Research on Sizing Method of Tram Vehicle Hybrid Energy Storage System

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Abstract—**In order to design a well-performing hybrid storage system for trams, optimization of energy management strategy (EMS) and sizing is crucial. This paper establishes a mathematical model of battery and supercapacitor, compares the topology used in trams. Using adaptive particle swarm optimization(PSO) to optimize the size of battery and supercapacitor. Simulation calculation based on the operating data of traction calculation curve and analyzes the impact of choosing different EMS and different topologies on the size results.**

Keywords- tram, hybrid storage system, sizing, energy management strategy, adaptive particle swarm optimization

I. INTRODUCTION

The modern tram is developed from the traditional tram in the 19th century. It has undergone four stages of birth, development, decline, and revival [1]. It is a low-to-medium rail transit system between traditional buses and light rail. Due to its energy saving, environmental protection, safety, comfort and beautiful appearance, it has developed rapidly in major cities and small and medium cities.

Because vehicle-mounted energy storage has the advantages of low cost and improving the urban environment, it has become a goal pursued by people [2]. However, it is difficult for a single energy storage element to meet the needs of train operation. Therefore, hybrid storage of battery and supercapacitor has greatly improved the power supply capacity of the energy storage system. In order to ensure the provision of greater energy and peak power under the same weight and volume, in addition to selecting a reasonable sizing of the energy storage system, it is also necessary to formulate an appropriate EMS based on actual train and line parameters so that the traction capacity, energy consumption, and operation efficiency of the entire system have reached a better state. Therefore, sizing and EMS of hybrid energy storage systems are key issues those need to be studied.

Most of the current sizing issues for hybrid energy storage are based on regular EMS. According to the optimization objective and considering the boundary conditions, combined with the optimization algorithm, a proper sizing result can be obtained. Commonly used optimization algorithms include PSO and genetic algorithms.

The optimization target set in [3] is the total cost of a multi-energy small ship hybrid energy storage system, which is optimized based on its minimum cost, and the capacity is optimized based on an improved genetic algorithm. In [4-6], the minimum life cycle cost of the vehicle-mounted energy storage system is used as the objective function, and the linear particle swarm optimization is used to optimize the sizing and energy management parameters of the vehicle-mounted energy storage system. Reference [7] is based on a dynamic threshold energy management strategy, and uses particle swarm optimization to simultaneously optimize the sizing of the hybrid energy storage system and the target cruise speed of each operating interval. The objective function selects the quality and cost of the hybrid energy storage system, total operating time and total loss of hybrid energy storage system. Reference [8] used the Pareto front of the NSGA-II algorithm system to balance the multiple objectives of the optimal allocation of capacity. The sizing results obtained at the same time reduced the total weight and energy loss of the hybrid energy storage system.

Sizing and EMS directly affect each other. Developing a proper EMS can better optimize the results of sizing.This parper optimizes the sizing of the hybrid energy storage system based on a regular energy management strategy. The objective function is to choose the minimum life cycle cost and the minimum weight, and use the adaptive particle swarm algorithm to optimize the sizing with the system SOC, voltage, and current as constraints.

This paper is organized as follows. Section II provides the model of hybrid storage system. Section III optimizes the sizing based on two rules of energy strategy. The objective function is selected as the full life cycle cost, and the total weight of the hybrid energy storage system is considered comprehensively, which is converted into a single objective function through weighting. An adaptive PSO algorithm is used for optimization, which can effectively prevent particles from falling into the local optimal solution.Section IV conducts simulation analysis based on traction calculation curve, and compares the impact of different EMS and different topologies on sizing. And Section V is the conclusion of the paper.

II. HYBRID ENERGY STORAGE SYSTEM MODEL

Before sizing, we need to mathematically model the battery and supercapacitor and determine the topology of the hybrid energy storage.

A. Lithium Battery Model

In this paper, the first-order RC model of the battery is selected. On the basis of the internal resistance model, the parallel internal resistance and capacitance are connected in

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series to express the polarization phenomenon of the battery, which can accurately express the dynamic characteristics of the battery, and compared with PNGV model, it is easy to program and simulate.

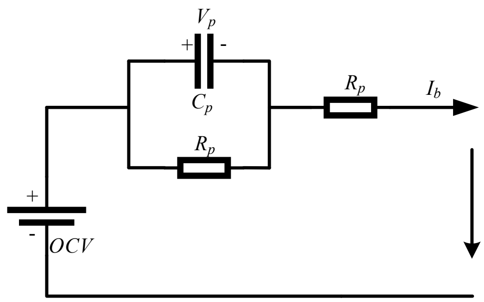


Figure 1. Lithium battery model

According to the lithium battery model, the characteristic equation describing the battery can be calculated by (1).

$$\begin{cases} I_b(t)=\dfrac{P_b(t)}{V_o(t)} \\ V_p(t)=V_p(t-1)e^{-\frac{\Delta t}{\tau}}+R_p\times I_b(t-1)\times(1-e^{-\frac{\Delta t}{\tau}}) \\ V_0(t)=OCV(t)-I_b(t)R_0-V_p(t) \\ P_{bloss}(t)=I_b(t)^2\times R_o+\dfrac{V_p(t)^2}{R_p} \\ \tau=R_p\times C_p \end{cases} \tag{1}$$

Where, V_p represents the polarization voltage of the battery, Δt is the time interval,τ is the time constant, I_b represents the battery current, R_p,C_p and R_o respectively represent the polarization resistance, polarization capacitance and ohmic internal resistance of the battery, OCV represents the open circuit voltage of the battery,V_o represents the terminal voltage,P_b represents the output rate of the single battery, and P_{bloss} represents the loss power of the single battery.

The formula for calculating the charged state of the power battery can be obtained by using the ampere-hour integral method.

$$SOC(t)=SOC(0)-\frac{\int_0^t I_b dt}{Q} \tag{2}$$

B. Supercapacitor Model

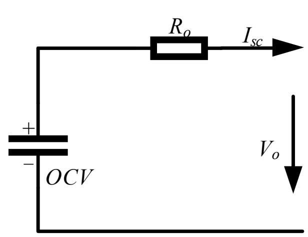


Figure 2. Supercapacitor simplified model

In this paper, a simplified model with easily identifiable parameters is used to express the external electrical characteristics of supercapacitor during the charge-discharge process. The equivalent circuit diagram is shown in Fig.2.

Based on the simplified model,the characteristic equation of supercapacitor can be calculated by (3).

$$\begin{cases} OCV(t)=OCV(0)-\dfrac{\int_0^t I_{sc}dt}{C_{sc}} \\ V_0(t)=OCV(t)-I_{sc}(t)R_o \\ I_{sc}(t)=\dfrac{OCV(t)-\sqrt{OCV(t)^2-4R_oP_{sc}(t)}}{2R_o}, I_{sc}>0 \\ I_{sc}(t)=-\dfrac{OCV(t)-\sqrt{OCV(t)^2+4R_oP_{sc}(t)}}{2R_o},\ I_{sc}<0 \\ P_{scloss}=I_{sc}(t)^2\times R_o \end{cases} \tag{3}$$

The voltage SOC is used to express the SOC of the supercapacitor. The expression is shown in (4).

$$SOC_{SC}(t)=(\frac{OCV(t)}{OCV_{\max}})^2 \tag{4}$$

Where, OCV and V_o are respectively the open-circuit voltage and terminal voltage of the supercapacitor,I_{sc} is the current of the supercapacitor, R_o is the internal resistance of the supercapacitor.C_{sc} is the capacity of the supercapacitor, and P_{scloss} is the loss of the supercapacitor.

C. Tram Hybrid Energy Storage System Structure

This paper adopts the semi-active topology of battery shown in Figure 3.The characteristic of this topology is that the power of the battery can be directly controlled by DC-DC, and the life cycle of the battery can be extended by controlling the charge and discharge current of the battery, thus reducing the cost of battery replacement.Since the battery will lose energy when passing through DC-DC, this topology is suitable for the main power supply of supercapacitor and the auxiliary power supply of battery.Supercapacitor can adjust the power supply directly according to the change of dc bus voltage, and their response speed is faster.The disadvantage is that the supercapacitor have large voltage fluctuations, and many capacitors need to be connected in series to obtain a higher voltage to meet the dc bus voltage range requirements.

The solid line represents the energy flow when the train is pulling, and the dashed line represents the energy flow when the train is braking.The power required by the tram during the traction phase is provided by the battery and the supercapacitor, which loses some of its power when passing through the DC-DC.The power absorbed by the tram during the braking phase can be absorbed by the battery and the supercapacitor, and the power absorbed by the battery will lose some power when passing through DC-DC.The power required by the auxiliary power supply system can be provided by battery or supercapacitor.

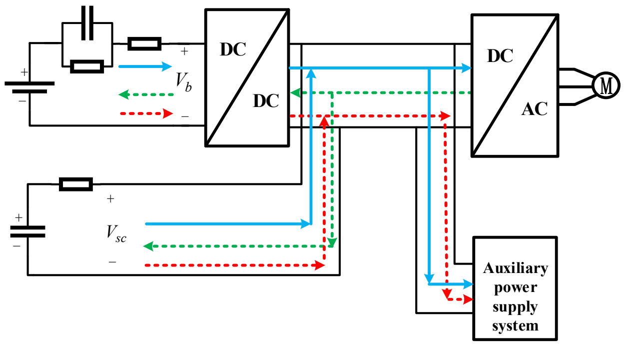


Figure 3. Semi-active Battery Topology

III. Optimization of Sizing for Hybrid Energy Storage Systems

For hybrid energy storage systems, EMS affect the results of sizing. Before optimizing sizing, choosing an appropriate EMS can not only reduce the total weight of the hybrid energy storage system, but also reduce system losses and use costs. This paper chooses two rules-based EMS and formulates appropriate energy management parameters. Under these two strategies, the total weight of the hybrid system and the life cycle cost are taken as the objective functions. With the current range, SOC range, and voltage range as constraints, the PSO algorithm was used to optimize the number of series and parallel connections of the battery and supercapacitor to obtain a sizing that meets the operating conditions.

A. Rule-Based EMS

The rule-based strategy is designed according to the actual conditions, and the corresponding power allocation is made by judging the running status of the train and the real-time status of the energy storage system. It has strong stability, fast response in real time, and is suitable for tram lines with relatively fixed operating conditions. It has been widely used in the engineering field. There are mainly proportional methods of the logical threshold method.

The logic threshold method is to set an appropriate threshold based on the actual power demand of the line. When the power required or absorbed by the system is within the threshold, its power is provided or absorbed by the battery, and the excess power is provided or absorbed by the supercapacitor. The equations are shown in (5).

$$P_b(t)=\begin{cases}P_{limit}, & P_{req}(t)>P_{limit}\\ P_{req}(t), & -P_{limit}<P_{req}(t)<P_{limit}\\ -P_{limit}, & P_{req}(t)<-P_{limit}\end{cases}$$
$$P_{sc}(t)=P_{req}(t)-P_b(t) \tag{5}$$

P_{req} is the power required during train traction or absorbed, P_{limit} is the set charge and discharge threshold, P_b is the power released or absorbed by the battery, and P_{sc} is the power discharged or absorbed by the supercapacitor.

The proportional method divides the power required or absorbed by the system into two parts according to the set ratio, which are provided by the battery and the supercapacitor, respectively. The expressions are shown in (6).

$$\begin{cases}P_b(t)=P_{req}(t)\times b\\ P_{sc}(t)=P_{req}(t)*(1-b)\end{cases} \tag{6}$$

b is the set proportion.

B. Objective Function

There are different requirements for capacity optimization in engineering. Common optimization goals include the lowest cost, lightest weight, longest life of an energy storage system, and a comprehensive consideration of multiple goals. The general processing method for multi-objective optimization is to convert each target to a single-objective function by weighting each target [9]. This paper selects the weight and the full life cycle as the objective function, and obtains a lower full life cycle cost while ensuring that the weight of the energy storage system is relatively light. The expression as shown in (7).

$$\begin{cases}\min F(N)=w_1\times\dfrac{M(N)}{M_0}+w_2\times\dfrac{COST(N)}{COST_0}\\ w_1+w_2=1\end{cases} \tag{7}$$

where $F(N)$ is the optimized objective function, $M(N)$ and $COST(N)$ are the total weight and life cycle $COST$ of the energy storage system, w_1 and w_2 are the weight coefficients of each optimization target, and M_0 and $COST_0$ are dimensionless coefficients. The single objective functions are calculated as follows:

$$M(N)=m_b\times N_{bs}\times N_{bp}+m_{sc}\times N_{scs}\times N_{scp} \tag{8}$$

$$COST(N)=COST_{cs}(N)+COST_{gh}(N)+COST_{loss}(N) \tag{9}$$

N_{bs}, N_{bp}, N_{scs} and N_{scp} are the total number of series and parallel connections between battery and supercapacitor respectively. m_b and m_{sc} are the monomer mass of battery and supercapacitor.$COST_{cs}$ is the initial purchase cost,$COST_{gh}$ is the replacement cost, and $COST_{loss}$ is the energy loss cost. The specific expression is shown below:

$$COST_{cs}=COST_b\times N_{bs}\times N_{bp}+COST_{sc}\times N_{scs}\times N_{scp} \tag{10}$$

$$COST_{gh}=COST_b\times N_{bs}\times N_{bp}\times N_{gh} \tag{11}$$

$$COST_{loss}=365\times year\times N_{cyc}\times COST_{df}\times\int\frac{P_{b-loss}+P_{sc-loss}+P_{dcdc-loss}}{3600}dt \tag{12}$$

$COST_b$ and $COST_{sc}$ are the purchase unit prices of battery and supercapacitor respectively. N_{gh} is the number of battery replacements during the whole life cycle. N_{cyc} represents the number of times a tram runs per day, and $COST_{df}$ represents the electricity bill.

C. The Boundary Conditions

Operating conditions constraints of vehicle-mounted hybrid energy storage system mainly include SOC, voltage and current constraints, series number constraints and real-time power constraints of the train. The constraint equations are shown in (13) and (14).

$$\begin{cases} SOC_{b\min} \le SOC_{b}(t) \le SOC_{b\max} \\ V_{sc\min} \le V_{sc}(t) \le V_{sc\max} \\ -I_{b\max} \le I_{b}(t) \le I_{b\max} \\ -I_{sc\max} \le I_{sc}(t) \le I_{sc\max} \\ N_{bs\min} \le N_{bs} \le N_{bs\max} \\ N_{scs\min} \le N_{bs} \le N_{scs\max} \end{cases} \tag{13}$$

$$P_b + P_{sc} \ge P_{req} + P_{loss} \tag{14}$$

SOC_{bmax} and SOC_{bmin} represent the upper and lower limits of the charged state of the battery respectively. V_{scmax} and V_{scmin} respectively represent the upper and lower limits of supercapacitor voltage. I_{bmax} and I_{scmax} respectively represent the maximum current constraint value of the battery supercapacitor. N_{bsmax} and N_{bsmin} respectively represent the upper and lower limits of the number of battery in series, which can be determined according to the working range of voltage on the low-voltage side of DC-DC. N_{scsmax} and N_{scsmin} respectively represent the upper and lower limits of the series number of supercapacitor, which can be determined according to the working range of dc bus voltage .

D. Optimization Procedures

PSO is an intelligent optimization algorithm proposed by American scientists.It is a swarm - based evolutionary algorithm. Compared with genetic algorithm(GA), PSO is characterized by less parameters, easy implementation and fast convergence. PSO is initialized as a set of random particles, and then iteratively finds the optimal solution. PSO mainly updates its speed and position according to the following formula[10]. The expression as shown in (15) and (16).

$$v_{id}(k+1) = w \times v_{id}(k) + c_1 r_1 (p_{id}(k) - x_{id}(k)) + c_2 r_2 (p_{gd}(k) - x_{id}(k)) \tag{15}$$

$$x_{id}(k+1) = x_{id}(k) + v_{id}(k) \tag{16}$$

Where, w is the inertia weight. PSO has strong global search ability when w is large, while PSO has strong local search ability when w is small. c_1 and c_2 for learning factor, respectively to adjust to the individual best particle and the global best particle flight direction of the large step, if its value is too small, the particles may be moving away from the target area, if its value is too large will cause particles suddenly fly to the target area, even flying over the target area, the appropriate c_1, c_2 can accelerate convergence and not easy to fall into local optimum. r_1 and r_2 are random numbers in [0,1].

Because the standard particle swarm algorithm is easy to fall into a local optimum, this paper uses an adaptive inertial weight method to improve it.

Reference [11] proposed that according to the size of the fitness variance of the population, it can be determined whether the population is in the state of premature convergence. When the fitness variance of the population is less than a certain threshold, it can be considered that the population is in the state of premature convergence. The expressions of fitness variance and inertia weight are shown in (17) and (18).

$$\sigma^2 = \sum_{j=1}^{sizepop} \frac{(f_j - \overline{f})}{f}, f = \begin{cases} \max|f_j - \overline{f}| & if \max\left|f_j - \overline{f}\right| > 1 \\ 1 & else \end{cases} \tag{17}$$

$$\omega = \begin{cases} \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \dfrac{\ln(\overline{f_{k+1}}) - \ln(f_{k+1})}{\ln(\overline{f_{k+1}})} & if \left|\sigma_{k+1}{}^2 - \sigma_k{}^2\right| > \mu \,\&\&\, f \ge \overline{f} \\ \omega_{\min} & if \left|\sigma_{k+1}{}^2 - \sigma_k{}^2\right| > \mu \,\&\&\, f < \overline{f} \\ \omega_{\max} & if \left|\sigma_{k+1}{}^2 - \sigma_k{}^2\right| < \mu \,\&\&\, f \ge \overline{f} \\ \omega_{\min} + (\omega_{\max} - \omega_{\min}) \times \dfrac{\ln(\overline{f_{k+1}}) - \ln(f_{k+1})}{\ln(\overline{f_{k+1}})} & if \left|\sigma_{k+1}{}^2 - \sigma_k{}^2\right| < \mu \,\&\&\, f < \overline{f} \end{cases} \tag{18}$$

Among them, f_j is the fitness of the j particle of the k+1generation. $\overline{f}$ is the average fitness of the current population. f is the normalization factor, the purpose is to limit the size of σ^2, σ_{k+1}^2 is the fitness variance of the population in the k+1 generation, u is the minimum, w_{max}, w_{min} are the upper and lower limits of w, respectively. The value of w changes dynamically with the population fitness variance of neighboring iterations and the fitness of the particles.

IV. Case Analysis

This paper chooses energy type lithium titanate battery and supercapacitor, the parameters are shown in Tab. 1. Based on the above power requirements, with 20 years as the full life cycle, trams run 12 times per day, with the life cycle cost and the total weight of HESS as the objective function, combined with constraints, the EMS adopted is the logical threshold method and proportional method, and use battery semi-active topology and dual DC-DC topology for comparative analysis. The battery and supercapacitor configurations obtained by using PSO algorithm are shown in Tab.2.

TABLE I. Parameters of Cell and Supercapacitor

parameter	*cell*	*supercapacitor*
Rated voltage(V)	2.3	2.7
Rated capacity	20Ah	3000F
Internal resistance(mΩ)	1.2	0.29
Maximum Continuous Current(A)	120(6C)	200(A)
Weight(kg)	0.515	0.51
Cycle life	13000	2000000

TABLE II. SIZING OPTIMIZATION RESULTS

topology	*EMS*	*Nbs*	*Nbp*	*Nscs*	*Nscp*
Battery semi-active	Logical threshold	177	11	255	18
Battery semi-active	Ratio	159	9	298	16
Double DC - DC	Logical threshold	145	15	138	25

Fig.4 and Fig.5 are schematic diagrams of power allocation simulation based on logic threshold method and proportional method. It can be seen from the figure that the energy management strategy based on logical thresholds. When the power demand of a tram is within the threshold, the power is completely provided by the battery, and the part that exceeds the threshold is provided by the supercapacitor. Based on the ratio-based energy management strategy, the battery and supercapacitor provide power according to the set ratio, which is in line with the initial setting. The proportional method is equivalent to the strategy of changing the threshold, which guarantees the energy supply of the supercapacitor at every moment.

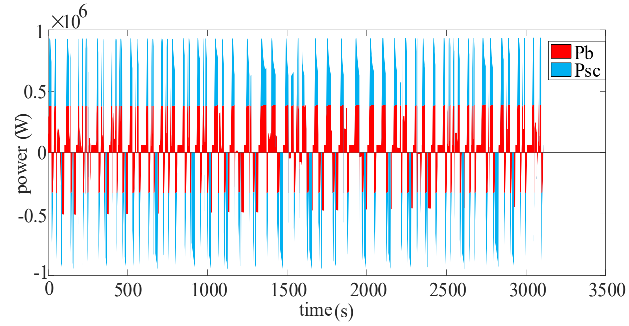


Figure 4. Power distribution curve based on threshold

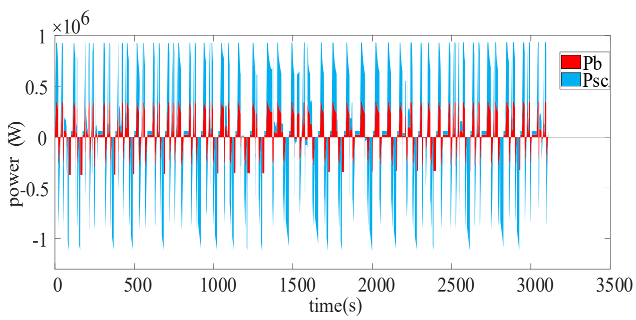


Figure 5. Power distribution curve based on proportional

Fig. 6 and Fig.7 are simulation diagrams of the SOC of the energy storage system with logic threshold method and proportional method over time. It can be seen from the Figure that due to the large energy density of the battery, its SOC fluctuation range is small. The supercapacitor has a small energy density and a large SOC fluctuation range. The high energy density of the battery can provide the power required by the train for a long time, which can extend the station spacing of the charging piles installed and reduce the initial construction cost.

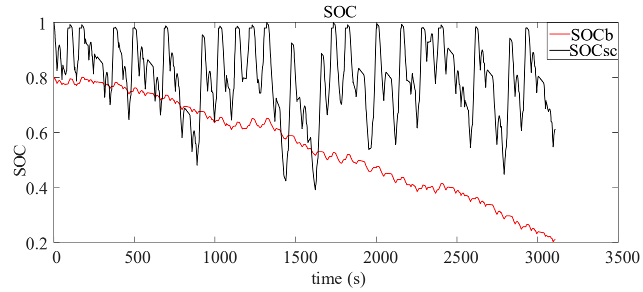


Figure 6. SOC curve based on threshold

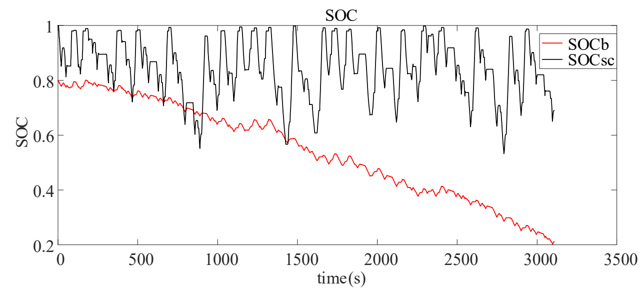
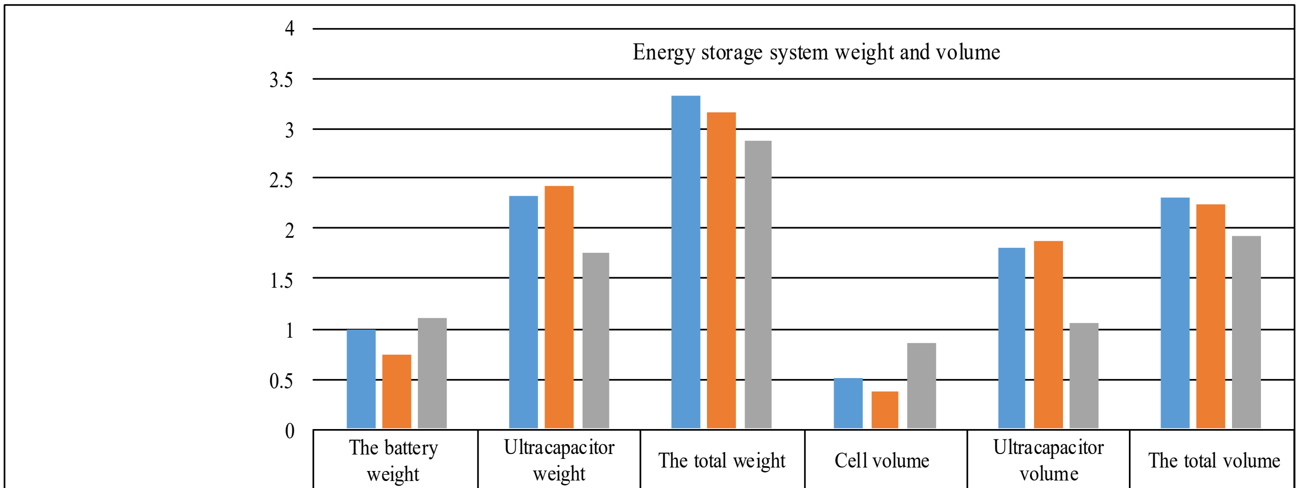


Figure 7. SOC curve based on proportional

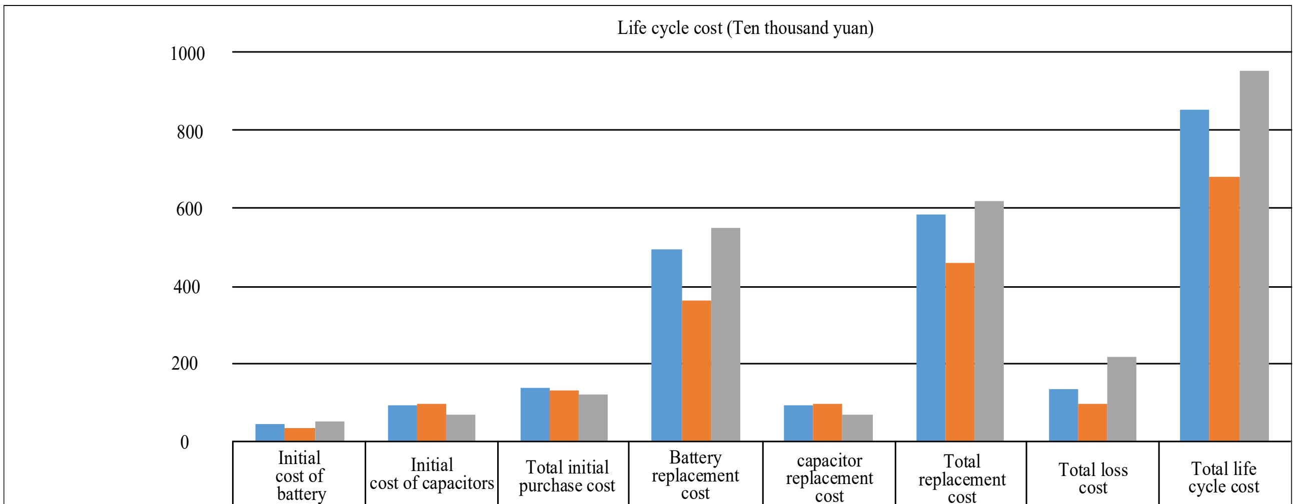
Fig. 8 and Fig. 9 show the economic comparison of two power allocation methods and two topologies.Based on the analysis with the above chart, the sizing obtained based on different EMS are different. The number of battery configurations obtained by the allocation method based on the proportional method is small, and the number of supercapacitor configurations is large. However, the overall configuration of the integrated energy storage system is 0.175t less in weight and 0.0638m^3 less in volume than the threshold method. The configuration obtained by the proportional method has a smaller volume and weight.

In terms of cost, the full-life-cycle cost obtained by the proportional method is 68.411 million yuan, which is 17.278 million yuan less than the threshold method. Specifically, the battery configuration is less, and the initial purchase is 119,800 yuan less than the threshold method. Because the battery life obtained by the two strategies is not much different, the battery replacement cost obtained by the corresponding proportion method is 1.27 million yuan less The corresponding battery internal resistance loss cost is 167,300 yuan less than the threshold method. Because the topology is a semi-active structure, its energy loss is related to the battery configuration, so the corresponding DC-DC energy loss cost is 26.325 yuan less than the threshold method, and the total loss cost is 375,200 yuan. Although the configuration of the supercapacitor is increased compared to the threshold method, there is no DC-DC energy loss due to its long service life, small internal resistance, and direct connection to the DC bus. Therefore, its configuration has a smaller impact on replacement cost and total loss cost than the battery.For the energy management parameters set in this paper, the proportional method is the better power allocation strategy.



	The battery weight	Ultracapacitor weight	The total weight	Cell volume	Ultracapacitor volume	The total volume
Single DC - DC Logical threshold	1.0027	2.3409	3.3436	0.5062	1.8131	2.3193
Single DC - DC Ratio	0.737	2.4317	3.1687	0.3721	1.8834	2.2555
Double DC - DC Logical threshold	1.11	1.7696	2.8796	0.8591	1.0692	1.9283

Figure 8. Comparison of weight and volume



	Initial cost of battery	Initial cost of capacitors	Total initial purchase cost	Battery replacement cost	capacitor replacement cost	Total replacement cost	Total loss cost	Total life cycle cost
Single DC - DC threshold	44.781	91.8	136.581	492.591	91.8	584.391	132.253	853.255
Single DC - DC Ratio	32.913	95.36	128.273	362.043	95.36	457.403	94.7352	680.411
Double DC - DC threshold	50.025	69	119.025	550.275	69	619.275	215.064	953.364

Figure 9. Comparison of life cycle costs

The sizing obtained by different topologies is also different. The DC-DC loss cost of the active topology is much higher than that of the battery semi-active topology. Therefore, the corresponding topology structure should be selected based on different optimization objectives and control effects to optimize sizing.

V. CONCLUSION

This parper mainly introduces the sizing method in detail. First, it introduces two rule-based energy strategies. Subsequently, the principle and model of sizing are described in detail. Finally, considering the weight and life cycle cost, the adaptive PSO algorithm is used to optimize it, and the optimization result based on the minimum objective function is obtained. An economic comparison analysis of the results obtained under two different power allocation strategies concludes that a reasonable EMS can optimize the results of sizing and reduce the life cycle cost of HESS. Choosing different topologies also affects the result of sizing. Therefore, we should choose different topologies for sizing optimization based on different optimization goals and control effects.

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