An On-line Strategy based on Rolling State Prediction for Hybrid Energy Storage System of Tram

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Abstract-- **This paper aims at a hybrid tram with the onboard battery-supercapacitor storage system. This paper proposes an on-line strategy based on rolling state prediction (ROS). A wavelet neural network (WNN) is used to predict the running state of the tram in a certain period of time in the future according to the historic data, and the dynamic programming (DP) algorithm is used to optimize the energy management strategy (EMS) during the period. The strategy aims to optimize the system efficiency and battery life. Compared with classical rule-based (RB) strategy, ROS greatly increases the system efficiency and lengthens lifespan of battery and achieves real-time optimization.**

Index Terms-- **Dynamic programming, Energy management strategy, Hybrid energy storage system, Prediction**

I. Introduction

As an important part of urban rail transit, modern tram has made great progress in recent years. It has the advantages of small environmental pollution, high speed and large traffic volume, and thus it can effectively alleviate the congestion problem in small and medium-sized cities. In order to reduce the damage to the urban landscape, more and more trams use on-board energy storage system (ESS) instead of catenary. There is no catenary between stations, and it is used for charging in the parking stations. Common ESSs include battery, supercapacitor, etc. However, due to the immaturity of the existing technology, ESSs have some shortcomings. Battery has high energy density, but it also has low power density, while supercapacitor is the opposite. In order to reduce the weight and volume of on-board ESS and improve its power density and energy density at the same time, the hybrid energy storage system (HESS) composed of battery and supercapacitor is welcomed.

The performance of HESS depends on the way of collaborative work between battery and supercapacitor, that is, the EMS. Common EMS can be divided into RB strategies and optimized strategies. The rules of RB strategy are usually set by engineers according to the characteristics of EMS and the requirements of vehicle operation. The rules include general rules [1-2] and fuzzy rules [3-4]. This kind of strategy has good robustness and high reliability, but it depends strongly on the designer's engineering experience and thus cannot realize the optimization of the system. The optimization strategies are divided into global optimization and real-time optimization. Global optimization usually uses DP algorithm [5-6], Pontryagin minimum principle (PMP) [7-8] based algorithm, genetic algorithm (GA) [9] or other optimization algorithms [10-11] to optimize the EMS. This kind of strategy can obtain the optimal value in theory, but it is difficult to realize real-time application because of its long calculation time. It is often used as the reference standard of RB strategies. Real-time optimization is to simplify the computation in the optimization process by simplifying the model and sectional optimization, and to realize the real-time optimization of HESS. This strategy can not only realize the system optimization, but also be applied to engineering problems. It is a research hotspot nowadays. Real-time control strategy usually uses optimization algorithm to optimize EMS in advance based on the future state prediction. There are two kinds of state prediction methods: intelligent transportation system (ITS) based [12-13] and prediction algorithm based. The former needs perfect communication and data processing system to provide the future state of tram and line for HESS. However, the current ITS is not perfect, and the method is still in the stage of theoretical analysis and simulation. Most of the applications are based on the prediction algorithm to predict the running state of vehicles. Based on the analysis of a large number of operation data, the method predicts the future state according to the historical state of vehicle operation, and then optimizes the EMS. Prediction algorithms are mainly based on Markov chain algorithm (14-16) and neural network (NN) algorithm (17-19). The algorithm based on Markov chain predicts the future state through the Markov characteristics of vehicle's running state, but this also leads to the problem of low prediction accuracy caused by the small number of historical states. If the order of historical data is increased, the operation time will be significantly improved. NN has no such problems, and its input and output are more flexible. It can be adjusted at any time according to the operation requirements. NN has many improved algorithms, which greatly improves the prediction accuracy. Prediction algorithms are often combined with global or local optimal algorithms.

The main contributions of this paper are as follows: Firstly, the HESS of tram is modeled. Secondly, ROS strategy is proposed. The running state is predicted by wavelet neural network (WNN), and then the EM is optimized by rolling optimization based on DP alorithm. Finally, the ROS strategy is simulated and validated by a practical case, and the superiority of the strategy is illustrated by comparing with the RB strategy.

The structure of this paper is as follows: Chapter □ is the introduction of tram and the HESS. Chapter □ introduces the optimization process of ROS strategy, including state prediction and rolling optimization based on DP strategy. Chapter □ analyses the actual operation of tram and Chapter □ makes the conclusion.

II. System Composition

During the operation of the tram, the HESS provides 100% traction power and absorbs all of the braking power. Owing to its large weight and volume, the HESS is usually separated and placed on the top of different carriages. Fig. 1 is a schematic diagram of a tram. While the tram is running, the pantograph does not work. When the tramcar needs to be charged in the station, the pantograph rises and contacts with the traction network to charge the HESS.

The HESS of tram consists of battery pack and supercapacitor pack, which charges or discharges through control signals, supplies power for traction motors and auxiliary system and absorbs regenerative braking energy. To make a quick response, this paper chooses the topology in which supercapacitor is directly in parallel with the DC bus and the battery is in parallel with the DC bus through a DC/DC converter, just as Fig.1 shows.

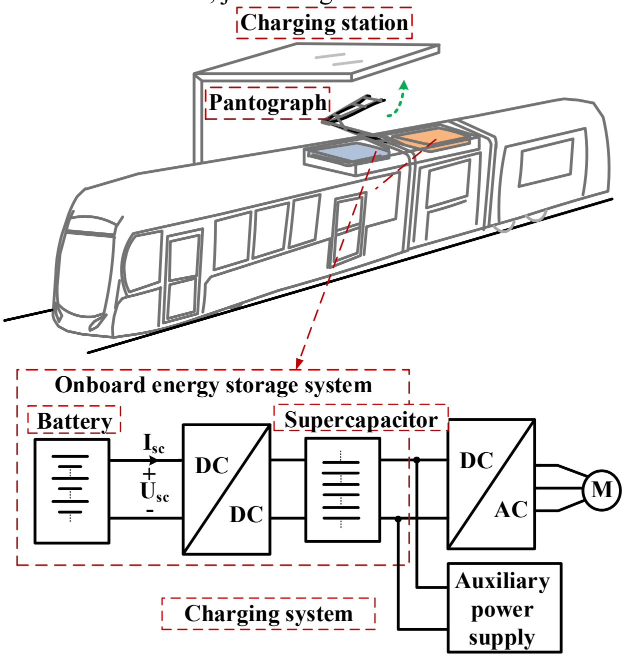


Fig. 1: The topology of hybrid storage system

The work of HESS involves power allocation, which can be expressed as:

$$\begin{cases} P_{req} = P_b \cdot \eta_{dc} + P_{sc}, P_{req} \geq 0 \\ P_{req} = P_b / \eta_{dc} + P_{sc}, P_{req} < 0 \end{cases} \tag{1}$$

Where η_{dc} is the efficiency of the DC/DC converter, and it is a constant value in this paper. P_b is the output power of the battery, and P_{sc} is the output power of the supercapacitor.

And the relation among the current, voltage and power of battery is shown in equation (2):

$$I_b = \frac{U_b - \sqrt{U_b^2 - 4 \cdot R_b \cdot P_b}}{2 \cdot R_b} \tag{2}$$

where I_b is the battery current, U_b is the terminal voltage of the battery, and R_b is the resistance of the battery. The equation for supercapacitor is the same.

And the SOC of the two storage systems can be expressed as:

$$\begin{cases} SOC_b(k+1) = SOC_b(k) - \dfrac{I_b(k) \cdot \Delta t(k)}{Q_{b0}} \\ SOC_{sc}(k+1) = SOC_{sc}(k) - \dfrac{P_{sc}(k) \cdot \Delta t(k)}{E_{sc0}} \end{cases} \tag{3}$$

Where Δt is the time interval between k+1 and k and is set as 1s here. Q_{b0} is the charge of the battery, and E_{sc0} is the energy of the supercapacitor.

In order to protect energy storage components, it is necessary to pay attention to the use of batteries and supercapacitors to meet certain conditions during operation.

$$\begin{cases} SOC_{blow} \leq SOC_b(\mathrm{k}) \leq SOC_{bhigh} \\ SOC_{sclow} \leq SOC_{sc}(\mathrm{k}) \leq SOC_{schigh} \\ |I_b(\mathrm{k})| \leq I_{b\max} \\ |I_{sc}(\mathrm{k})| \leq I_{sc\max} \end{cases} \tag{4}$$

where SOC_{blow}, SOC_{bhigh}, SOC_{sclow}, SOC_{schigh}, I_{bmax}, I_{scmax} means the minimum SOC of battery, maximum SOC of battery, minimum SOC of supercapacitor, maximum SOC of supercapacitor, maximum current of battery, maximum current of supercapacitor, respectively.

III. On-line Strategy Based on Rolling State Prediction

A. State prediction

The ROS is based on the operation state of the time interval in the future. The process is shown in Fig. 2.

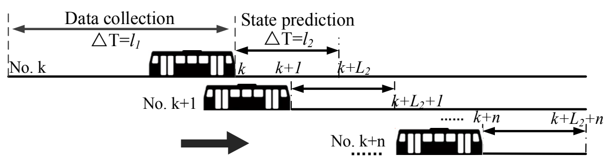


Fig. 2: Process of rolling State prediction

Based on the data analysis in the past period of time l_1, this paper extracts the eigenvalues and uses them to predict the operation state in the future period of time l_2.

The WNN is used for prediction there. The neural network is improved by BP neural network. Based on the three-layer structure of classical BP neural network, WNN replaces the transfer function of the original hidden layer node with the wavelet basis function. Taking speed prediction as an example, $v_{h1}, v_{h2}, \ldots, v_{hl1}$ are the input parameters of the WNN, representing the previous l_1 velocity data, and $v_{p1}, v_{p2}, \ldots, v_{pl2}$ are the predictive output representing l_2 data in the prediction horizon. And ω_{wij}, ω_{wjk} are the weights. Among them, the formula for calculating the output of the hidden layer is as follows:

$$h(j)=h_j\left[\frac{\sum_{i=1}^{l1}\omega_{wij}v_{hi}-b_j}{a_j}\right]\quad j=1,2,...,m \qquad (5)$$

Where $h(j)$ is the output value of the jth node of the hidden layer, b_j is the shift factor of the wavelet basis function h_j, a_j is the stretch factor of the wavelet basis function h_j.

The wavelet basis function used in this paper is Morlet mother wavelet basis function. And the formula is as follows:

$$y=\cos(1.75x)e^{-x^2/2} \qquad (6)$$

The formula for calculating the output layer is as follows:

$$v_{pk}=\sum_{i=1}^{m}\omega_{wik}h(i)\quad k=1,2,...,l_2 \qquad (7)$$

In this paper, two sets of neural networks are used to predict the speed and acceleration of trams respectively.

B. On-line strategy based on DP

The EMS is optimized in the interval time of l_2 after the operation demand of tram is obtained by state prediction. In this paper, DP algorithm is used to make the optimization. The global optimal solution in the corresponding prediction interval can be obtained through DP, and the whole-line optimization is combined with the rolling optimizations.

During the optimization, the state variable x is the supercapacitor voltage U_{sc}, and the decision variable u is the supercapacitor's output power P_{sc}. The P_{sc} with the optimal value of target at each discrete (1s) can be obtained through the comparison and selection. The voltage of battery has no big change during the time interval and is set as the fixed value. The state transfer formula and the current calculation formula are shown as follows.

$$\begin{cases} x(k+1)=x(k)-\dfrac{I_{sc}(k)\bullet\Delta t(k)}{C} \\ I(k)=\dfrac{x(k)-\sqrt{x^2(k)-4\bullet R_{sc}\bullet u(k)}}{2\bullet R_{sc}} \\ k=1,2,...,N \end{cases} \qquad (8)$$

The schematic diagram is shown in Fig. 3.

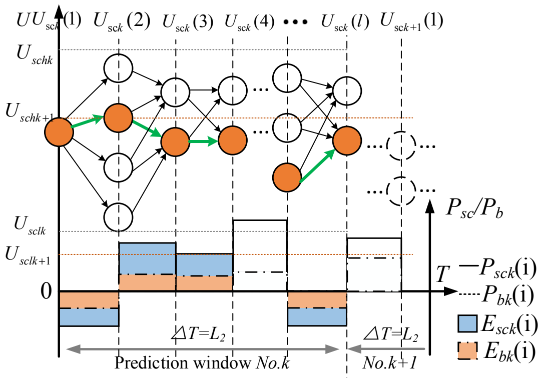


Fig. 3: Schematic diagram of DP

Efficiency should be firstly considered during the optimization of the EMS. The HESS with high efficiency can not only reduce the power consumption, but also reduce the heating of the system and prolong the working time of the equipment. At the same time, the life of battery is the key factor affecting the life-cycle cost of HESS. The life of battery is closely related to temperature, charge-discharge rate (C rate) and depth of discharge (DOD) [20]. Considering the actual needs, the configuration of battery has redundancy, so the battery always works in a very small DOD range, and the tram's cooling system keeps the battery temperature within a reasonable range. Therefore, this paper only needs to consider the impact of C rate, and the root mean square (RMS) current is usually used to measure the characteristic. In summary, the weighted values of system loss and the square of battery current are used as optimization objectives. Among them, the system loss formula and the weighting formula are shown as (9)-(10):

$$\begin{cases} (P_b+P_{sc})\bullet(1-\eta_{dc})+I_b^2\bullet R_b+\ I_{sc}^2\bullet R_{sc},\ \ P_{req}\ge 0 \\ (P_b+P_{sc})\bullet(\dfrac{1-\eta_{dc}}{\eta_{dc}})+I_b^2\bullet R_b+\ I_{sc}^2\bullet R_{sc},\ P_{req}>0 \end{cases} \qquad (9)$$

$$\min F=\omega\bullet\frac{P_{los}}{P_{los\max}}+(1\text{-}\omega)\bullet\frac{I^2{}_b}{I^2{}_{b\max}} \qquad (10)$$

Where P_{los} is the power loss of the HESS, η_{dc} is the efficiency of the DC/DC converter, P_{losmax} is the maximum value of the power loss, and the I_{bmax} is the maximum value of battery current, and ω is the weight of the power loss.

At the same time, considering the limited output energy and power of the supercapacitor and preventing the imbalance of the HESS, the battery is needed to provide a certain proportion of power:

$$\begin{cases} P_b\ge p_{br}\bullet P_{req}/\eta_{dc}\ ,P_{req}\ge 0 \\ |P_b|\ge p_{br}\bullet|P_{req}|\bullet\eta_{dc}\ ,P_{req}<0 \end{cases} \qquad (11)$$

where p_{br} is the battery's minimum power ratio.

IV. Numerical Simulation And Comparison

A. Line and tram conditions

This paper takes a tram line in China as the research object. The length of the line is 15.8km, and the line is shown by the red line in Fig.4. This paper takes a certain interval to make the analysis, and the time length is 812s.

Fig. 4. Route map of the tram line.

And the parameters of the tram and its HESS are shown in Table 1.

TABLE I
PARAMETERS OF VEHICLE AND CONFIGURATION OF HESS

Parameter	Value	Parameter	Value
Number of motors	2	Sizing of battery	135S10P
Number of trailer cars	3	Sizing of SC	300S3P
Weight (AW0,t)	52.2	Energy(kWh)	67.37
Maximum velocity(km/h)	70	η_{dc}(%)	96
Monomer of supercapacitor	3000F,2.7V,510g,0.29mΩ	Battery cell	20Ah,2.3V,515g,1.2mΩ
SOC_{schigh}	1	I_{scmax} (A)	700
SOC_{sclow}	0.25	I_{bmax}(A)	1200
SOC_{bhigh}	0.8	p_{br}	0.2
SOC_{blow}	0.2	ω	0.5
l_1 (s)	50	l_2 (s)	5

B. Simulation and experimental analysis

The velocity curve predicted by wavelet neural network is shown in Fig.5.

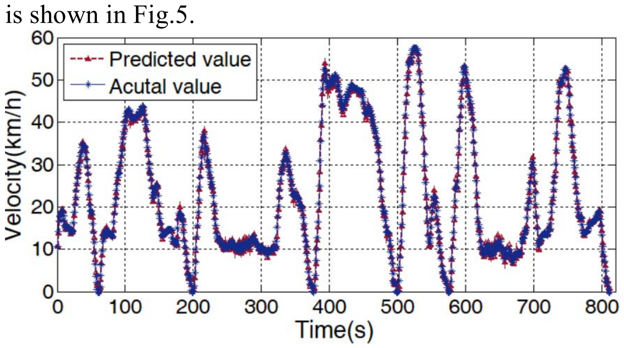


Fig. 5. Curves comparison between actual velocity and predicted velocity.

The accuracy of state prediction directly affects the effect of subsequent EMS optimization. In order to measure the accuracy of prediction, this paper uses three parameters: mean absolute error (MAE), root mean square error (RMSE) and mean relative error (MRE) to make the quantization. The calculation formulas are as follows:

$$\begin{cases} MAE=\dfrac{1}{N}\bullet\sum_{i=1}^{N}\left|y_i-d_i\right| \\ RMSE=\sqrt{\dfrac{1}{N}\bullet\sum_{i=1}^{N}(y_i-d_i)^2} \\ MRE=\dfrac{1}{N}\bullet\sum_{i=1}^{N}\left|\dfrac{y_i-d_i}{d_i}\right| \end{cases} \tag{12}$$

where y_i is the predicted value and d_i is the actual value. The results show that the MAE, RMSE and MRE of velocity prediction are 0.52, 0.71 and 0.08, respectively. Compared with the results of classical BP neural network, the accuracy is improved by 12.8%.

According to the predicted velocity and acceleration, the power demand in the predicted interval can be obtained. The formula is shown as follows.

$$P_{pre}=M\bullet a_{pre}\bullet v_{pre} \tag{13}$$

Where M is the total weight of the tram, a_{pre} is the predicted acceleration, v_{pre} is the predicted speed.

And the required power curve can be obtained after calculation. The comparison between predicted power curve and actual power curve can be shown in Fig.6.

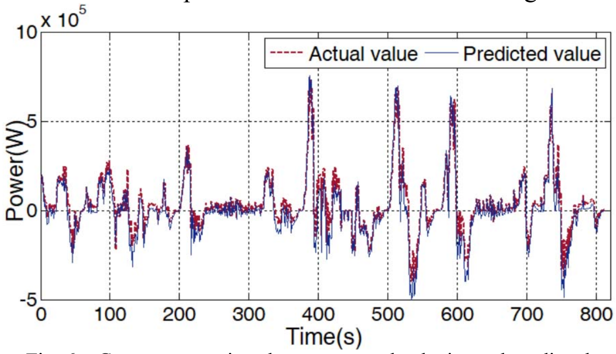


Fig. 6. Curves comparison between actual velocity and predicted velocity.

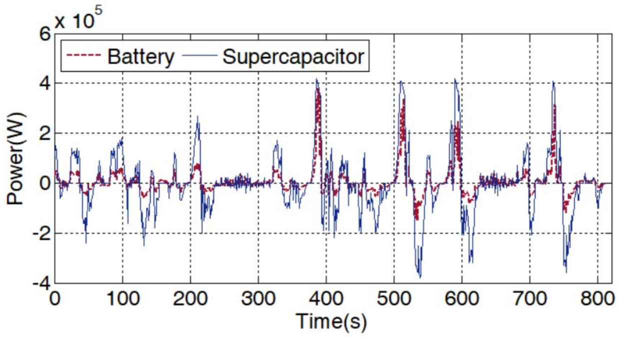
After the power demand curve is obtained in each prediction space, ROS algorithm is used for rolling optimization. The simulation results show that the calculation time of rolling optimization in each prediction space is less than 1 s and less than the discrete time value, which can realize the real-time control of HESS.

After the optimization of ROS, the power distribution curves of battery and supercapacitor are shown in Fig. 7(a).

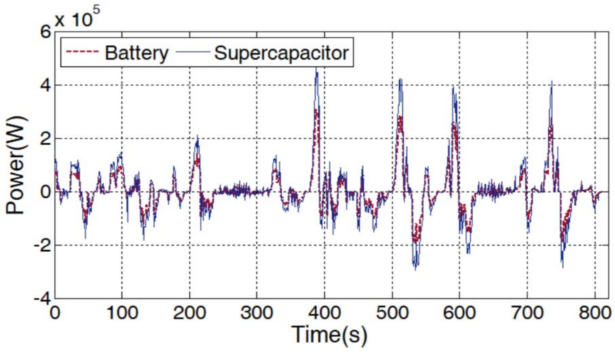
To verify the effect of ROS, the result is compared with that under the RB strategy. The formula of the RB strategy is shown as follows:

$$\begin{cases} P_b(\mathrm{k})=p_b\bullet P_{req}(k)/\eta_{dc}\,, P_{req}(k)\geq 0 \\ P_b(k)=p_b\bullet P_{req}(k)\bullet\eta_{dc}\,, P_{req}(k)<0 \\ P_{sc}(k)=P_{req}(k)-P_b(k) \\ k=1,2,\ldots,n \end{cases} \tag{14}$$

The key point of the strategy is to set the proportion p_b. In order to lengthen the lifespan of the battery, p_b is set to 0.4. This value guarantees the minimum output of the battery within all the limitations. And the power distribution curves under the strategy are shown in Fig. 7(b).



(a) ROS



(b) RB

Fig. 7. Power distribution curves.

As for the redundant configuration of the battery, the fluctuation of SOC is not obvious in this section and thus the comparison is only for the supercapacitor below, and the curves are shown in Fig.8.

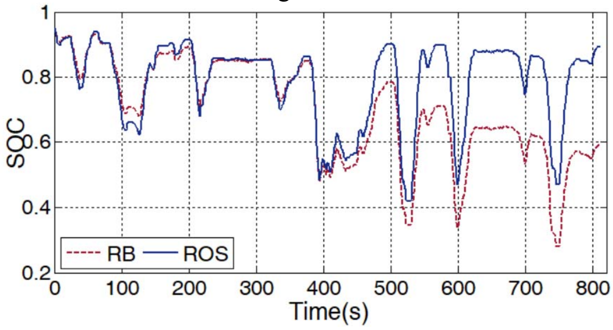


Fig. 8. Voltage curves of supercapacitor under different strategies

From the comparison of the two power curves, the proportion of batteries in ROS is much lower than that in RB strategy in low power demand area (before 350s). This is because the supercapacitor can provide enough power under low power demand. Therefore, the supercapacitor can work with the maximum output power ratio to optimize the objective function. In the high power demand area (after 350s), as for the supercapacitor cannot satisfy the power demand alone, the p_b during the traction mode increases. At the same time, in order to keep the SOC of supercapacitor in a suitable range, the proportion of regeneration power of supercapacitor increases, which makes supercapacitor absorb more energy. For RB strategy, the power proportion is fixed, and it cannot be adjusted according to the change of power demand. As shown in Fig. 8, the difference of energy consumption of supercapacitor is not obvious in low power demand area, but in high power demand area, the SOC of supercapacitor under RB strategy is much lower than ROS, and has been reduced to the critical value. If the tram cannot be charged in time, the HESS will not work properly.

And the real-time power loss curves under the two strategies are shown below.

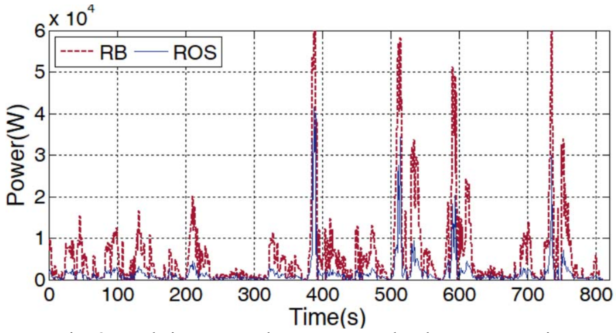


Fig. 8. Real-time power loss curves under the two strategies.

It can be seen that the real-time power loss under RB strategy is higher than that under ROS. Power loss not only increase energy consumption of HESS, but also cause equipment heating, and thus results in shorter system life. So ROS optimizes the system efficiency and further prolongs the system life.

RMS currents, average power losses and the weighted values under the two strategies are shown in Table 2.

Table. Ⅱ: Calculated results

Type of strategy	ROS	RB
RMS(A)	171.31	216.02
Average power loss(W)	1.66e3	5.80e3
weighted value	0.5396	1

It can be seen from the table that compared with RB strategy, RMS current under ROS is reduced by 20.7%, average power loss is reduced by 71.4%, weighted target value is reduced by 46.04%, and performance is significantly improved.

V. Conclusion

This paper proposes the ORS to realize real-time optimal control of battery-supercapacitor HESS. This strategy divides tram's traveling time into short horizons, predicting the states in advance and then making the rolling optimization based on DP. The prediction results show that the prediction accuracy of the optimized WNN is about 92% and is 12.8% higher than that of the classical BPNN. The accuracy of the prediction value will affect the optimization result of the subsequent EMS. And compared with the RB strategy, the optimization value is reduced by 46.4%, and the optimization effect is remarkable. At the same time, the calculation time of every short horizon is shorter than the discrete time, which meets the requirements of real-time control. In the next step, the practical application conditions of trams will be taken into account to further simplify the strategy, and experimental verification will be carried out on the on-board HESS.

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