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LONG CYCLE LIFE ORIENTED BATTERY/ULTRACAPACITOR HYBRID ENERGY STORAGE SYSTEM IN ELECTRIC VEHICLES USING MULTI-OBJECTIVE OPTIMIZATION

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ABSTRACT

This work presents a multi-objective optimization based design method for battery/ultracapacitor hybrid energy storage systems used in electric vehicles. Long life mileage and low normalized cost are our optimization objectives. Firstly, the degradation model of lithium-ion battery and a rule based power splitting strategy are introduced. Then the multi-objective optimization is formulated to solve the optimal size and control parameters simultaneously. Finally, the solutions from the Pareto front are compared with the battery only system. The results show that the proposed design method can significantly reduce the battery's degradation, with a whole life mileage increased by over 26%. Meanwhile, the recommended size of the hybrid energy storage system brings a normalized cost increase by 29.1%.

Keywords: lithium-ion battery, hybrid energy storage system, energy management strategy, multi-objective optimization

1. INTRODUCTION

Electric vehicles (EVs) have rapidly grown in recent years, providing a good solution for carbon emission reduction. However, due to the limited cycle life of lithium-ion batteries (LIBs), the promotion of EVs is restricted. The ultracapacitors (UCs) have the capability of large power exchange and long cycle life. The proposal of LIB/UC hybrid energy storage system (HESS) seems to become a reasonable solution for cutting down the battery power and extending battery life [1].

In order to design a HESS that can be used in EV, two main issues need to be considered [2]. Firstly, the size of the UC module must be appropriate. Too many UC cells will greatly raise the cost, while too few UC cells cannot make a difference. Secondly, the energy management strategy must be well designed. That is to say the load power demand is well distributed to UC and battery, so that the energy waste can be the least and the battery life can be the longest.

In the literature, a lot of research has been done on each of the issues [3]. However, the two issues are coupled to each other [4]. It is for sure that the change of UC size will affect the optimal power distribution, and that the ideal energy management strategy under some UC sizes does not fit all the possible UC sizes. Thus, it is better to solve them simultaneously. In this work, the design of HESS is transferred into a multi-objective optimization problem to find the optimal size and control parameters at the same time. Both the whole life mileage and the normalized cost are taken as the optimization objectives. Then the optimal Pareto front can be acquired, which is considered as the reasonable tradeoff between the two objectives.

The rest of the paper is organized as follows: Section 2 gives the modeling of the HESS, where the basic configuration of the battery module is determined, a battery degradation model and a rule based power splitting strategy are adopted. The multi-objective optimization problem is formulated in section 3. The results of the Pareto front are given and the performance of HESSes with different configurations are compared with the battery only system. Section 4 gives the final conclusions.

2. MODELING

2.1 Hybrid energy storage system

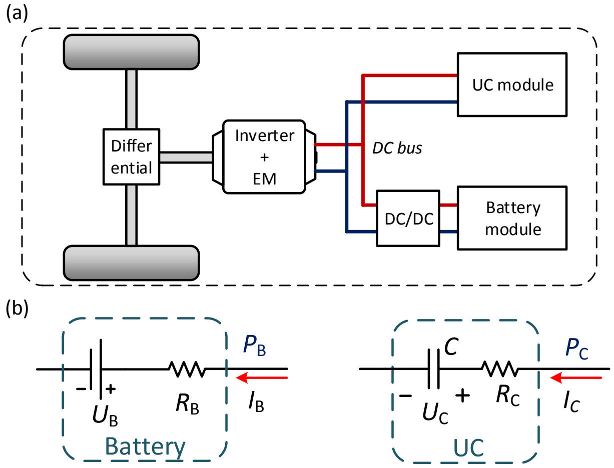

Fig 1 Power system of EV

The EV discussed in this work is a typical road vehicle, whose configuration is illustrated by Fig 1(a). The battery module works as the main energy storage, while the UC module works as a power bank. In order to satisfy the designed mileage per charge, the size of the battery module is pre-determined. The relevant parameters of the vehicle and its battery module are listed in Table 1.

Table 1 Vehicle and energy storage parameters

Item	Value	Unit
Vehicle		
Mass without ESS	1360	kg
Nominal range in NEDC	150	km
Motor transmission efficiency	0.9	-
Average DC/DC efficiency	0.95	-
Electricity cost	1.4	¥/kWh
Battery cell		
Manufacturer	A123 system	-
Type	ANR26650M1	-
Mass	70	g
Working voltage	2.5-3.65	V
Nominal voltage	3.2	V
Nominal capacity	2.2	Ah
Stored energy	7.6	Wh
Internal resistance	10	mΩ
Nominal cycle life	>1,000	-
Price	3.95	¥/Wh
Battery module		
Nominal voltage	480	V
Series and parallel number	150s16p	-
UC cell		
Manufacturer	Maxwell	-
Type	K2-BCAP3000	-
Mass	510	g
Working voltage	1.35-2.7	V
Nominal capacity	3000	F
Stored energy	3.04	Wh
Internal resistance	0.29	mΩ
Nominal cycle life	1,000,000	-
Price	0.076	¥/F

For battery and UC modeling, the simplest *Rint* equivalence circuit model is applied. The relevant circuits are plotted by Fig 1(b).

2.2 Battery degradation model

The $LiFePO_4$ battery cell is selected in this work. According to the work by Bloom et al. [5], the percentage capacity loss to the initial capacity, can be decided by the following equation.

$$Q_{\rm loss} = B(c)\exp(-E_{\rm a}(c)/RT)(A_{\rm h})^z \tag{1}$$

Where Q_{loss} is the percentage capacity loss (in %), c is the discharge C-rate (set as 1C=2A), A_h is the discharge ampere-hour throughput (in Ah), E_a is the activation energy, B is the pre-exponential factor, R is the ideal gas constant, T is the cell temperature (in K). The parameters can be decided as follows according to the data from [6].

$$\begin{gathered} B(c) = 448.98c^2 - 6301.1c + 33840 \\ E_{\rm a}(c) = (31370 - 370.3c)\text{J/mol} \\ R = 8.31\text{J/(mol}\cdot\text{K)},\ T = 313.15\text{K},\ z = 0.55 \end{gathered} \tag{2}$$

Thus, the total ampere-hour throughput that a cell can discharge before EOL $A_{h,EOL}$ can be predicted as follows.

$$A_{\rm h,EOL} = \left(\frac{Q_{\rm loss,EOL}}{B(c)\exp(-E_{\rm a}(c)/RT)}\right)^{1/z} \tag{3}$$

Where $Q_{loss,EOL}$ is the percentage capacity loss at EOL, which is usually set as 20.

Since Eq. (3) is relevant to the discharge C-rate, which is rather dynamic in common driving cycles, the average discharge current can be used to reflect the life discharge level.

2.3 Rule based power splitting strategy

A rule based power splitting strategy is adopted in this work to manage the energy behavior in HESS [7]. In this strategy, the SOC and voltage protection is firstly provided to ensure safety. Then comes with the load power splitting part, where the relationship between UC power and the load power is provided. The power behavior of UC can be described by three line segments. For different P_L conditions, the power splitting rules are given as follows.

$$P_{\mathrm{C}}=\begin{cases}P_{\mathrm{L}}+P_{\mathrm{C,chg}},\ P_{\mathrm{L}}>-P_{\mathrm{C,chg}}\\ 0,\ -P_{\mathrm{C,chg}}<P_{\mathrm{L}}<P_{\mathrm{B,thd}}\\ \alpha(P_{\mathrm{L}}-P_{\mathrm{B,thd}}),\ P_{\mathrm{L}}<P_{\mathrm{B,thd}}\end{cases} \tag{4}$$

Eq. (4) decides the UC power, the battery serves the rest of the load power demand. It can be seen that there exist three key parameters in the strategy: the battery power threshold $P_{\mathrm{B,thd}}$, UC charge power $P_{\mathrm{C,chg}}$, and the power splitting fraction α.

3. MULTI-OBJECTIVE OPTIMIZATION

3.1 Optimization problem

In order to design a HESS with long life performance and relatively low cost, the optimal size and power splitting parameters should be acquired.

The optimization goals of the HESS could be concluded as two points: 1. Maximum the whole life mileage of the EV without a substitution of battery module. 2. Minimum the average cost of the power system during the whole life.

The NEDC driving cycle is used to evaluate the EV's performance in this work. As for the first point, EV's whole life mileage M_{life} can be predicted as follows.

$$M_{\mathrm{life}}=M_{\mathrm{NEDC}}A_{\mathrm{h,EOL}}/A_{\mathrm{h,NEDC}} \tag{5}$$

Where $A_{\mathrm{h,NEDC}}$ is the discharge ampere-hour throughput during a single NEDC cycle, and can be calculated as follows.

$$A_{\mathrm{h,NEDC}}=\frac{1}{3600}\int_0^{t_{\mathrm{NEDC}}} f_I(t)\mathrm{d}t \tag{6}$$

Where, $f_I(t)$ is defined as follows.

$$f_I(t)=\begin{cases}\left|I_{\mathrm{B,cell}}(t)\right|,\ I_{\mathrm{B,cell}}(t)<0\\ 0,\ I_{\mathrm{B,cell}}(t)\ge 0\end{cases} \tag{7}$$

Similarly, the NEDC average discharge current rate c_{NEDC} can be calculated as follows.

$$c_{\mathrm{NEDC}}=\frac{1}{2t_{\mathrm{NEDC,dch}}}\int_0^{t_{\mathrm{NEDC}}} f_I(t)\mathrm{d}t \tag{8}$$

According to the battery degradation model in 2.2, Eq. (5) can be further developed as the following equation.

$$M_{\mathrm{life}}=\frac{M_{\mathrm{NEDC}}}{A_{\mathrm{h,NEDC}}}\left(\frac{Q_{\mathrm{loss,EOL}}}{B(c_{\mathrm{NEDC}})\exp(-E_{\mathrm{a}}(c_{\mathrm{NEDC}})/RT)}\right)^{1/z} \tag{9}$$

For the second point, the normalized cost per 100km can be taken as the objective function. The whole life cost of the power system should include the following parts: 1. The HESS cost, which depends on the size of the battery and UC modules. 2. The electricity cost during the whole life. In each NEDC cycle, the consumed energy eventually comes from the battery, which can be calculated as follows.

$$E_{\mathrm{NEDC}}=\int_0^{t_{\mathrm{NEDC}}} P_{\mathrm{B}}(t)\mathrm{d}t \tag{10}$$

Therefore, the normalized cost per 100km C_{100km} can be expressed by the following equation.

$$C_{\mathrm{100km}}=\frac{100}{M_{\mathrm{life}}}\left(C_{\mathrm{HESS}}+\frac{A_{\mathrm{h,EOL}}}{A_{\mathrm{h,NEDC}}}\left|E_{\mathrm{NEDC}}\right|C_{\mathrm{Ele}}\right) \tag{11}$$

Where C_{ele} is the electricity price per Wh, and C_{HESS} is the total cost of HESS installation, both in RMB yuan.

Now the multi-objective optimization problem can be described as follows:

$$\min:\begin{cases}-M_{\mathrm{life}}(N_{\mathrm{UC,s}},N_{\mathrm{UC,p}},\alpha,P_{\mathrm{B,thd}})\\ C_{\mathrm{100km}}(N_{\mathrm{UC,s}},N_{\mathrm{UC,p}},\alpha,P_{\mathrm{B,thd}})\end{cases} \tag{12}$$

subject to

$$\begin{gathered}50\le N_{\mathrm{UC,s}}\le 170,\ 1\le N_{\mathrm{UC,p}}\le 3\\ 0.5\le\alpha\le 1,\ -15\mathrm{kW}\le P_{\mathrm{B,thd}}\le -2.5\mathrm{kW}\end{gathered} \tag{13}$$

The optimization variables and their boundaries are listed by Eq. (13). The UC charge power $P_{\mathrm{C,chg}}$ is not taken as an optimization variable for it changes in a very small range. It is set as a constant of 700W in this work.

The size of UC module and parameters of power splitting strategy are our concern. Since they are coupled to each other, it is better for us to optimize them simultaneously. Consider that the two objectives are conflicting to each other, the non-dominated sorting genetic algorithm II (NSGA-II) [8] is applied to solve the optimization problem. Then the Pareto front can be offered, which is considered as a reasonable tradeoff between the two objectives.

3.2 Results and discussion

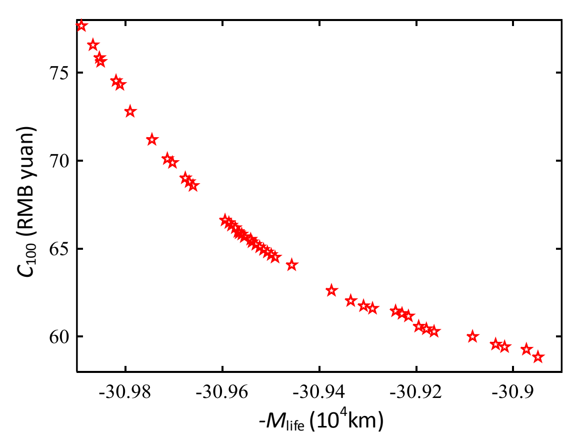

Fig 2 The Pareto front obtained by NSGA-II

By executing the NSGA-II several times, the Pareto front of the two objectives is acquired. The results are plotted in Fig 2.

In Fig 2, there are altogether 45 optimal solutions to form the Pareto front. The size of the UC module varies from 85 series 2 parallel to 142 series 3 parallel. This result suggests that the size of less than 2 parallel is not recommended, for it cannot lower the normalized cost per 100km C_{100km} significantly. Also, the size over 142 series is not recommended for it cannot extend the whole life mileage M_{life} significantly.

Every solution in the Pareto front is meaningful, for it reaches some kind of balance between the mileage and the cost, but the EV costumers may not buy it. To further investigate the difference in performance of those solutions, three of them are selected and their performance is compared. And the performance of the battery only (BTO) energy storage system is also compared. The comparison results are listed in Table 2.

Table 2 Vehicle and energy storage parameters

Item	BTO	HESS1	HESS2	HESS3
UC series	-	85	89	142
UC parallel	-	2	3	3
$P_{B,thd}$(kW)	-	-6.46	-4.97	-6.65
α	-	0.71	0.60	0.73
Average battery discharge rate(C)	0.427	0.265	0.265	0.264
Battery discharge ampere-hour throughput (Ah/NEDC cycle)	0.223	0.174	0.173	0.173
Electricity cost (¥/NEDC cycle)	1.762	1.863	1.859	1.858
Energy storage system cost(10^4¥)	7.20	12.91	15.14	18.80
M_{life}(10^4km)	24.45	30.90	30.96	30.99
M_{life} raised(%)	-	26.4	26.6	26.8
C_{100km}(¥)	45.57	58.84	65.92	77.66
C_{100km} raised(%)	-	29.1	44.7	70.4

From the table, it can be seen that application of HESS can raise M_{life} by at least 26% compared with the BTO system. The average battery discharge rate is significantly lowered, as well as the battery discharge ampere-hour throughput per NEDC cycle. However, the normalized cost per 100km C_{100km} is also raised. This comes from two reasons. Firstly, the energy storage system cost is directly raised due to the use of UC. Secondly, the energy waste from DC/DC converter and UC module has raised the electricity cost per NEDC cycle slightly.

With the increase of UC cells, the normalized cost per 100km increases directly. Compared with the BTO system, the cost increase varies from 29.1% to 51.9%, meanwhile the whole life mileage is raised by no more than 27%, which is shown in Fig 3.

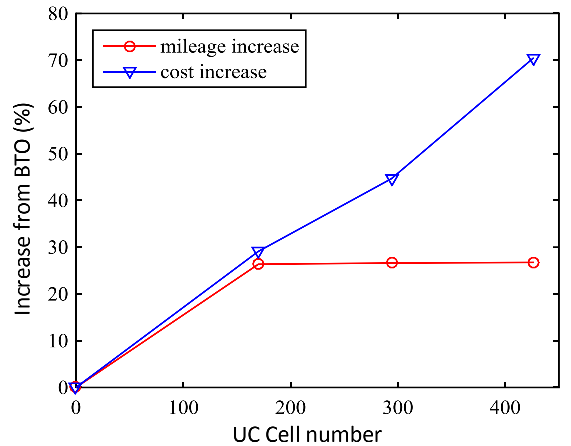

Fig 3 Comparison of different UC usage

Thus, from the economic point of view, it is recommended to choose the HESS size with the least UC cell number from the possible solutions. This is mainly because the current price of UC is still relatively high, which makes the increase in cost not bring about a corresponding increase in mileage.

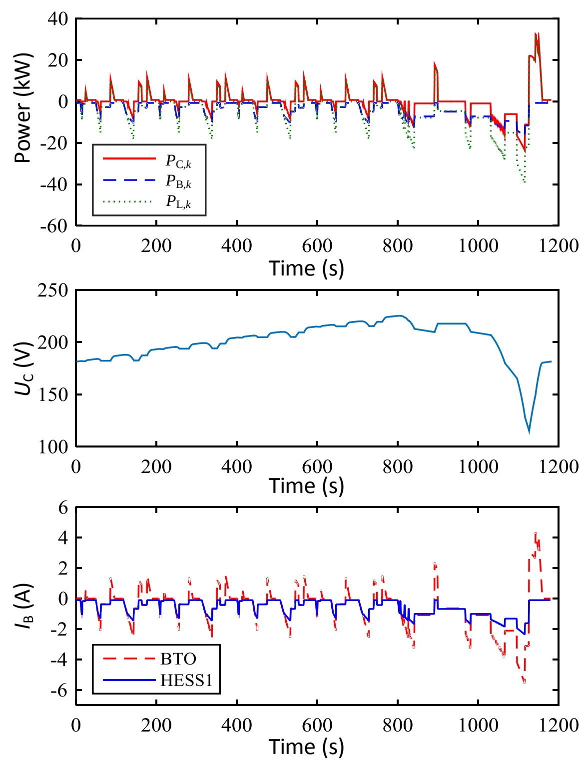

Fig 4 NEDC Performance of HESS type1

The power splitting performance of the first type HESS in Table 2 is plotted by Fig 4, where the configuration of the UC module is 85 series 2 parallel. From the figure, it can be seen that the UC module helps to reduce the battery current significantly.

4. CONCLUSIONS

A multi-objective optimization based HESS design method is presented in this work. The basic HESS configuration of EV is firstly provided. Then a degradation model of lithium battery and a practical rule based power splitting strategy are adopted. Based on that, the optimization problem is formulated to seize the optimal size and power splitting parameters. The whole life mileage and the normalized cost per 100km are the two objectives. NSGA-II is applied to solve the optimization problem, by which altogether 45 optimal solutions are given to form the Pareto front. Each solution in the Pareto front has reached a reasonable tradeoff between the two objectives. The whole life mileage can be raised by at least 26% with the use of the UC module. But the increase of UC cell number will bring the increase of normalized cost. Hence the optimal solution with the least UC cells in the Pareto front is recommended, whose normalized cost per 100km is raised by 29.1% compared with the BTO system.

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