RESEARCH ON ENERGY REDISTRIBUTION OF DIESEL-ELECTRIC HYBRID SYSTEM CONSIDERING THERMAL MANAGEMENT CONSTRAINTS

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Thermal management is one of the key factors affecting the performance of hybrid vehicles. However, most traditional energy management strategies lack the consideration of thermal constraints under harsh operating conditions. In this paper, taking a specific type of diesel-electric hybrid system as the research object, a strategy for energy redistribution under thermal management constraints is proposed. The diesel-electric hybrid system model is built and verified. Based on the model, the cooling capacity indexes are selected, and the weight coefficient of each cooling capacity index is determined by neighborhood component analysis. Then a comprehensive thermal evaluation system is obtained. Combined with the thermal evaluation system, the energy redistribution strategy based on the momentum gradient descent method is proposed. Two typical working conditions of high altitude and battery cooling system deterioration are selected, and the energy redistribution strategy is simulated and analyzed in real-time under both working conditions. The results show that the energy redistribution strategy can significantly improve the thermal state of the system at the expense of less overall energy consumption, take into account the economy and thermal balance, and ensure the reliable operation of the vehicle.

Key words*: diesel-electric hybrid system; comprehensive thermal evaluation system; energy redistribution; momentum gradient descent; real-time simulation*

1. Introduction

With the development of science and technology and economy, the number of global car owners continues to increase, among which hybrid vehicles can effectively reduce fuel consumption and emissions [1,2]. Balancing thermal management and energy management is critical to the performance of hybrid vehicles [3,4]. There have been many studies on hybrid vehicle energy management. Wenran Geng et al. [5] aimed at the problem that the dynamic programming of traditional energy management usually does not consider power consumption and deviates from the optimal solution, and proposed a cascaded energy management strategy that integrates dynamic programming and equivalent power consumption minimization strategies. The strategy achieved a 19.9% energy efficiency improvement. To solve the problem that the enormous computation intensity, massive data training and rigid requirement of prediction of future operation state hinder the substantial exploitation of learning based algorithms, Yonggang Liu et al.[6] developed an imitation reinforcement learning-based algorithm with optimal guidance for energy control of hybrid vehicles to accelerate the solving process and meanwhile achieve preferable control performance. The results showed that the proposed method provided preferable energy reduction for HEVs in arbitrary driving scenarios. The above studies obtain more ideal fuel economy after adopting appropriate optimization methods. But the lack of consideration of vehicle thermal management performance may cause the system to work in an abnormal temperature range, which in turn affects vehicle economy and reliability.

Regarding energy management strategies that consider the influence of the thermal management system, scholars have also conducted research. Qiuhao Hu et al. [7] proposed a multi-level model predictive control (MH-MPC) method applied to connected hybrid systems, taking into account power and thermal management. This method used the battery SOC and engine coolant temperature as the state variables, and the battery output power as the optimization variable. The results showed that the energy state could operate at or near its allowable boundary to improve performance. However, the study does not consider the influence of changes in vehicle operating conditions on the thermal management system, and only optimize the strategy under ideal working conditions.

As an important subsystem of hybrid vehicles, the thermal management system has a great impact on vehicle durability and reliability [8,9]. However, most traditional energy management strategies lack the consideration of thermal constraints under harsh working conditions, which means that their application scenarios deviate from the actual situation. In this paper, a certain P2 architecture parallel diesel-electric hybrid vehicle is used as the research object to construct a comprehensive thermal evaluation system that can reflect the thermal state. Two typical working conditions of high altitude and battery cooling system deterioration are selected. Combined with the thermal evaluation system, the power distribution strategy based on momentum gradient descent method is used for real-time simulation analysis. The results show that in the real-time environment, the strategy improves the thermal state of the system at the expense of less overall energy consumption, takes into account the economy and thermal balance, and ensures the reliability of the vehicle.

2. Diesel-electric hybrid system modeling

2.1. Real-time simulation model building

The vehicle and component parameters of the single-shaft parallel hybrid system are shown in tab.1. Using the given parameters, a power system model including a real-time model of a diesel engine, a motor model based on MAP, a power battery pack model based on equivalent circuits, and a cooling system model matching the power system are built in GT-Suite.

Table 1. Technical parameters of the whole vehicle and its components

project	parameter	project	parameter
Rated Motor power [kW]	60	Maximum engine torque [Nm]	692
Maximum speed of motor [$rmin^{-1}$]	2600	Maximum engine speed [$rmin^{-1}$]	2600
Maximum motor torque [Nm]	2000	Rated capacity of battery [Ah]	60
Maximum engine power [kW]	147	Rated Battery voltage [V]	330

2.2. Model validation

The speed following effect under China typical urban driving cycle (CTUDC) is shown in fig. 1, and the speed error is kept within ±3km/h, which has good accuracy.

The battery temperature trajectory and the temperature characteristic parameters trajectories of the diesel engine cooling system under the target working condition are shown in fig. 2. It can be seen that all parameters of the diesel engine cooling system are stable within a reasonable range, and the diesel engine cooling system can meet the cooling needs. The battery temperature trajectory changes within a safe range, and the battery cooling system can meet the cooling needs of the battery. Therefore, the vehicle system model has good accuracy to meet the needs of subsequent research.

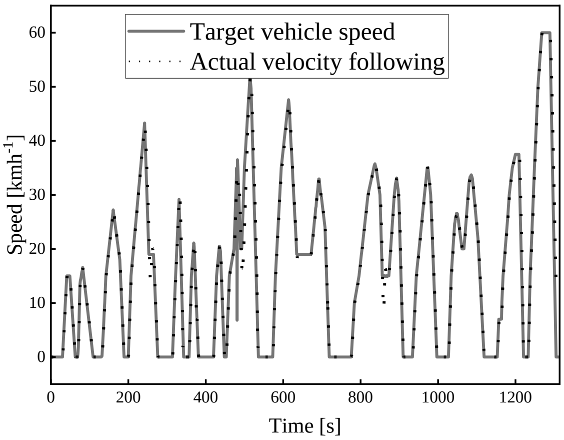

Figure. 1. Vehicle speed following

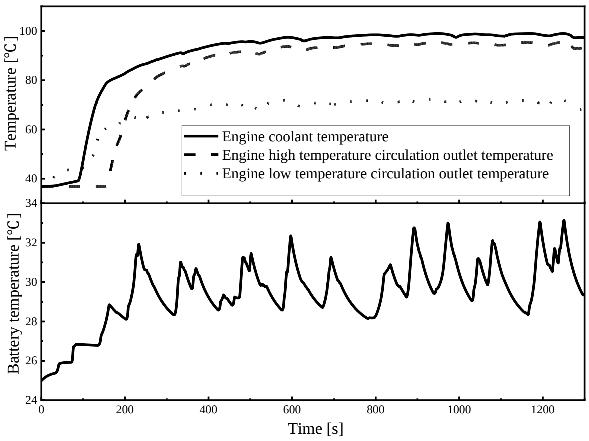

Figure. 2. Temperature trajectories of the diesel engine cooling system and the battery

3. Comprehensive thermal evaluation system

For the diesel-electric hybrid vehicle cooling system, the 1225s to 1304s section of CTUDC is selected as the target working condition of the simulation study, and the whole duration is the 80s, as shown in fig. 3. At this target speed, the vehicle is first driven by an electric motor, switches to a hybrid drive of diesel engine and motor as the drive torque gradually increases, and then switches to regenerative braking mode as the drive torque gradually decreases. This driving phase includes acceleration and deceleration, mode switching, and stopping, and can fully obtain the required data samples.

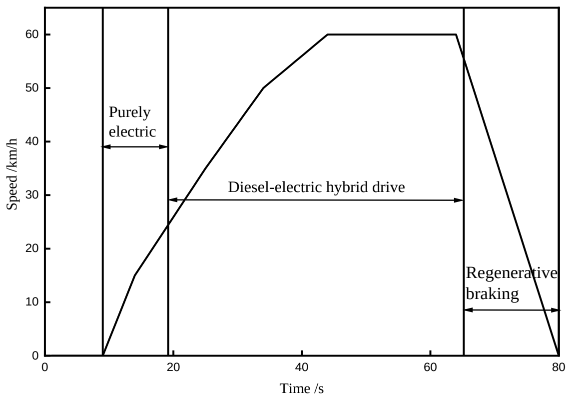

Figure. 3 Target working condition

3.1. Cooling capacity indexes

The cooling capacity indexes are composed of multiple characteristic signals as the input of the comprehensive thermal evaluation system of the diesel-electric hybrid system. The number of characteristic signals also determines the amount of data in the sample. The selection of characteristic signals should follow the following basis: since all characteristic signals sources are simulation results from the model built above, all selected characteristic signals must be included in the hybrid model. In addition, to take into account the compatibility of the control algorithm on the vehicle controller, the selected characteristic signals should be the input signals of the vehicle controller as much as possible, that is, the signals that can be collected by the sensor on the real vehicle.

For the diesel-electric hybrid system, high-altitude environment, diesel engine cooling system deterioration, and battery cooling system deterioration are selected as input for harsh working conditions. Combined with the change of the characteristic parameters of the cooling system model under harsh working conditions and the application of the actual vehicle [10,11], the seven variables are finally determined: diesel engine exhaust temperature, diesel engine high temperature circulation outlet temperature, diesel engine low temperature circulation outlet temperature, diesel engine coolant temperature, oil temperature, battery temperature and battery outlet temperature, which are used as the basis for the subsequent construction of the evaluation system.

The limiting index of each index is determined in combination with the early warning value of the corresponding characteristic signal of the real vehicle, as shown in tab. 2. Among them, the limiting index of diesel engine exhaust temperature comes from the external characteristic index provided by the manufacturer and it changes with the diesel engine speed, as shown in fig. 4.

Table 2. Limiting indexes of characteristic signals of cooling system

Characteristic signals	Limit value
Diesel engine high temperature circulation outlet temperature [℃]	110
Diesel engine low temperature circulation outlet temperature [℃]	80
Diesel engine coolant temperature [℃]	110
Oil temperature [℃]	110
Battery temperature [℃]	35
Battery outlet temperature [℃]	30

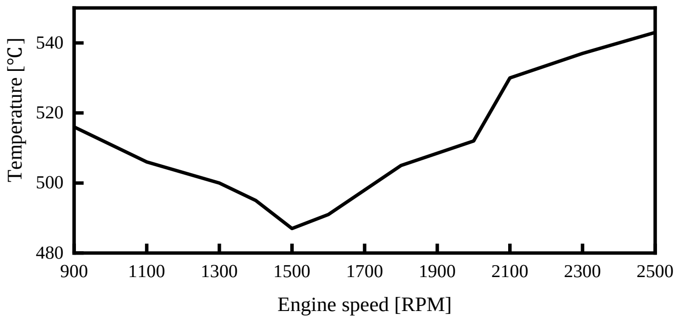

Figure. 4 Diesel engine exhaust temperature limiting index

3.2. Weights confirmation based on NCA method

Another key factor that constitutes the objective function of the evaluation system is the allocation of weight coefficients. The allocation of weight coefficients can be done based on experience, such as the allocation of weight coefficients according to the intensity of changes of different characteristics under harsh working conditions, but the adaptation of the specific object is poor according to experience [12]. In this paper, the neighborhood component analysis (NCA) in the feature selection method is used to assign the weight coefficients.

The NCA algorithm randomly selects the nearest neighbors, obtains the transformation matrix through the results of cross-examination, and completes dimensionality reduction and feature analysis in this process [13]. The algorithm runs as follows:

Suppose there is an n-dimensional sample space S, $S=\{(x_i,y_i),i=1,2,\cdots,n\}$, where x_i is the input sample and y_i is the corresponding type label. The input sample x_i is obtained randomly in the sample space, and the goal is to make neighbor classification better between x_i and the next random input sample x_j. The probability of a random sample x_i being selected is $P(\mathrm{Re}\,f(x)=x_j|S)$, the probability of another sample x_j being selected is related to the distance between the two, so the goal is to find a distance measure that makes the distance between the two minimize. The distance between the two is expressed as follows:

$$d_w(x_i,y_i)=\sum_{r=1}^{p} w_r^2 \left|x_i-x_j\right| \tag{1}$$

The probability of x_j being selected as a x_i nearest neighbor is as follows:

$$P(\mathrm{Re}\,f(x)=x_j|S)\propto K\left(d_w(x,y_j)\right) \tag{2}$$

The magnitude of K is negatively correlated with the distance between two points, and the smaller the $d_w(x,y_j)$, the larger the value of K.

1300 sets of data are collected from each of the normal working condition, high-altitude working condition, diesel engine cooling system deterioration working condition, and battery cooling system deterioration working condition as a sample set, and each set of data included seven cooling indexes. Use the NCA algorithm to obtain the corresponding weight values, as shown in fig. 5. Among them, the weights of diesel engine exhaust temperature, diesel engine coolant temperature, and battery temperature are relatively large, and they are also in line with the changes of the acquisition signal of the cooling system on the real vehicle.

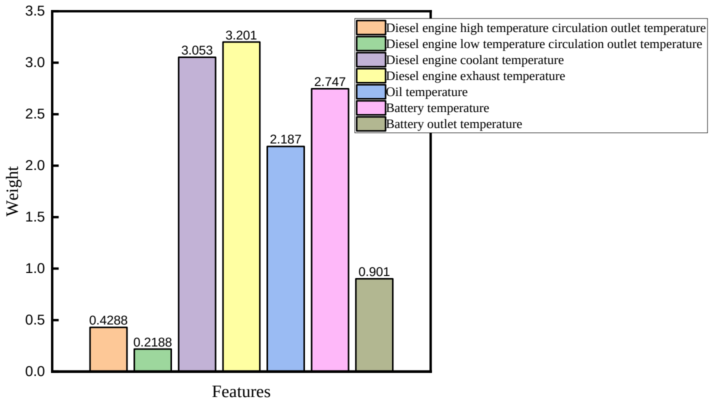

Figure. 5 The weights of cooling capacity indexes

3.3. Determination of comprehensive thermal evaluation system

After selecting the cooling capacity indexes and determining the feature weight coefficients, the data are dimensionally normalized and the comprehensive evaluation system is determined. The objective function is as follows:

$$A = k_1 N_1 + k_2 N_2 + \cdots + k_n N_n \tag{3}$$

4. Power distribution strategy based on momentum gradient descent method

4.1. Momentum gradient descent method

Gradient descent is a method of solving the minimum of the objective function along the direction of the negative gradient at the current position, and the function continuously solves the gradient at the current position as the direction of progress for the next moment. When there is more than one kind of information in the dataset, there is a multidimensional feature, that is, the multivariate gradient descent method corresponding to the multiple linear regression function. The algorithm retrieval process is as follows [14,15]:

(1) Given the objective function and the search initial point, the specific formula of the gradient descent method is as follows:

$$\theta_{t+1} = \theta_t - \varepsilon_t \frac{1}{s} \sum_{i=1}^{s} \nabla f_i(\theta_t) \tag{4}$$

It can be seen that as the number of iterations gradually increases, the gradient will gradually tend to zero, and the result will gradually tend to the optimal solution.

(2) Data normalization

In the face of multi-dimensional feature problems, to ensure that the features have similar scales, the feature scaling through the "mean-variance" method can help the gradient descent method converge faster, and its calculation formula is as follows:

$$x = \frac{x - \bar{x}}{\sigma} \tag{5}$$

(3) Determine whether the condition for stopping iteration is met: $\left\| \theta_{t+1} - \theta_t \right\| \leq \eta$, if the above condition is met, stop the iteration, otherwise return to continue.

4.2. Control theory based on heat dissipation power

4.2.1 Heat dissipation power

The power required for the hybrid system is borne by the diesel engine and the power battery, so this section analyzes the heat dissipation power of both. The heat dissipation power of the diesel engine is the heat generation power minus the power of other destinations when the fuel is completely burned, and its formula is shown in Eq. (6).

$$q_w = q_t - q_e - q_r - q_{res} \tag{6}$$

The formula of the heat dissipation power of power battery pack is as follows:

$$q_b = n\left((\frac{P_b}{\eta_T U_m \eta_m \eta_b})^2 R - mC\Delta T \right) \tag{7}$$

The sum of the heat dissipation power of the diesel engine and the power battery pack:

$$q_{total} = q_w + q_b = q_w + n\left((\frac{P_b}{\eta_T U_m \eta_m \eta_b})^2 R - mC\Delta T \right) \tag{8}$$

4.2.2 Determination of energy redistribution strategy

Since the cycle condition is known, the vehicle speed v and the vehicle demand power P_{req} are used as known measurable interferences in the simulation. When the power allocation strategy is optimized, the output is the diesel engine demand power proportion coefficient φ in order to be more convenient to calculate, and the diesel engine demand power $P_e(i) = \varphi(i) \cdot P_{req}(i)$; Power battery pack demand power $P_b(i) = (1-\varphi(i)) \cdot P_{req}(i)$.

In this paper, the power allocation strategy based on the momentum gradient descent method is used to study. Because the power distribution ratio can directly affect the heat dissipation power of the hybrid system, the iteration formula of the diesel engine demand power ratio coefficient φ is as follows:

$$\varphi = \varphi - \varepsilon_{q_{total}} \frac{\partial q_{total}}{\partial \varphi} = \varphi - \varepsilon_{q_w} \frac{\partial q_w}{\partial \varphi} - \varepsilon_{q_b} \frac{\partial q_b}{\partial \varphi} \tag{9}$$

Based on the above analysis, when some components of the diesel-electric hybrid system are overheated, the main steps in the optimization calculation of the power allocation control strategy are shown in fig. 6. When the target result is reached, the control system is stopped and the driving pattern and power distribution of the vehicle are controlled by the rule-based energy management control strategy in the model.

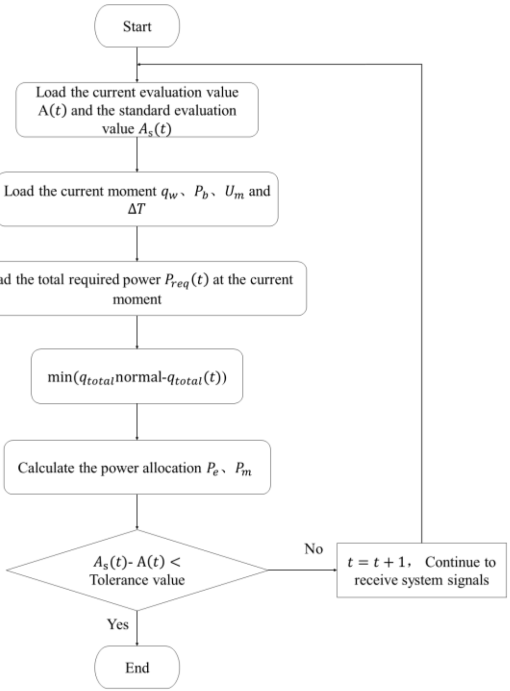

Figure. 6 Control strategy solution flowchart

5. Real-time simulation

5.1. Building of real-time simulation platform based on iHawk

The real-time simulation platform architecture based on the iHawk system is shown in fig. 7: as the controller, the host computer receives the real-time characteristic signals transmitted by the iHawk platform and calculates the real-time power distribution signal after the deviation between the real-time evaluation value and the standard evaluation value reaches the threshold of 0.05, then transmits it to the iHawk platform. As a vehicle system, the iHawk platform runs a real-time model and transmits characteristic signals such as diesel engine exhaust temperature, battery temperature, and demand power to the host computer. Data transmission between the iHawk platform and the host computer is carried out via the CAN bus.

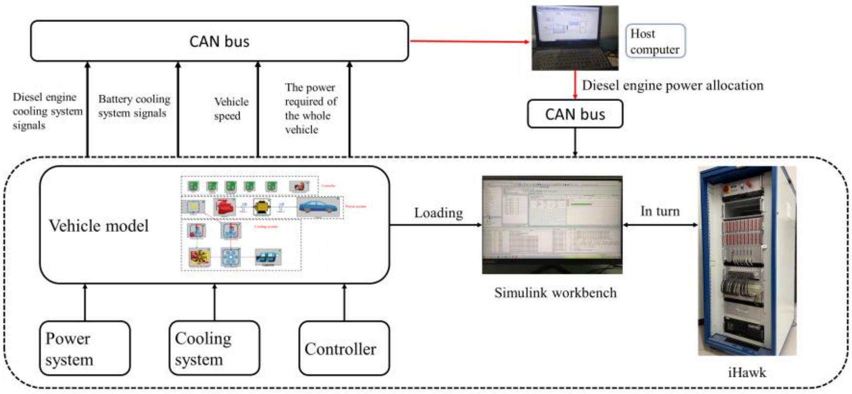

Figure. 7 Real-time simulation system architecture

5.2. Real-time simulation results and analysis

5.2.1 Analysis of results at high-altitude condition

For the high-altitude condition, the relevant parameters curves when feedback control is performed on the diesel-electric hybrid system is shown in fig. 8. It can be seen from the figure that when the system condition changes to the high-altitude condition in the 20s, the combustion condition deteriorates due to the decrease in atmospheric pressure and insufficient intake volume, and the working performance of the heat dissipation system decreases. The performance indexes of the cooling system, including the exhaust temperature of the diesel engine, begin to deteriorate, and the evaluation value begins to gradually deviate from the standard value. At 25s, the exhaust temperature continues to rise and the deviation of the evaluation value reaches the feedback standard, and the power distribution control system based on the gradient descent method starts to redistribute the power of the diesel-electric hybrid system. With the gradual reduction of diesel engine demand power, the exhaust temperature gradually decreases and the strategy avoids dangerous working condition that is very close to the early warning line at 33-35s. The heat dissipation of the diesel engine cooling system also gradually reduces. Finally, the cooling system is out of the dangerous working condition with an improvement of the evaluation value, which guarantees the thermal balance and reliability of the vehicle.

The consumption curves of the diesel-electric hybrid system during feedback control are shown in fig. 9. Due to the reduced power demand, the fuel consumption of the diesel engine in the feedback working cycle reduces, which reduces by 3.77% during the target working condition; At the same time, the power battery pack takes on more power demand, and battery power consumption increases, increasing by 51.4% during the target working period; According to the conversion relationship between electric energy and fuel volume, electric energy consumption is converted into fuel volume consumption by recalculating based on fuel heating value. The overall energy consumption of the diesel-electric hybrid system is increased by 7.43%. This is because in order to reduce the thermal effect of the system and eliminate the damage caused by the cooling system being exposed to the dangerous work area for a long time, the rule-based energy management method is discarded during feedback control, resulting in an increase in the overall energy consumption of the system.

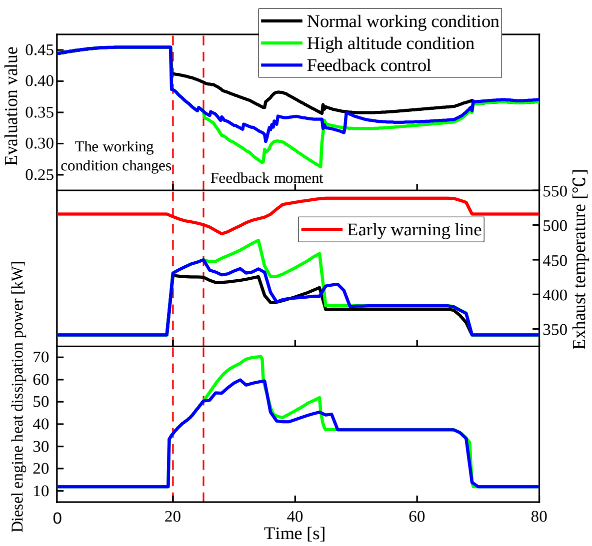

Figure. 8 Relevant parameters curves during feedback control

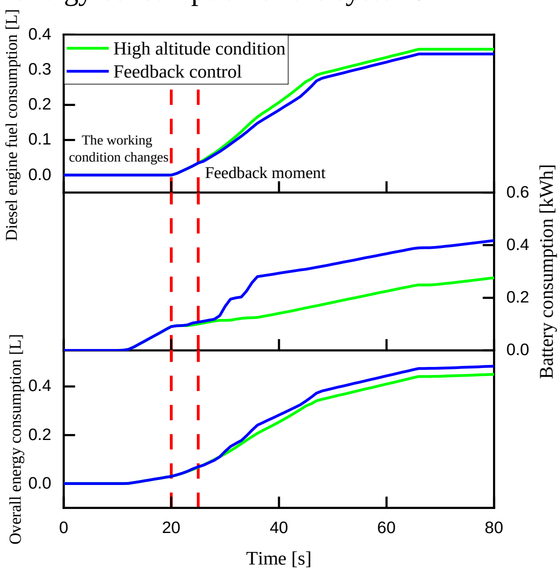

Figure. 9 Consumption curves during feedback control

5.2.2 Analysis of results at battery cooling system deterioration condition

For the battery cooling system deterioration condition, the characteristic parameters curves after the power distribution control system based on the gradient descent method starts to work are shown in fig. 10. It can be seen from the figure that when the system condition changes to the battery cooling system deterioration condition in the 20s, the coolant temperature cannot be adjusted to the normal temperature in time due to the decline in the performance of the battery cooling system. The battery temperature and battery outlet temperature gradually increase; At 46s, the evaluation value deviation reaches the feedback standard, and the power distribution control system begins to redistribute the power of the diesel-electric hybrid system. With the rapid decrease of battery demand power, the evaluation value deviation gradually decreases. but due to the persistence of deterioration of the battery cooling system, the evaluation value deviation always exists; The battery temperature also drops rapidly. After the demand power drops to 0 and the driving mode is switched to the diesel engine separate drive mode, the battery temperature can never drop to the normal working condition, which is always about 1.5 °C higher than the normal working condition; Since the coolant temperature still cannot be adjusted in time, the outlet temperature of the battery has hardly changed; In general, although there is a deviation from the normal working condition after power redistribution, the battery is freed from the trend of continuous deterioration of performance under battery cooling system deterioration condition, which guarantees the thermal balance and reliability of the vehicle and achieves the purpose of power redistribution.

The consumption curves of the diesel-electric hybrid system during feedback control are shown in fig. 11. When the power redistribution begins in the 46s, the diesel engine takes on more power demand, and the fuel consumption increases in the feedback working cycle, which increases by 13.45% during the target working condition; At the same time, the power demand of the battery decreases rapidly, and the battery power consumption reduces, which reduces by 30.46% during the target working condition. According to the conversion relationship between electric energy and fuel quantity, the overall energy consumption of the diesel-electric hybrid system has increased by 4.15%. This is because to deal with thermal imbalances such as excessive battery temperature, the rule-based energy management method is discarded during feedback control, and the operating mode is changed from hybrid drive mode to diesel engine individual drive mode, increasing the overall energy consumption of the system.

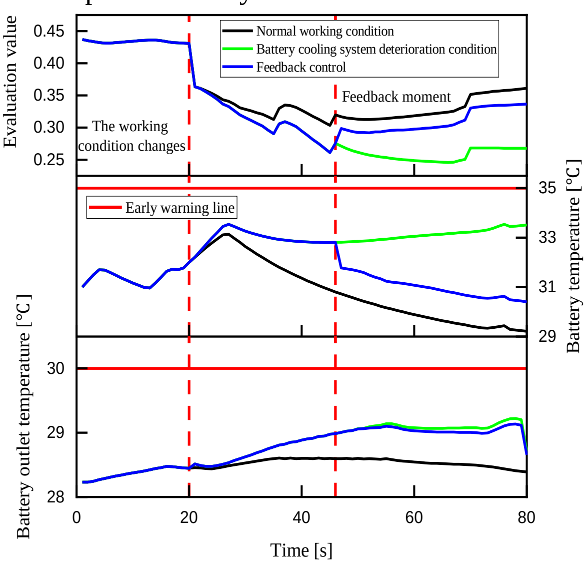

Figure. 10 Relevant parameters curves during feedback control

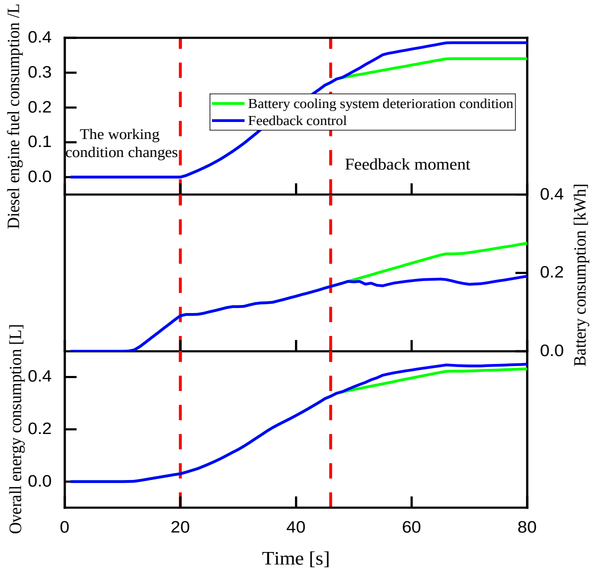

Figure. 11 Consumption curves during feedback control

6. Conclusions

The thermal management system has a great impact on vehicle durability and reliability. This paper proposes an energy redistribution strategy considering thermal management constraints.

(1) Taking a certain diesel-electric hybrid system as the research object, the real-time system model is constructed and verified. Based on the system model, the cooling capacity indexes are selected. The NCA method is used to analyze and determine the weight coefficients of the cooling capacity indexes. Then the comprehensive thermal evaluation system is obtained after dimensional unification, in which the evaluation value reflects the thermal state of the system.

(2) Combined with the thermal evaluation system, an energy redistribution strategy based on the momentum gradient descent method is proposed. Based on the iHawk system, the real-time simulation platform is built and verified that it can better simulate the required real-time environment. Two typical working conditions of high altitude and battery cooling system deterioration are selected, and

the real-time simulation analysis of the energy redistribution strategy under the two working conditions is carried out to verify the feasibility of the strategy.

(3) Under the high-altitude condition, the strategy significantly improves the thermal state of the system. The overall energy consumption increases by 7.43%; Under the battery cooling system deterioration condition, the strategy makes the battery out of the trend of continuous deterioration of performance under thermal imbalance and improves the evaluation value. The overall energy consumption increases by 4.15%;

The results show that the energy redistribution strategy can effectively improve the thermal state of the system at the expense of less overall energy consumption in the real-time environment, take into account the economy and thermal balance of the whole vehicle, and ensure the reliability of the vehicle.

Nomenclature

w_r	-feature weight value	q_e	-effective power, [kW]
K	-kernel function reflecting the distance between two points	q_r	-power taken away by the exhaust, [kW]
A	-final comprehensive evaluation value of the cooling system	q_{res}	-residual losses, [kW]
k_n	-weight coefficient	q_b	-heat dissipation power of power battery pack
N_n	-value of the cooling index after the unification of the dimension	n	-number of batteries in the power battery pack
θ_t	-tth parameter sought	P_b	-required power of the power battery pack, [kW]
ε	-learning rate	U_m	-battery pack bus voltage, [V]
s	-number of samples	m	-mass of the single cell, [kg]
$f(\theta)$	-loss function	R	-internal resistance of the single battery, [$m\Omega$]. The internal resistance of the single cell is 3$m\Omega$.
$\nabla f(\theta)$	-first derivative of the loss function	C	-battery capacity, [Ah]
$\bar{x}$	-mean value of x	ΔT	-temperature change of the power battery, [K]
σ	-standard deviation of x	η_T	-drive train efficiency
η	-accuracy when the search is stopped	η_m	-motor efficiency
q_w	-heat dissipation power of diesel engine, [kW]	η_b	-battery discharge efficiency
q_t	-power produced by the complete combustion of the fuel, [kW]		

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