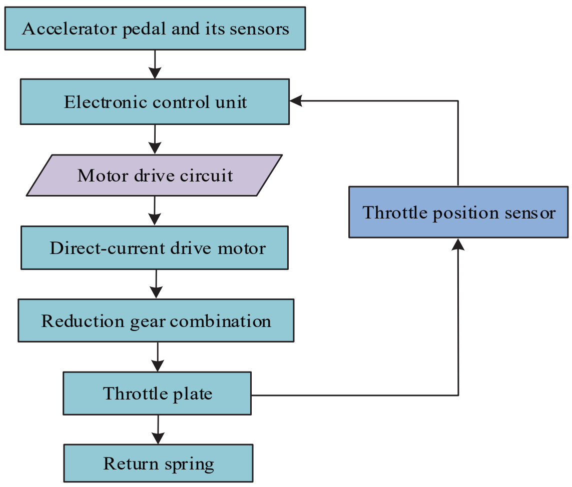


Figure 2 Working principle diagram of the electronic throttle control system for parallel HEV

To ensure more accurate intake of the engine during operation, this study considers the nonlinear aspect of the electronic throttle system and builds an ESO model for HEV grounded on CS algorithm to reasonably control the electronic throttle. The purpose is to lift the dynamic response characteristics of the electronic throttle, thereby lifting the fuel economy and emission performance of the entire vehicle. Integer order PID is widely used in linear systems, but there are shortcomings in the control response of nonlinear systems. Therefore, the study introduced fractional order PID, and the differential equation is Eq. (10).

$$u(t) = K_p e(t) + K_i D^{-\lambda} e(t) + K_d D^{\mu} e(t) \tag{10}$$

In Eq. (10), K_p, K_i, and K_d represent the proportional, the integral, and the differential control parameters, respectively. λ and μ represent the integral part index and the differential part index, respectively. D represents the transformation substitution of the integral and differential parts in integer order PID controllers. But the PID control strategy can lead to a longer response time of the system. In response to this issue, a PID control strategy with gain was further proposed, and its structural diagram is shown in Fig. 3.

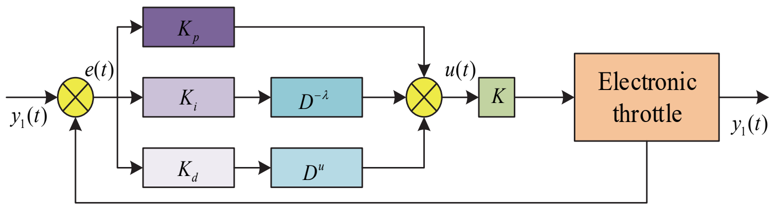


Figure 3 Structure of PID control strategy with gain

The differential equation with gain fractional order PID is shown in Eq. (11).

$$u(t) = K\left(K_p e(t) + K_i D^{-\lambda} e(t) + K_d D^{\mu} e(t)\right) \tag{11}$$

In formula (11), K represents gain. When controlling the electronic throttle system, the restoring torque generated by the return spring has a significant impact on the entire system. Therefore, a fractional order PID control strategy should be used to preliminarily control the entire system, obtaining information on the throttle opening and calculating the recovery torque generated by the return spring. At this point, there is an overshoot in the system. Then, considering the DC drive motor torque and the return torque of the return spring in the electronic throttle system, K is used as the compensation voltage. To adjust the system response time and reduce overshoot and system response time, better control results can be achieved [20]. The relationship between motor torque and return spring torque is Eq. (12).

$$\Delta T_m \cdot a = T_{sp} \tag{12}$$

In Eq. (12), ΔT_m represents the change in motor torque. a represents the proportional coefficient. The calculation of compensation voltage is shown in Eq. (13).

$$K = U_m = R\frac{k_{sp}(\theta - \theta_0) + D\,sgn(\theta - \theta_0)}{ak_t} \tag{13}$$

In Eq. (13), U_m represents the compensation voltage. There are 6 control parameters in the gain fractional order PID control strategy. During the parameter debugging process, each parameter has a certain impact on the system response. At the same time, manual debugging requires a lot of time and effort, which is uncertain. The CS algorithm is a heuristic algorithm that addresses optimization matters by simulating the parasitic breeding of certain species of cuckoo birds. It is widely used in engineering optimization problems. Compared to traditional methods of parameter optimization, the CS algorithm is less likely to become trapped in local optima, making it easier to obtain globally optimal control parameters. Additionally, it is well-suited for nonlinear and complex systems. When adjusting the control parameters of the gain fractional order PID control strategy, it can more effectively handle the non-linearity and complexity of the system. Therefore, the study introduces the CS algorithm to tune control parameters, thereby improving the stability and achieving the optimal control effect. The CS is an intelligent optimization algorithm that simulates the cuckoo birds searching for the optimal host nest to lay eggs, and establishes the Levy flight formula to update population individuals. It is beneficial for fewer algorithm parameters and strong optimization ability. The CS algorithm mainly follows three idealization rules. Firstly, each cuckoo can only lay one egg at a time and choose any nest to place it in. Secondly, nests with high-quality eggs will be inherited to the next generation [21]. Thirdly, the quantity of parasitic nests is fixed and unchanging, and the parasitized nests have a certain probability of discovering parasitic eggs. Levy flight is a true flight strategy for birds in nature. Its position update is Eq. (14).

$$\begin{cases} X_{t+1} = X_t + \alpha \cdot S \\ \alpha = \alpha_0 (X_i - X)_j \end{cases} \tag{14}$$

In Eq. (14), X_{t+1} represents the new position. X_t represents the position before the update. α represents the step coefficient, usually taken as 1. S represents the step size. X_i and X_j represent any different solution during the search process. S satisfies the Levy distribution, as shown in Eq. (15).

$$Levy(\lambda) \sim \mu = t^{-\lambda}\,(1 < \lambda < 3) \tag{15}$$

After the discovery of parasitic eggs, the update of the position path for rebuilding the nest is based on a random walk strategy, as shown in Eq. (16).

$$X_{t+1} = X_t + r \cdot Heaviside(Pa - \varepsilon) \cdot (X_i - X_j) \tag{16}$$

In Eq. (16), r and ε represent random numbers that follow a uniform distribution. *Heaviside* represents a skip function. Pa represents the probability of discovery. In summary, the specific process of the CS algorithm is Fig. 4.

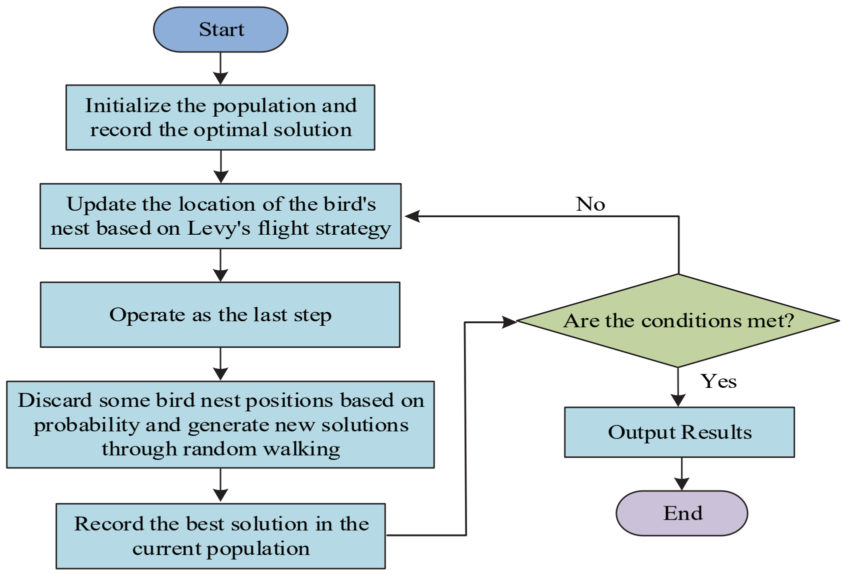


Figure 4 The process of cuckoo bird search algorithm

3 ANALYSIS OF THE EFFECT OF ENERGY MANAGEMENT AND OPTIMIZATION MODEL FOR HPS BASED ON DYNAMIC PROGRAMMING AND CS ALGORITHM

To verify the effectiveness of the proposed model, this study analyzes it from two perspectives. Firstly, the effectiveness of the proposed EMS is verified by examining three aspects: motor output torque, EOT, battery SOC changes, and engine fuel consumption. The second part of the analysis focuses on the effectiveness of the proposed ESO model. This is done by examining the system response characteristics of the electronic throttle under different control methods, tracking error, and response time of the electronic throttle under four typical operating conditions.

3.1 Analysis of the Effectiveness of EMS for HPS Based on Dynamic Programming

To assess the impact of the hybrid system EMS based on dynamic programming on parallel hybrid vehicles, this study conducted simulation analysis on MATLAB using the World Light Vehicle Test Cycle (WLTC). The WLTC is a standardized test cycle used to evaluate the fuel economy and emission performance of light vehicles. The initial SOC value of the battery is 0.5. The motor output torque and EOT are shown in Fig. 5. In Fig. 5a, the output torque of the motor is relatively small between 0 - 500 s, reaching a maximum of around 280 N×m at around 1500 s, which is greater than the maximum torque of the selected motor. In Fig. 5b, the EOT is around 75 N×m, and after 1500 s, the output torque can reach 150 N×m, exceeding the maximum torque of the selected engine. Therefore, the proposed energy management strategy can balance the output torque of the motor and generator in most cases, maximize the utilization of electrical energy, improve fuel economy and energy utilization efficiency, and make the operation of the entire hybrid power system more stable. But when the vehicle needs to accelerate, it can also increase the output torque of the motor and generator, providing temporary reserve power for the vehicle and enhancing its adaptability to emergency situations. The results indicate that on the basis of DPA, the EMS for HPS has certain feasibility and effectiveness.

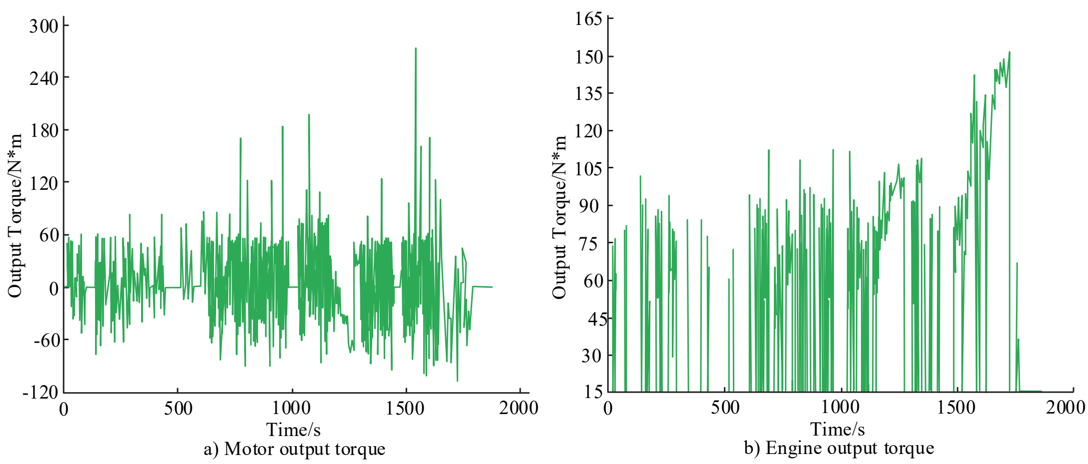
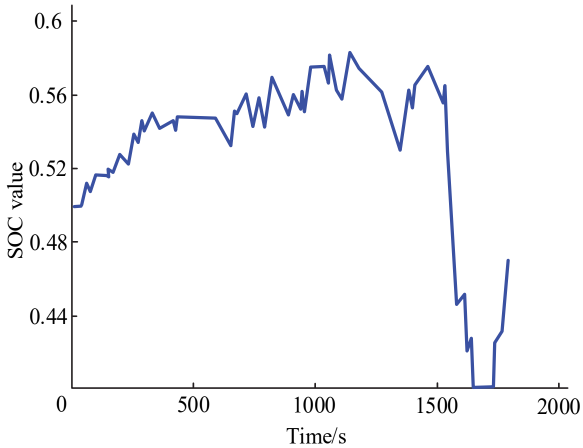
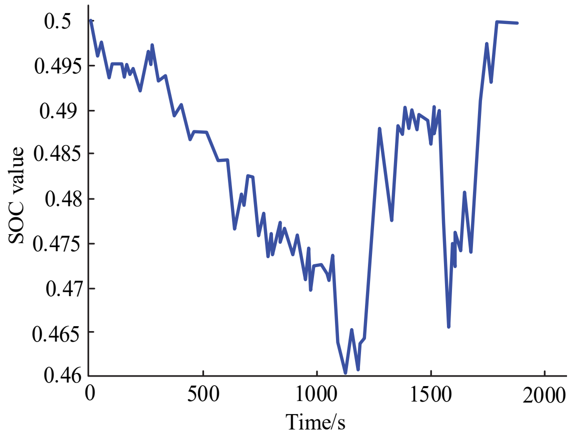


Figure 5 Motor output torque and EOT

To verify the stability of the EMS for HPS, a study was conducted under WLTC conditions, using the battery SOC value as an evaluation indicator. When the SOC value is high, it indicates that the battery stores more energy, reduces fuel consumption of the internal combustion engine, and maintains the battery SOC within an appropriate range. This maximizes energy utilization efficiency and improves the FEoEV. The battery SOC changes obtained from this model were compared with the EMS based on logical rules under WLTC operating conditions [22, 23]. Fig. 6 displays the results. In 6 (b), under the entire cycle condition, the fluctuation of battery SOC is relatively small, with a fluctuation range of 0.45 - 0.5, indicating a higher efficiency of the battery. At the end of the working condition, the SOC value of the battery can be restored to 0.5, consistent with the initial state. Furthermore, when compared to the EMS constructed using logical rules, the SOC value fluctuation range is smaller in this study's approach. Additionally, the SOC value consistently remains below the initial set value throughout the calculation process. This is because although the energy management strategy based on logical rules can allocate the working mode of the entire vehicle, it cannot consider the impact of electronic throttle opening on engine output torque and fuel consumption. The results indicate that the battery SOC has better stability under this research strategy.



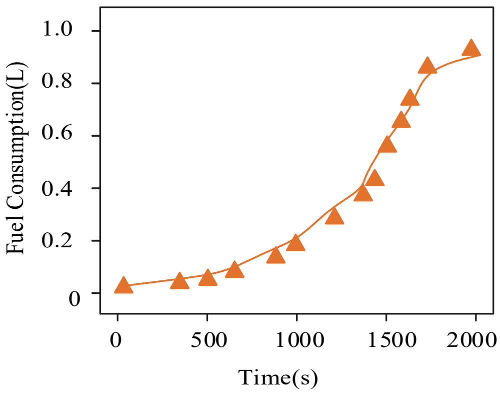
a) SOC variation diagram under logical rules



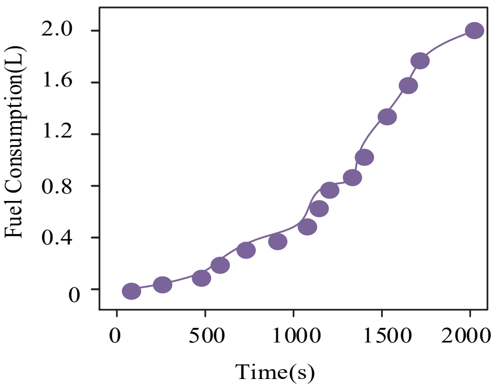
b) SOC variation chart under the model of this study

Figure 6 Comparison results of changes in battery SOC

To verify the impact of dynamic programming based HPS EMS on vehicle fuel economy, the study compared the obtained engine fuel consumption with the EMS based on logical rules. Fig. 7 shows the specific results. The less fuel consumption, the better the effect of EMS. From the figure, the fuel consumption of the two strategies' engines is increasing in a stepped manner, with the horizontal part being when the entire vehicle is in parking mode, pure electric mode, or regenerative braking mode. However, compared to the EMS based on logical rules, this strategy has a lower fuel consumption of 4.31 L per 100 kilometers, and the overall fuel economy of the vehicle is stronger. The results indicate that the EMS of HPS based on dynamic programming has a certain effect on improving the FEoEV.



(a) Dynamic programming algorithm for engine fuel consumption



(b) Engine fuel consumption under logical rules

Figure 7 Comparison of Engine Fuel Consumption under Two Strategies

3.2 Analysis of ESO Model for HEV Based on CS Algorithm

To evaluate the effectiveness of the ESO model for HEV based on the CS, this study comprehensively considers the nonlinear aspect of the electronic throttle and uses Simulink software to build a simulation model. The number of iterations is set to 100, the probability of discovery is 0.25, and the number of bird nests is 1000. The proportional part, integral part, differential part, integral part index, differential part index, and gain control parameters are 6, 5, 4, 3, 2, and 1, respectively. A step signal is used as the input signal, and the system response characteristics of the electronic throttle under different control methods are observed. Tab. 2 shows the meaning of the simulation curve under the step signal.

Table 2 Meaning of each curve in step signal response simulation

Curve	Meaning
1	Step signal output
2	Simulation results without controller added
3	Fractional PID simulation results
4	Simulation results of fractional order PID with gain
5	Simulation results of CS algorithm optimized fractional order PID with gain

This study uses response time as the evaluation indicator, and the shorter the response time, the more sensitive the electronic throttle response will be. The system response characteristics of the electronic throttle under different control methods are shown in Fig. 8. Among the four methods in the figure, the electronic throttle without a controller has the longest response time, which is 0.712 seconds. After optimizing the CS algorithm with gain fractional order PID control, the response time of the system is greatly reduced to 0.0132 seconds. The results indicate that the ESO model for HEV based on CS has the features of short response period and sensitivity.

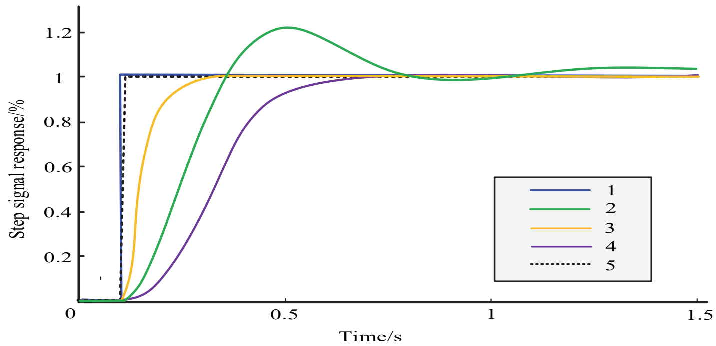


Figure 8 System response characteristics of electronic throttle under different control methods

The study compares the following errors of the four methods, including the state without controller, PID, gain PID, and research algorithm, denoted as a, b, c, and d. The smaller the tracking error, the higher the control accuracy. The following error under different control methods is shown in Fig. 9. Among the four methods, the CS algorithm proposed in this study has the smallest tracking error with gain fractional order PID after optimization, which can reach 0. This indicates that the ESO model for HEV based on CS algorithm has relatively small error, and has certain feasibility and effectiveness.

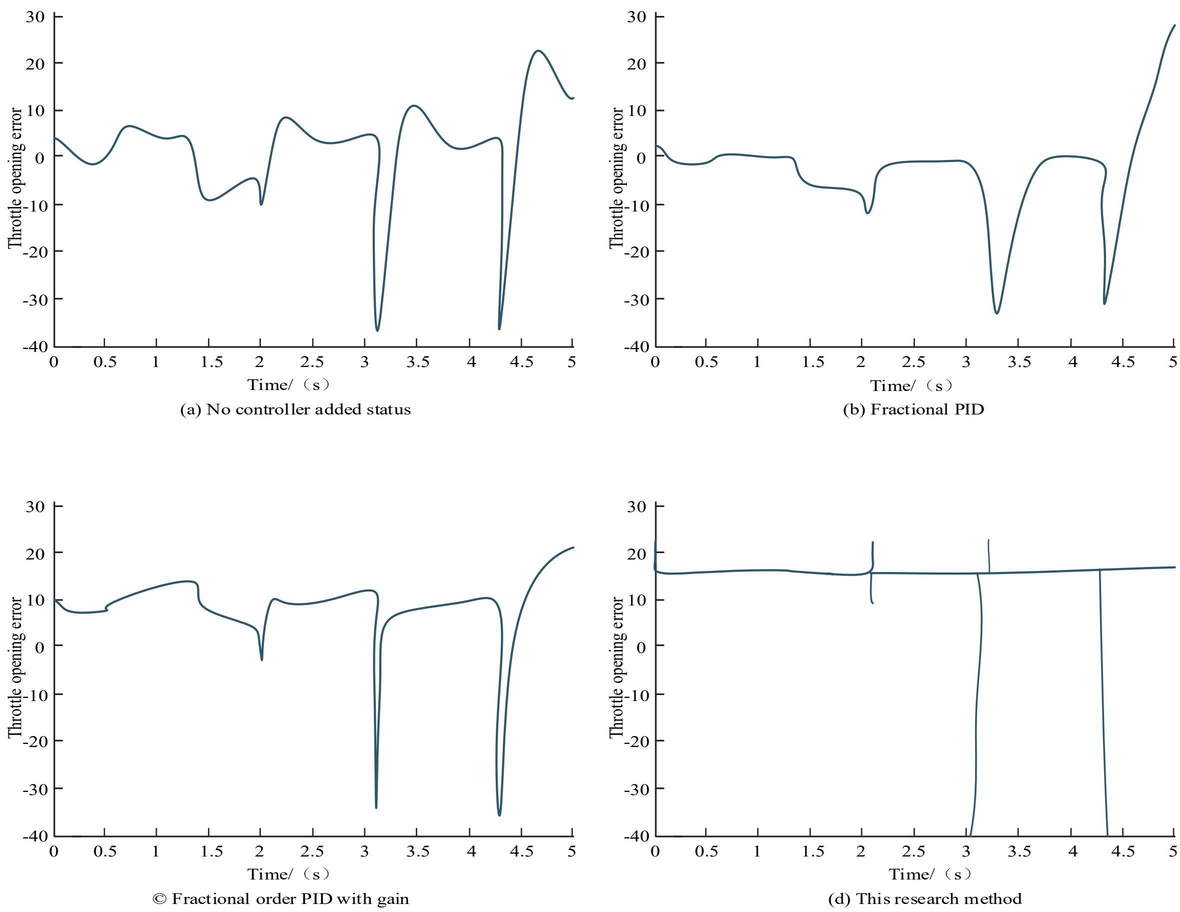


Figure 9 Follow error curves for different control methods

To verify the CS's impact based ESO model for HEV on the response time of electronic throttle, a comparison was conducted for four different typical operating conditions. They are: engine start to idle state (condition 1), idle state to stall state (condition 2), vehicle emergency braking process (condition 3), and uniform acceleration and deceleration process at low speed (condition 4). The response times of different methods are shown in Tab. 3. Among the four methods, the CS algorithm optimized with gain fractional order PID has the shortest response time, which is 0.012 seconds in condition 1 and 0.019 seconds in condition 4. The results indicate that the ESO model of HEV based on CS algorithm has a certain effect on reducing the response time of electronic throttle. In summary, the research model has demonstrated feasibility and effectiveness in actively responding to energy-saving and environmental protection policies. It enables more efficient utilization of various energy sources in HPSs, improves energy utilization efficiency, reduces energy consumption, and enhances vehicle driving and handling performance.

Table 3 Response time of four methods under four operating conditions

Curve	Condition 1	Condition 2	Condition 3	Condition 4
a	0.41 s	0.45 s	0.40 s	0.39 s
b	0.18 s	0.31 s	0.89 s	0.24 s
c	0.14 s	0.25 s	0.32 s	0.12 s
d	0.012 s	0.014 s	0.015 s	0.019 s

Under the entire cycle conditions, the test results of the battery SOC value fluctuation, fuel consumption per 100 kilometers, electronic throttle response time, and tracking error of the method proposed in this study are shown in Tab. 4.

Table 4 The various test results of the proposed model

Test items	Result
Battery SOC value	0.45 ~ 0.5
Fuel consumption per 100 kilometers	4.31 L
Electronic throttle response time	0.0132 s
Following error	0

This means that maintaining the battery SOC within an appropriate range helps maintain the stability and reliability of the hybrid system, indicating a higher efficiency of the battery [24]. The simulation experiments have proven that the proposed model can allocate power more reasonably to the power source, improve the response speed of the throttle valve, and thereby enhance fuel utilization while reducing emissions [25, 26]. The purpose of this study has been achieved.

4 CONCLUSION

With the development of technology and the intensification of environmental pollution, hybrid vehicles are becoming increasingly popular in the market. To optimize power distribution of the power source, this study designed an EMS based on dynamic programming for hybrid systems and an ESO model for HEV based on CS algorithm. The response speed of the throttle valve was improved to enhance fuel efficiency and reduce emissions. The results showed that the EOT was around 75 N×m, and after 1500 s, the output torque could reach 150 N×m. When the working condition was finished, the SOC value of the battery could be restored to 0.5, consistent with the initial state. Compared with the EMS based on logical rules, this strategy had a lower fuel consumption of 4.31 L per 100 kilometers, and the overall fuel economy of the vehicle was stronger. The electronic throttle without a controller had the longest response time, which is 0.712 seconds. After optimizing the CS algorithm with gain fractional PID control, the response time of the system was greatly reduced, which was 0.0132 seconds. After optimizing the CS algorithm, the tracking error of the fractional order PID with gain was minimal and could reach 0. The error was small and had certain feasibility and effectiveness. It had the shortest response time, which is 0.012 seconds when the engine is started to idle state. The longest response time was 0.019 seconds when the acceleration and deceleration process is uniform at low speed. In summary, the research model has demonstrated feasibility and effectiveness in actively responding to energy-saving and environmental protection policies. It enables more efficient utilization of various energy sources in HPSs, improves energy utilization efficiency, reduces energy consumption, and enhances vehicle driving and handling performance. However, in designing the EMS in this study, only the FEoEV was considered, which may affect the actual application effect of the model. Therefore, this paper suggests that additional attention should be given to the powertrain and exhaust emissions of the entire vehicle. This will aid in the development of more comprehensive energy management strategies, improve vehicle performance and environmental impact, and support the stable growth of the hybrid vehicle industry.

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