Contents list available at CBIORE journal website

International Journal of Renewable Energy Development

Journal homepage: https://ijred.cbiore.id

Research Article

Adaptive control of plug-in hybrid electric vehicles based on energy management strategy and dynamic programming algorithm

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Abstract. This study mainly analyses the fuel consumption of plug-in hybrid vehicles during operation. A new control method for automobiles based on energy management strategy and dynamic programming algorithm is proposed. The new method plans and analyses the minimum electricity consumption, and then uses dynamic programming algorithms to analyse this parameter. The research results indicated that the vehicle state was constantly changing with the variation of SOC value during driving. The energy mobilization of the vehicle was more obvious after adding dynamic programming strategy. The efficiency of the vehicle was relatively high in driving state 1, with a minimum value of 70%, which was about 20% higher than in driving state 4. The average fuel consumption in driving state 2 was 1.8L higher than in other driving states. The overall efficiency of automobiles after incorporating dynamic programming was improved, with a shorter time to reach the lowest efficiency point compared with not incorporating dynamic programming algorithms. The highest efficiency value was 7.86% higher than that of not incorporating dynamic programming models. The new control method can reduce energy consumption and improve the energy management and control effect. The study provides a better research direction for energy management and control of hybrid electric vehicles in the future.

Keywords: Electric vehicles; Consumption; DP algorithm; Energy management; Control; efficiency.

Received: 12th July 2024; Revised: 26th Sept 2024; Accepted: 7th Oct 2024; Available online: 16th Oct 2024

1. Introduction

With the acceleration of globalization and industrialization, energy consumption and environmental pollution issues are becoming increasingly severe. Carbon emissions in the transportation sector have caused enormous pressure on the environment (Jia *et al.,* 2023). Plug in Hybrid Electric Vehicle (PHEV), as an energy-saving and emission reducing transportation vehicle, is a new type of vehicle that can work together through internal combustion engines and electric motors. This not only effectively reduces energy consumption, but also reduces vehicle emissions, which is crucial for achieving energy conservation and emission reduction in transportation (Song *et al.,* 2020). The energy efficiency and environmental performance of PHEV largely depend on the optimization of energy management strategies. The Dynamic Programming (DP) algorithm has shown great advantages in optimizing PHEV energy management strategies due to its global optimal solution characteristics (Peng *et al.,* 2020). However, DP still faces high computational complexity and a high demand for information in practical applications, which limits their application in real-time or near real-time energy management systems. Therefore, how to effectively apply DP to the energy management of PHEV has become an important direction in current PHEV energy management (Kashif *et al.,* 2021).

Currently, many experts have carried out in-depth research on the energy management of PHEVs. Sidharthan et al. proposed a novel adaptive intelligent hybrid Energy Management Strategy (EMS) to optimize the energy management of hybrid electric tricycles. The new strategy utilized absolute energy sharing algorithm and fuzzy logic controller to ensure efficient utilization of power source and motor power demand. Compared with BEV, the new strategy could significantly reduce battery peak power, reduce battery capacity loss, and lower total operating costs, demonstrating significant advantages in energy management of hybrid electric vehicles (Sidharthan *et al.,* 2023). The strategy significantly reduces the peak battery power and decreases the battery capacity loss. However, the strategy may not have sufficient global optimisation capability compared to the DP algorithm. Belkhier et al. proposed a hybrid battery-FCS energy storage and management system and passive control technology to improve the power efficiency and response speed of hybrid electric vehicles. The research results indicated that the technology could ensure that hybrid electric vehicles obtained sustained electricity from hybrid energy resources. The research results indicated that the new method achieved high-power integration and improved the operating speed of electric vehicles (Belkhier *et al.,* 2024). The research proposes a hybrid battery-fuel cell system and passive control techniques that can improve the power efficiency and responsiveness of hybrid electric vehicles. However, the method has some problems with the stability and durability of the fuel cell under different driving conditions and environments. Yao et al. proposed a novel offline online hybrid deep reinforcement learning strategy to optimize

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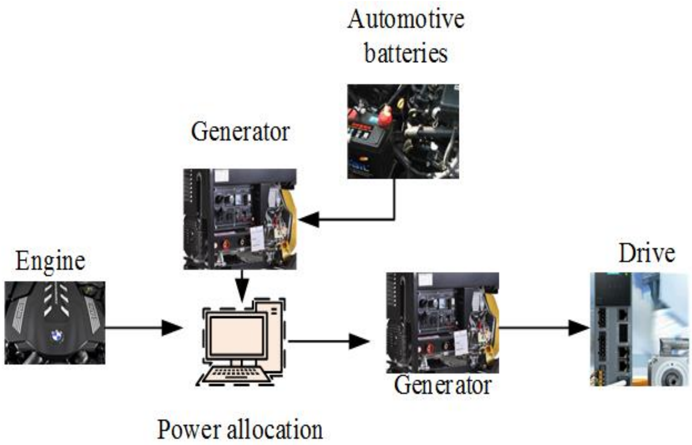


Fig 1 Hybrid structure vehicle model

the powertrain control strategy of hybrid electric vehicles and improve fuel economy. The new strategy utilized offline vehicle data to establish an initial model and explored new control strategies through online learning algorithms. Compared with online learning algorithms, the new method could learn faster and more stably, significantly improving fuel economy (Yao *et al.,* 2023). The proposed offline-online hybrid deep reinforcement learning strategy is able to build an initial model from offline vehicle data. However, its performance may be insufficient in variable real-world road conditions with high real-time requirements. Younes et al. proposed a fuzzy logic controller ground on predetermined motor torque and battery charging state to optimize the renewable energy management of hybrid intelligent vehicles. The new controller could adjust energy consumption while maintaining driving performance. Through the implementation and evaluation of simulation models for in vehicle hybrid power systems, the research results showed that the new management algorithm could effectively reduce changes in battery charging status, improve power system efficiency, and perform outstandingly in different driving cycles and harsh environments (Younes *et al.,* 2023). The controller proposed in the study is able to flexibly adjust the energy consumption according to the real-time conditions of the vehicle. However, the controller relies on predetermined motor torque and battery status parameters, which may be limited in practical applications. Cao et al. focused on hybrid electric vehicles as a reliable choice to improve fuel economy and reduce emissions. To fully leverage its advantages, energy management and torque distribution were important directions for control strategies. A comprehensive evaluation method was proposed based on relevant literature. The research results indicated that energy management strategies provided important references for the development, control, and optimization of hybrid vehicles (Cao *et al.,* 2023). The methodology proposed in the study shows the potential to improve fuel economy and reduce emissions. However, the study may limit the credibility and replication of the methodology in practical applications.

In summary, most of the current research on energy management in automobiles only focuses on power and fuel consumption management, and only includes one method for analysis. There are few directions for optimizing energy management in automobiles. Therefore, a novel method based on EMS and DP algorithm is designed. The automotive EMS is used to analyze the energy consumption status at different stages, fully understanding the energy consumption of the vehicle during driving. At the same time, DP is added to reduce fuel consumption during the driving process and improve the efficiency of the driving process.

2.Method

2.1 Construction of power vehicle model based on energy management strategy

When PHEV performs power adaptive control, it is necessary to first conduct energy analysis on the vehicle model and working system to build a driving model for the vehicle's operation. The hybrid charging process of PHEVs mainly has three modes: series, parallel, and series parallel hybrid. In the series connection, when the vehicle's battery is low, it is transmitted through the engine to generate electricity. The parallel structure allows for direct control of the automotive system through the interaction between the generator and engine. The hybrid structure combines series and parallel structures (He *et al.,* 2021). The hybrid structure vehicle model is shown in Figure 1.

From Figure 1, in the hybrid structure, the engine and electric motor are connected through mechanical shafts. The power of the two engines is distributed through a power distribution system. Secondly, the motor is connected to the driving system of the vehicle through mechanical shafts, driving the hybrid vehicle and achieving vehicle operation. The vehicle's battery will be connected to the inverter through a connecting wire during charging, and then connected to the generator and electric motor through the inverter to achieve the charging. There are five operating modes in the PHEV system, including pure electric operation, engine operation, hybrid operation, engine charging for the motor, and regenerative braking mode.

The pure electric working mode is where only the generator operates to provide the system power for the PHEV. However, in this mode, the operation needs to satisfy certain requirements for the speed of the motor. If the speed requirements cannot be met, the power drive of the vehicle will not be solely driven by the motor. The working mode of the generator is the process in which the engine drives the vehicle separately. In this mode, the generator and other motors of the vehicle do not work, which can minimize the consumption. The hybrid working mode is when the vehicle system rotates at a high speed and both the engine and generator cannot reach the operating speed of the motor, and both operate together. In this driving mode, the main engine is used as the auxiliary motor. When the power of the

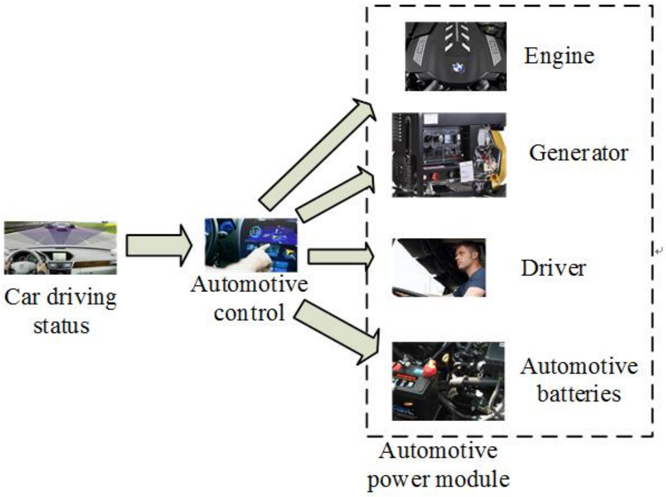


Fig 2 Automotive system structure

engine cannot meet the system requirements, the remaining power is supplied by the motor. The vehicle charging mode is operated by the engine as the power drive system to charge the engine when the vehicle's battery is low. The braking mode of a vehicle is powered by a generator and stores energy. The vehicle is displayed in Figure 2.

From Figure 2, the vehicle model framework includes vehicle driving, vehicle control, and vehicle power modules. The vehicle control module is mainly driven by the driver's operation. The control module consists of several modules, including the vehicle's engine, generator, transmission, and power battery. The driving module is the main signal emitting module of the vehicle model, which analyzes the parameters of the decision-maker through a PI controller and transmits the parameters into the vehicle control system to achieve vehicle control. The relationship between automotive control parameters is shown in equation (1) (Rasool *et al.,* 2023).

$$\theta = K_p(v_{cur} - v_{ref}) + K_p \frac{1}{T_i} \int (v_{cur} - v_{ref}) dt \quad (1)$$

In equation (1), θ represents the parameter value of the vehicle brake plate. K_p signifies the proportional value of the parameter. T_i signifies the integral constant of time. v_{cur} represents the current driving speed. v_{ref} signifies the target driving speed. The model needs to manage and analyze its energy. Therefore, the power system is subjected to pattern analysis, which is to analyze the fuel consumption of the power system. The fuel consumption of a vehicle is shown in equation (2) (Punyavathi *et al.,* 2024).

$$b_e = f(T_{eng}, n_{eng}) \quad (2)$$

In equation (2), b_e represents the fuel consumption efficiency of power reduction. T_{eng} represents the rotational torque.$(N * m)$.n_{eng} represents the rotational speed, measured by $(g/(kw * h))$. The power of the engine is displayed in equation (3) (Zhang *et al.,* 2023; Mohammed *et al.,* 2023).

$$P_e = \frac{T_{eng} * n_{eng}}{9550} \quad (3)$$

In equation (3), P_e represents the engine power. To obtain a more effective power output, the product of torque and speed is divided by 9550. The 9550 in the formula is obtained through unit conversion, which is used to convert the product of torque and speed into a value in kilowatts (kW). The efficiency of the electric motor is shown in equation (4) (Venkitaraman & Kosuru, 2023; Milbradt *et al.,* 2023).

$$\eta_{mot} = f(T_{mot}, n_{mot}) \quad (4)$$

In equation (4), η_{mot} represents the efficiency of the electric motor. T_{mot} represents the rotational moment of the electric motor. n_{mot} represents the rotational speed of the electric motor. The working efficiency of the electric motor at this time consists of two parts. When the rotational moment of the electric motor is greater than 0, it means that the vehicle is in the electric motor working mode. At this time, the power is shown in equation (5) (Gao *et al.,* 2023; Wang *et al.,* 2023).

$$P_m = \frac{T_{mot} * n_{mot}}{9550 * \eta_{mot}} \quad (5)$$

In equation (5), P_m represents the working power of the generator. When the electric motor is working for the engine, its power magnitude is shown in equation (6) (Usman & Abdullah, 2023; Song *et al.,* 2023, Ma *et al.,* 2024; Shi *et al.,* 2023).

$$P_m = \frac{T_{mot} * n_{mot} * \eta_{mot}}{9550} \quad (6)$$

To simplify the energy management process of automobiles, the influencing factors of automobiles are simplified to only consider the impact of the remaining electricity of the automobile. The remaining power of a vehicle is shown in equation (7) (Hua *et al.,* 2023; Yang *et al.,* 2024).

$$SOC = soc_{in} - \frac{\int_0^t I_{bat}(t) dt}{Q_{bat}} \quad (7)$$

In equation (7), SOC represents the current charging status of the battery. soc_{in} represents the initial amount of remaining electricity in the vehicle. Q_{bat} represents the battery charge loading capacity of the vehicle. I_{bat} represents the current of the battery at time t. The EMS for automobiles has two directions: automobile power utilization and power maintenance (Tian *et al.,* 2024; Millo Fetal, 2023).

2.2 Control strategy of stage dynamic programming algorithm for automobiles

DP is an optimization control model for solving multi-stage operation decisions of automobiles, mainly for planning energy decision-making strategies of automobiles. By conducting functional analysis on the minimum nodes in the automotive phase, the optimal decision-making method for each operational phase of the vehicle can be obtained. The decision-making process of the algorithm is shown in Figure 3.

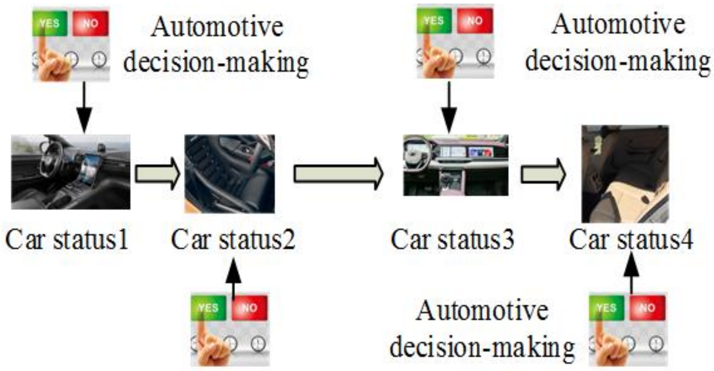


Fig 3 Algorithm decision process

From Figure 3, when the state parameters are input, the state parameters of the vehicle are first judged. Then, stage decisions are made through the DP. Aftermaking the decision, the state is judged before entering the next DP stage. Its state can be represented by equation (8) (Vignesh *et al.,* 2023; Cao *et al.,* 2023; Abd-Elhaleem *et al.,* 2023).

$$x_{k+1} = f(x_k, u_k) \tag{8}$$

In equation (8), x_k represents the discrete system of the DP. u_k represents the control method in the system variable. u_k belongs to a set of variables in system space. When the algorithm performs control at different stages, the objective function size of the current stage can be obtained by solving the state function of the algorithm, as shown in equation (9) (Ruan *et al.,* 2023; Gnanaprakasam *et al.,* 2023; Chen *et al.,* 2024).

$$J_\psi(x_0) = l_N(x_N, u_N) + g_N(x_N, u_N) + \sum_{k=0}^{N-1}[l_k(x_N, u_N) + g_k(x_N, u_N)] \tag{9}$$

In equation (9), $J_\psi(x_0)$ denotes the cost function starting from the initial state x_0.x_0 denotes the initial state vector of the system.$l_k(x_N, u_N)$ denotes the immediate cost function at stage k.N denotes the total number of time steps. x_N denotes the final state at state N, and u_N denotes the control inputs at state N. $g_k(x_N, u_N)$ denotes the immediate additional cost function at stage k. $g_N(x_N, u_N)$ denotes the additional cost function at state N . $l_N(x_N, u_N)$ denotes the additional cost function at state N . $l_k(x_N, u_N) + g_k(x_N, u_N)$ represents the instantaneous cost and punishment level at the end of the stage. $\sum_{k=0}^{N-1}[l_k(x_N, u_N) + g_k(x_N, u_N)]$ represents the total cost at that time. If the driving status is already known at this point, then, the vehicle status is controlled to obtain more suitable parameters and kinetic energy. The energy control equation of the vehicle at this time is shown in equation (10) (Cui *et al.,* 2024; Hao *et al.,* 2023).

$$\begin{cases} x(k) = SOC(k) \\ u(k) = [T_m(k), gear(k)] \end{cases} \tag{10}$$

In equation (10), $SOC(k)$ represents the remaining power of the transmission. T_m represents the rotational moment of the generator. $gear(k)$ represents the variable size that the algorithm system can manipulate. $x(k)$ signifies the system state. $u(k)$ signifies its control variable. At this point, the state of SOC is shown in equation (11) (Gao *et al.,* 2024; Vignesh & Ashok, 2023).

$$SOC(k+1) = SOC(k) - \frac{U_{oc}(k) - \sqrt{U_{oc}^2(k) - 4*R_o(SOC(k)*P_{bot}(k))}}{2*R_o(SOC(k))*Q_{bot}} \tag{11}$$

In equation (11), $U_{oc}(k)$ signifies the open circuit voltage of the battery. R_o signifies the battery resistance. Q_{bot} represents its charge capacity. P_{bot} represents the electrical power of the battery. Therefore, for the stage DP of automobiles, it is necessary to first discretize the remaining driving power of the vehicle, as shown in equation (12) (He *et al.,* 2024).

$$X_k = \{x_k^0, x_k^1, \cdots, x_k^{N+1}\} = \{SOC_k^0, SOC_k^1, \cdots, SOC_k^{N+1}\} \tag{12}$$

In equation (12), SOC_k^{N+1} represents the $N+1$-th state of stage k . X_k represents the discrete processing state of remaining electricity. After completing the discrete processing, the optimal parameters for each charging stage are solved to obtain the optimal control cost for each stage. Finally, the control state parameters of the vehicle during the operation phase are obtained by calculating the state. After continuously repeating this process, the DP for the automotive phase is completed. DP can provide energy control optimization for the entire stage (Jung *et al.,* 2024). However, there is also a prerequisite for using

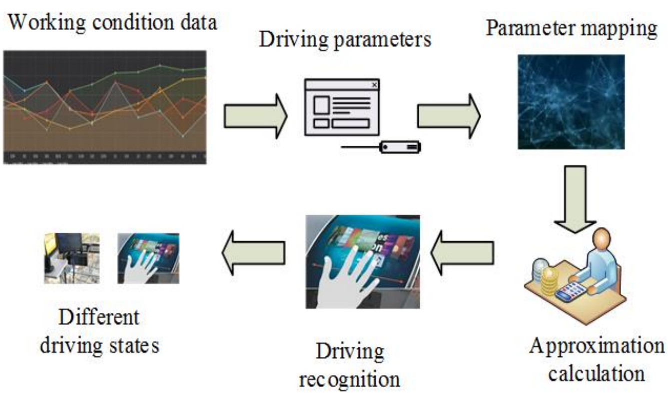


Fig 4 Driving state process

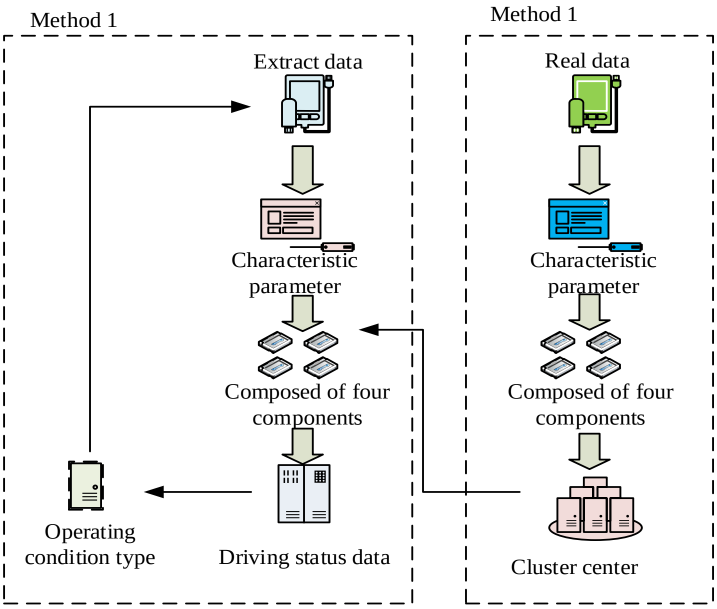


Fig 5 Driving state recognition process

this optimization method, which is to determine the driving state. Due to the uncertainty of the driving status, there is uncertainty in the DP of automobiles, making it more difficult for DP algorithms to control and manage energy strategies. Therefore, the driving status of automobiles need to be recognized (Cipek *et al.,* 2023). The driving process is shown in Figure 4.

From Figure 4, the driving state requires first extracting the state data of the vehicle, followed by calculating the feature parameters of the current driving state. By mapping the parameter data to the main space, the spatial driving state is obtained. The approximate value of the driving state is calculated, and the driving state is classified and recognized. Finally, the characteristic state data of the driving state are output. Therefore, there are two calculation methods for identifying the driving status of a vehicle. One approach is to analyze past data on the driving status of a vehicle and obtain characteristic parameters of its historical state. Another way is to map its parameters through past driving states, obtain different parameter components, and finally calculate similar values to obtain the driving state through similar values (He *et al.,* 2024). The driving state recognition process is shown in Figure 5.

From Figure 5, among the two methods, the parameter clustering state obtained by the first method can be transmitted into the principal component of the second method to connect the two methods. The second method can continuously judge the parameters by clustering analysis, and finally obtain the optimal parameters of the vehicle's driving state. This means that the second method has a better data parameter processing method compared to the first method. Finally, if the vehicle is powered by an electric motor throughout its journey, there is no

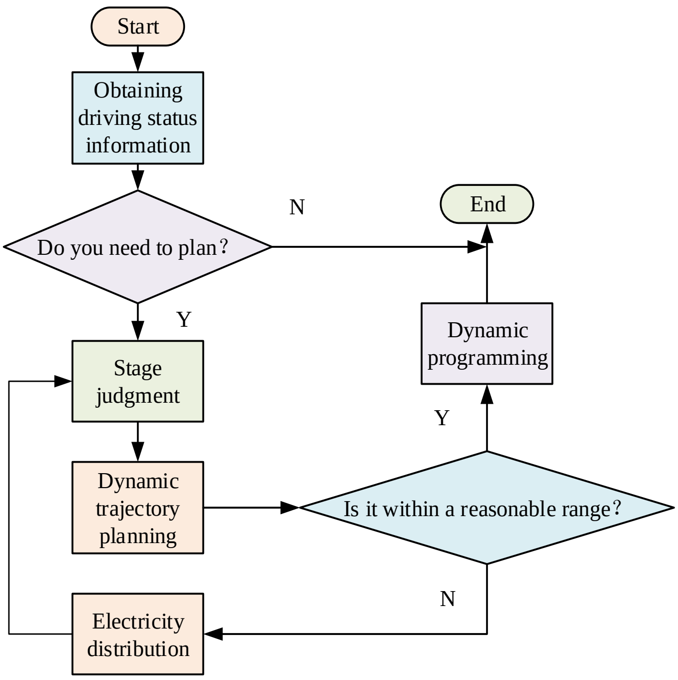


Fig 6 Special state process

need to plan the vehicle's energy throughout the entire process. When the driving state of a vehicle exceeds its total mileage, it is also necessary to plan the energy of the vehicle. The process of this special state is shown in Figure 6.

From Figure 6, during the planning process, firstly, the driving status information of the vehicle is obtained to determine whether energy planning for the vehicle is currently required. If so, the driving status and distance of the vehicle are evaluated in stages. Then, the dynamic trajectory planning is performed again. Secondly, it is necessary to determine whether the energy allocation in the current state is within a reasonable range. If so, the electricity in each stage is allocated. Then, the DP is performed again. If not, the driving status planning will be directly carried out. If electricity planning is required, the process will be ended directly.

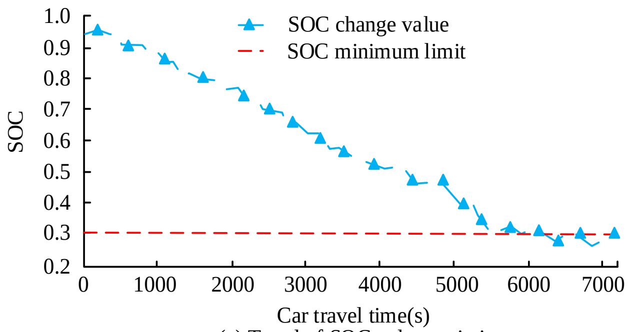
3. Result and discussion

3.1 Results analysis of automotive energy management strategies

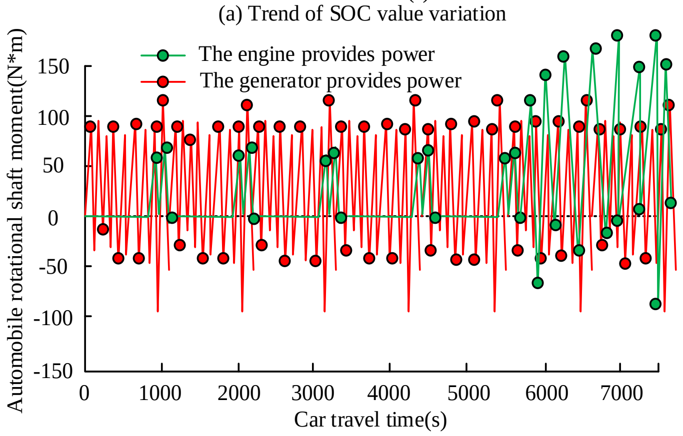
To prove the feasibility of the EMS, the MATLAB software is used to simulate and analyze the EMS. The initial value of remaining electricity is 0.95. The limit value of remaining electricity during energy phase switching is 0.30. The common NEDC driving state is selected as the driving state. Strategies based on DP, Deep Reinforcement Learning (DRL) (He *et al.,* 2024) and Model Predictive Control (MPC) (Jung *et al.,* 2024) combined with dynamic planning are compared, respectively. He H et al. found that traditional energy management and control methods for electric vehicles were hindered by technological bottlenecks, resulting in poor real-time generalization ability of control strategies. Therefore, the DRL method was used for control. The results indicated that this method effectively improvedthe traditional generalization ability (He *et al.,* 2024). Jung et al. proposed a tram energy control strategy based on MPC to address the limitations of traditional tram energy control methods and enhance the practical application of tram energy control strategies. The new method reducedthe energy consumption of vehicles and improved the energy control effect of trams (Jung *et al.,* 2024). It can be seen that the traditional tram energy control method cannot control the tram energy well, so it is necessary to use more advanced control strategy for control. The remaining power consumption process and energy strategy planning during the driving state of the vehicle are shown in Figure 7.

From Figure 7 (a), the SOC value of the vehicle decreased with time during driving. When the remaining battery was high, the battery decreased significantly. When the driving time reached around 5500s, the SOC value reached the set minimum value. At this time, the SOC value began to fluctuate. When the SOC value dropped to the set threshold, the vehicle began to enter the energy storage state. When the SOC value exceeded the set threshold, the vehicle engaged in a hybrid braking state. From Figure 7 (b), during the driving, when the rotational moment of the vehicle was large, the vehicle was mainly powered by the generator. Therefore, the rotational moment of the vehicle at this time remained high, and the entire variation was between -50 Nm and 100 Nm. When the driving time reached 1000s, the rotational moment of the vehicle was larger. The power supply of the vehicle was completed jointly by the generator and the engine. This indicates that as the wheelbase increases, the vehicle begins to operate in an engine powered state. Compared with Figure 7 (a), at around 5500s, the SOC value of the vehicle decreased. At this time, the vehicle's energy was mainly supplied by the engine, so the engine's rotational torque started to be at a high value and lasted for a relatively long time. The driving process conforms to the EMS process. The vehicle data in different energy management strategies is displayed in Figure 8.

From Figure 8 (a), the driving speed of the vehicle was the same under different strategies, so the energy use and mobilization of the vehicle were the same. From Figure 8 (b),



(a) Trend of SOC value variation



(b) Changes in the rotational axis moment of a car

Fig 7 Remaining energy consumption process and energy strategy planning of automobile driving state

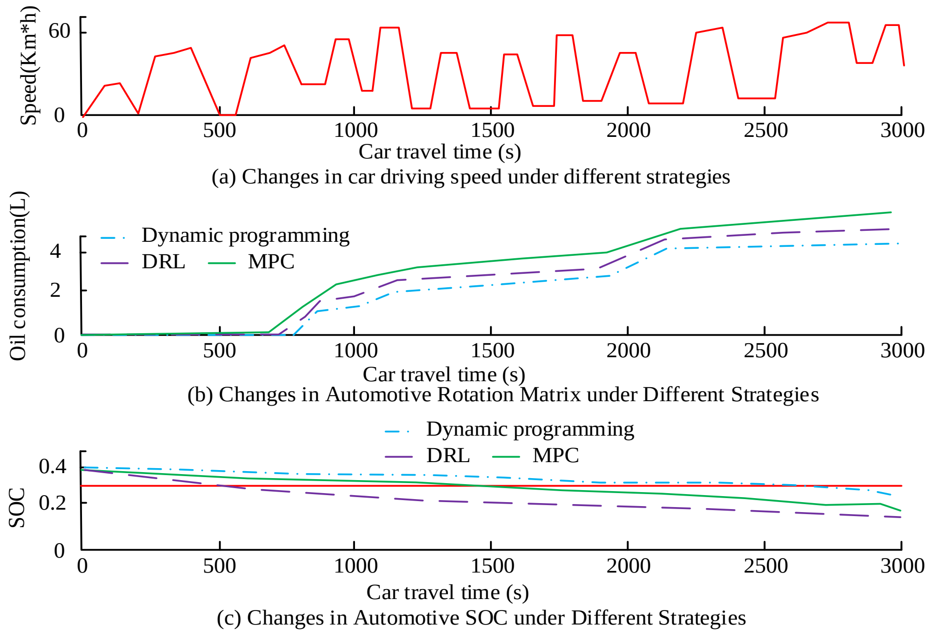


Fig 8 Comparison of vehicle parameters with different energy management strategies

different energy management strategies had the same change trend, gradually decreasing with time. When the set threshold was reached, only the DP-based EMS decreased in magnitude. This shows that the strategy used in the study can better adjust the vehicle state after reaching the threshold. This method can better manage and analyze the energy of vehicles. From Figure 8 (c), when the driving time of the vehicle reached 700s, the vehicle began to enter fuel consumption. At this stage, it indicates that the electric motor power of the vehicle enters a phased charging stage, and the fuel consumption begins to show an increasing trend with time. However, the fuel consumption of the research method is relatively low, and the consumption time is also relatively late. This indicates that the energy management method used in the study has better management strategies.

3.2 Simulation results analysis of automotive dynamic programming algorithm

To verify the effectiveness of vehicle energy management in various strategies, the initial goal of SOC is set to 0.95, and the threshold is set to 0.3. The driving state of the vehicle is also NEDC. Based on the comparison of parameters under different driving states, the driving state parameters are displayed in Table 1. *Ave* signifies the average value, *std* signifies the standard deviation, max represents the maximum value, dec represents the deceleration stage, *acc* represents the acceleration stage, *idle* represents the deceleration stage vehicle speed, and *uni* represents the rated power.

From Table 1, in the first state of vehicle driving, the vehicle may be driving at a moderate speed, with a stable driving speed and relatively average deceleration and acceleration time. This situation generally belongs to urban driving sections. In the second vehicle driving state parameter analysis, the vehicle's driving speed is relatively fast, and the acceleration and deceleration time is relatively short. The vehicle speed is the highest among the three driving states, with 40.5246 km/h, indicating that this state may be high-speed driving. The average speed of the third state is low, with 13.4588 km/h, and the acceleration and deceleration time is relatively short. The speed of the driving state is not significantly different, indicating

Table 1
Different driving state parameters

Vehicle driving parameters	NEDC 1	NEDC 2	NEDC 3	NEDC 4
V_{ave}	16.9076	40.5246	13.4588	3.6986
u_{ave}	24.0884	46.9208	15.8051	6.9774
V_{std}	15.9368	25.9348	10.5941	5.2648
V_{max}	55.7117	89.1258	39.9595	18.3034
a_{ave}	0.4066	0.3458	0.3684	0.2935
a_{dec}	-0.4563	-0.4485	-0.3660	-0.2839
a_{max}	0.8791	1.2238	0.6984	0.4898
a_{min}	-1.1236	-1.6316	-0.8712	-0.5835
a_{std}	0.1912	0.2113	0.1475	0.0885
$P(t_{idle})$	26.5996	15.7632	14.6452	46.9917
$P(t_{acc})$	26.5996	24.6142	29.9457	13.9845
$P(t_{dec})$	24.0577	22.2183	29.4171	15.0415
$P(t_{uni})$	23.0321	38.3839	25.6024	23.9627

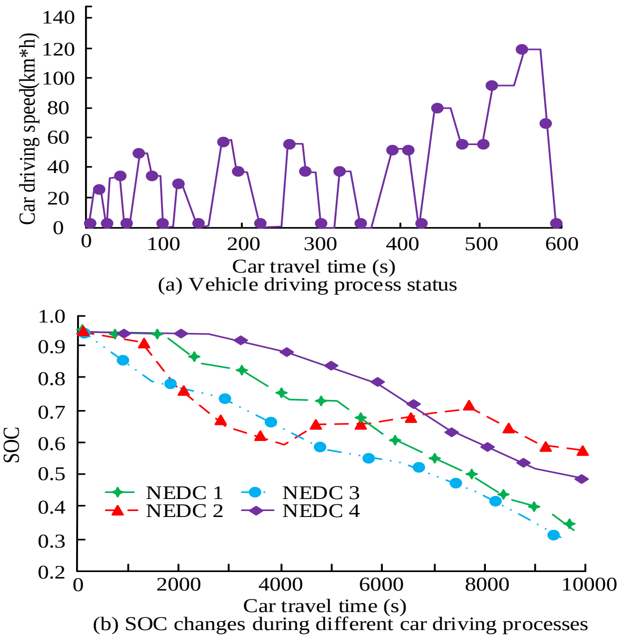


Fig 9 The DP image of the vehicle in four driving states

that the vehicle travels more evenly and the driving speed is not fast in this state. The average speed in the fourth driving state is 3.6986 km/h. In this state, the driving speed is not fast, which m ay be the driving state when the roads in the city are relatively congested. Figure 9 displays the DP image of the vehicle in four driving states.

From Figure 9 (a), during the driving process, the speed change did not gradually change with the increase of time, but there was a phased change. The speed may remain unchanged with the increase of time and may be in an upward or downward phase. This may be caused by different road conditions during the driving, such as acceleration, urban road driving, rural road driving, etc. From Figure 9 (b), the SOC value changed differently when the vehicle was in different driving states. In the first, third, and fourth vehicle conditions, the driving state showed a decreasing trend over time. However, the SOC value of the second vehicle condition first decreased to 0.6, then showed an upward trend, rising to 0.75, and finally decreased again. This may be because during this process, the vehicle first drives at low speed, then starts driving at high speed, and finally drives at low speed again. The EMS can manage the driving of vehicles in different states. Figure 10 displays the comparison of vehicle efficiency and fuel consumption under different states.

From Figure 10 (a), in the three driving states of 1, 3, and 4, the utilization efficiency of the vehicle decreased with the increase of SOC value, with the lowest being driving state 4, which reached about 60%. Driving state 1 had higher efficiency, with a minimum value of 70%, which was about 20% higher than driving state 4. This may be due to the more reasonable energy planning in driving state 1. In driving state 2, the efficiency showed an upward trend, which may be due to the acceleration of the vehicle during this stage, causing an overall efficiency improvement. The lowest efficiency point was at 0.4SOC, which was 60%. From Figure 10 (b), the fuel consumption of the vehicle increased with the consumption of SOC, and its trend was the same in driving states 1, 3, and 4. The overall fuel consumption was about 3.4L per 100 Km. The fuel consumption per 100 Km in driving state 2 showed a significant upward trend at a 0.5SOC value, which may be due to the acceleration of this section. The average fuel consumption was about 5.2L, which was 1.8L higher than other driving states. The error comparison before and after using the DP model is shown in Table 2.

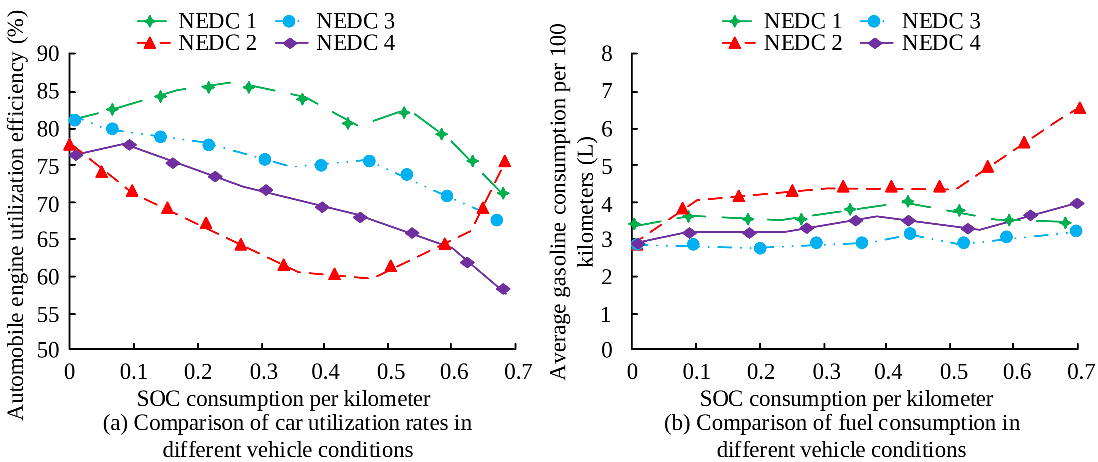


Fig 10 Comparison of vehicle efficiency and fuel consumption in different driving states

Table 2
Error comparison of different models

Travel time	SOC efficiency (%)	Efficiency of dynamic programming algorithm (%)	Efficiency deviation value (%)
465s	78.45	79.02	0.57%
832s	76.42	77.53	1.11%
2562s	60.24	61.25	1.01%
3354s	53.59	57.65	4.06%
4195s	50.36	51.26	0.90%
4968s	42.36	43.84	1.48%
5354s	39.21	39.62	0.41%
6265s	29.35	38.31	7.86%
6675s	29.35	29.98	0.63%

From Table 2, the overall efficiency of the vehicle was lower when the DP model was not used, and the trend gradually decreased with time, reaching the lowest value of 29.35% at 6265s. The efficiency change of the vehicle after adding the DP model also decreased with the increase of time, but the overall decrease value was smaller. At the same time, when reaching the lowest value, the time was 6675s. It was longer than before adding the strategy, with an efficiency of 29.98%, which was higher than the model without the strategy. The maximum efficiency difference between the model before and after adding was 7.86%, which may be due to the vehicle starting to decelerate during this period, resulting in the main movement being the motor movement. Jia et al discussed adaptive model predictive control in the context of fuel cell hybrid electric vehicles, providing new ideas for advanced energy management strategies beyond DP algorithms (Jia *et al.,* 2023). Peng et al. analyzed the efficiency of hybrid switches and inverters, which enhanced the analysis of vehicle efficiency and energy consumption, especially the effectiveness analysis with DP algorithm (Peng *et al.,* 2020). Venkitaraman and Kosuru introduced a hybrid deep learning approach to managing electric vehicle charging, which provided a comparative perspective on DP-based energy management strategies (Venkitaraman & Kosuru, 2023). This indicates that different studies can provide better research ideas for proposing new methods and better technical support for current research.

4. Conclusion

The research mainly focused on the insufficient adaptability of energy management strategies and high energy consumption during the driving process of hybrid electric vehicles. Therefore, a vehicle energy automatic adaptation method based on EMS and DP was proposed. The study first analyzed the EMS. Then, the DP was usedto optimize the model based on the EMS. The research results indicated that after incorporating the DP strategy, the energy mobilization of vehicles was more apparent. The average speed in several driving states was 16.9076 km/h, 40.5246 km/h, 13.4588 km/h, and 3.6986 km/h, respectively. Driving state 1 had a higher efficiency, with a minimum value of 70%, which was about 20% higher than driving state 4. In driving states 1, 3, and 4, the change was the same, and the overall fuel consumption was around 3.4L per 100 kilometers. The average fuel consumption in driving state 2 was about 5.2L, which was 1.8L higher than other driving states. The overall efficiency of automobiles after incorporating DP was improved, with a shorter time to reach the lowest efficiency compared with not incorporating the DP model. The highest efficiency was 7.86% higher than not incorporating the DP model. From this, the EMS can effectively manage the energy mobilization of vehicles. After incorporating the DP model, vehicle energy consumption can be effectively controlled. Although the research has achieved many results, there are still some shortcomings. For example, the study only analyzes the dynamic model of the vehicle, which cannot obtain the real state of the vehicle. Therefore, it is necessary to further analyze real vehicle data. At the same time, the study only analyzes several driving states. Therefore, further analysis will be conducted on more driving states in the future.

Data availability statement

Data is contained within the article.

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