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The battery-supercapacitor hybrid energy storage system in electric vehicle applications: A case study

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ABSTRACT

The hybrid energy storage system (HESS), which combines the functionalities of supercapacitors (SCs) and batteries, has been widely studied to extend the batteries' lifespan. The battery degradation cost and the electricity cost should be simultaneously considered in the HESS optimization. However, the continuous decline in the price of lithium batteries may weaken the effectiveness of HESS, as the battery degradation cost becomes less important. This paper analyzes the influence of different temperatures and battery prices on the integrated optimization of HESS, including the optimization of SC size and energy management strategy (EMS) for electric vehicle (EV) applications. Based on an average temperature, the HESS performance is examined considering a wide range of battery prices (from $143/kWh in 2028 to $257/kWh in 2018). Simulation results show that both the SC sizing and EMS optimization results are robust to the temperature and the battery price. In addition, the total cost of HESS for customers is shown to be 12% less than a battery energy storage system, even at low battery prices. The HESS is therefore validated to be effective in EV applications in the near future.

1. Introduction

Electric vehicles (EVs) are receiving considerable attention as effective solutions for energy and environmental challenges [1]. The hybrid energy storage system (HESS), which includes batteries and supercapacitors (SCs), has been widely studied for use in EVs and plug-in hybrid electric vehicles [2–4]. The core reason of adopting HESS is to prolong the life span of the lithium batteries [5], therefore the vehicle operating cost can be reduced due to the avoidance of replacing the battery pack during the vehicle life time [6]. A semi-active HESS employing only one DC/DC converter offers a good balance between performance and capital cost [7]. Thus a typical semi-active HESS, as shown in Fig. 1, is adopted in this study.

To effectively protect the battery by using the SC, both the SC size and the energy management strategy (EMS) should be optimized to reduce the HESS operating cost, which includes the electricity cost and the battery degradation cost [8]. EMS can be categorized as either on-line or off-line strategies. On-line strategies include, but are not limited to, the “all or nothing” control strategy [9], the filtration-based strategy [10], the rule-based control strategy [11], the model-predictive control strategy [12,13], equivalent consumption minimization strategy [14], and the fuzzy-logic control strategy [15]. The on-line strategies can be easily used in real-world controllers, but generally they cannot achieve optimal performance. In comparison, the off-line strategies, such as Pontryagin's minimum principle (PMP) [16] and dynamic programming (DP) approach [17,18], can achieve a globally optimal performance. However, it is difficult to employ these methods in practical applications due to their large computational cost [19]. Though PMP is promising in on-line applications, it is still difficult to identify the initial value of the co-state [20]. In terms of component sizing, the battery is generally sized to achieve the EV minimum mileage, while the SC size should be optimized to achieve the best performance, which is defined here as minimum operating cost [17]. Hung. et al. [7] proposed an integrated optimization approach to determine the best system design and energy management strategy. The integrated optimization problem for determining the best solution of SC size and EMS for an electric city bus is presented in Ref. [17], and it is verified that the SC sizing and EMS optimization processes influence each other and should be

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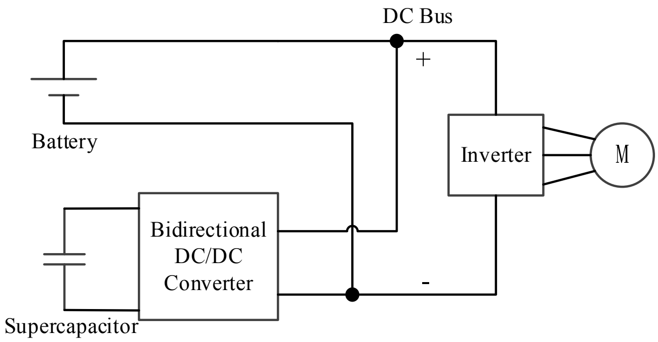


Fig. 1. The typical semi-active HESS topology.

considered simultaneously. Finally, a rule-based strategy is carefully designed and tuned based on the DP result [17]. A summary of the above-mentioned strategies is listed in Fig. 2.

It has also been shown that the environment temperature significantly influences the HESS optimization because the battery resistance and degradation rate vary significantly with the temperature [6]. Battery degradation becomes particularly severe at low temperature environments due to lithium plating of the negative electrode [21], and this will significantly increase the battery degradation cost. We note that the overall efficiency of HESS depends on the efficiency of the DC/DC converter. With the development of power electronics, the average efficiency of DC/DC converter is almost 95%, thus the efficiency of HESS is currently comparable with a battery energy storage system (BESS) [22]. As shown in Fig. 1, the SC should be used frequently and dramatically to reduce the battery degradation cost; however, the energy density of SC is relatively low. Thus the reduction amount of the battery degradation cost directly determines the amount of SC that should be adopted and how often SC operates. Furthermore, the battery degradation cost is proportional to the battery price (i.e., capital cost of the battery pack).

It is obvious that the HESS is promising and worth using widely when the battery is expensive. However, the price of lithium batteries has continuously decreased in recent years [23]. Therefore, temperature and battery cost should be considered in the HESS optimization, and the HESS performance should be quantitatively examined to verify its prospects in EV applications in the coming years.

To the best of our knowledge, the influence of different temperatures and battery prices on HESS optimization, which includes both the SC sizing and the EMS optimization, has not been reported in the existing literature. First, the influence of temperatures and battery prices on the integrated optimization of HESS, including the SC sizing and the EMS optimization, is analyzed. Simulation results show that the optimal SC size does not vary significantly with temperature and battery price. Based on the SC sizing result, the optimal on-line EMS is determined based on DP results. It is shown that a rule-based EMS can be used with acceptable performance. Finally, a case study is conducted considering different temperatures. Moreover, the HESS performance is examined as the battery price varies over a wide range (from \$143/kWh in 2028 to \$257/kWh in 2018). Simulation results show that the total cost of HESS for customers is reduced by more than 12% when compared to BESS, even at low battery prices. Therefore, it is verified that the HESS is still a promising technology in EV applications in the near future.

This paper is organized as follows: In Section 2, the dynamic model of the HESS is illustrated. Section 3 analyzes the influence of temperature variations and battery prices on the integrated optimization. In Section 4, a case study is conducted which considers the year-round temperatures and different battery prices. In comparison to the BESS, the HESS prospect is shown in Section 5. Conclusions are presented in Section 6.

2. System modeling

2.1. Hybrid energy storage system dynamics

As shown in Fig. 1, the bidirectional DC/DC converter is used to interface the SC with the DC bus. The controller uses measurements from SCs, batteries, and the powertrain to determine how much power to draw from the SC via the bi-directional DC/DC converter [6]. The relationship between the powertrain power demand, SC power, battery power, and DC/DC converter power can be determined [17]. The *Rint-Capacity* model is adopted to represent the SC response, and the battery behavior is represented by the *Rint* model due to their simplicity and sufficient accuracy. The parameters of the battery cell and the SC module are listed in Tables 1 and 2, respectively. Readers can refer to [6] and [17] to obtain more information about the adopted SC module and battery cell.

A dynamic battery degradation model, which is effective under various temperature conditions, has been proposed in Ref. [6], and

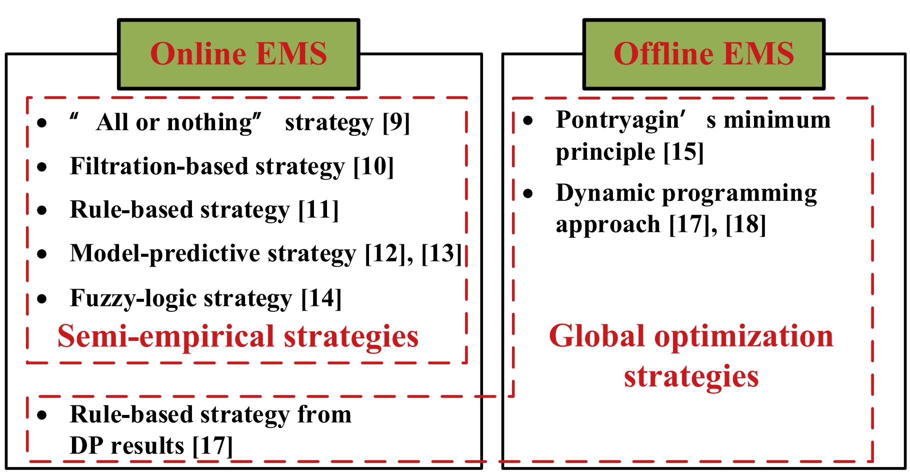


Fig. 2. Summary of the typical EMS for HESS.

Table 1
Parameters of the SC module.

Parameter	Value
Maximum voltage	27 V
Capacitance	140 F
Stored energy	14.2 Wh
Specific power	1700 W/kg
Specific energy	2.3 W/kg
Operating temperature range	−40 to 65 °C

Table 2
Parameters of the battery cell.

Parameter	Value
Cell nominal voltage	3.2 V
Cell capacity	60 Ah
Cell stored energy	0.192 kWh
Cell mass	2 kg
Discharging temperature range	−20−55 °C
Charging temperature range	0 to 45 °C
Recommended SOC usage window	10 to 90%

is based on a semi-empirical life model [24]. Within the model, four parameters: time, temperature, depth of discharge, and discharge rate are considered, as shown in Eq. (1):

$$Q_{loss} = Ae^{-\left(\frac{E_a + B \cdot C\_Rate}{zR(|T_b - T_{bat}| + T_C)}\right)}(A_h)^z, \tag{1}$$

where Q_{loss} is the battery capacity loss (which is normalized), A is the pre-exponential factor, E_a is the activation energy (J), R is the gas constant (J/(mol·K)), A_h is the amp-hour throughput, C_Rate is the battery discharge rate, B is the compensation factor of C_rate, and z is the time factor. In addition, T_b is the baseline temperature where the battery is assumed to work most effectively, and T_C is the compensation temperature. After experimental calibration [6], the final degradation model for the adopted battery is given as

$$Q_{loss} = 0.0032e^{-\left(\frac{15162 - 1516C\_Rate}{R(|285.75 - T_{bat}| + 265)}\right)}(A_h)^{0.849}. \tag{2}$$

The influence of different discharge rates and temperatures on the battery degradation rate is depicted in Fig. 3 (a). It is shown that the battery degradation rate increases with the increase in discharge rate and the absolute value of (T_{bat}-T_b). Regardless of the discharge rate, the battery experiences minimum degradation at about 15 °C. Moreover, as the discharge rate increases, the battery temperature influences the degradation rate more significantly. Therefore, temperature should be carefully considered in the HESS optimization process. The battery degradation model has been validated by the previous experiment. For the readers' convenience, the experimental verification result is shown in Fig. 3 (b). Due to the space limitations, this topic is not further extended, and the detailed information is provided by Ref. [6].

2.2. Electric vehicle modeling

A basic bus model is also provided in Ref. [17]. Given that the Chinese government requires the mileage of electric bus to be more than 150 km at a constant speed (40 km/h) on a flat road [25], the number of battery cells is set to 600 (5 parallel and 120 series connection) [17]. The analysis of this paper is conducted assuming the China Bus Driving Cycle (CBDC), which is a good representative of real-world driving cycles for public buses [26].

Based on the bus parameters listed in Table 3, the speed and power demand profiles of CBDC are shown in Fig. 4.

3. Integrated optimization of HESS

An integrated optimization analysis to determine the best solution of component size and EMS of HESS was conducted in Ref. [17]. It has been shown that the SC size significantly influences the EMS design, thus they should be optimized together. The integrated optimization is based on a preset cost function, which takes both the battery degradation cost and the electricity cost into consideration. To understand the maximum benefit of HESS, the DP approach is adopted to obtain the global optimization result. The HESS operation cost at any instant k is defined as follows:

$$\text{Minimize}\ \left\{\sum_{k=1}^{k=k_{max}} \frac{[Cost_{bat,loss}(k) + Cost_{ele}(k)]}{L_c}\right\}, \tag{3}$$

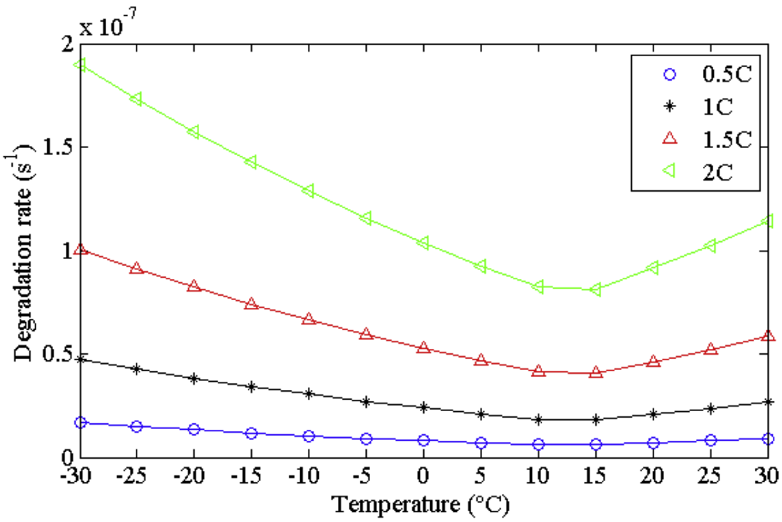
where

$$Cost_{bat,loss}(k) = \frac{C_{bat}V_{bat}price_{bat}}{0.2 \times 1000} \times \left[9.78 \times 10^{-4}\frac{|I_{bat}(k)|T_s}{3600M_{bat}}e^{-\left(\frac{15162 - 1516C\_Rate}{0.849R(|285.75 - T_{bat}(k)| + 265)}\right)}Q_{loss}(k-1)^{-0.1779}\right],$$

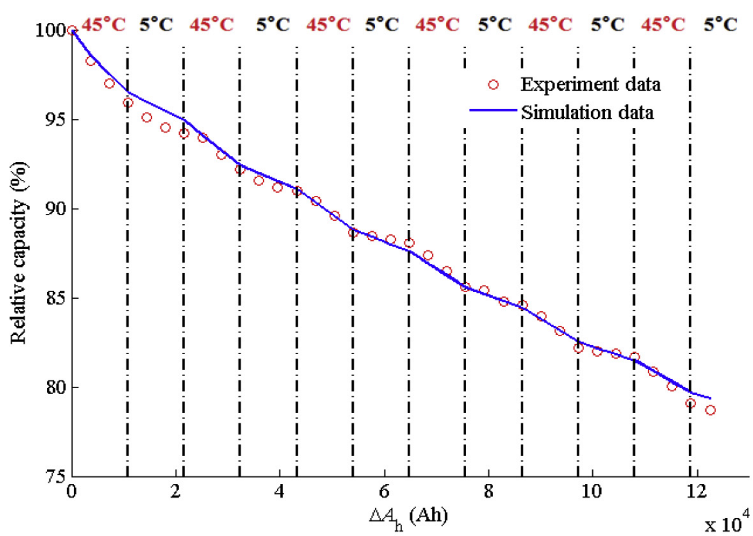
$$Cost_{ele}(k) = \frac{price_{ele}T_s}{3600}[P_{SC}(k) + P_{bat}(k)],$$

where T_s is the sample time (which is set to 1s), $Cost_{bat,loss}(k)$ is the battery degradation cost of the time instant k, $price_{bat}$ and $price_{ele}$ are the battery and electricity prices, respectively, C_{bat} is the capacity of the battery pack, V_{bat} is the voltage of the battery pack, M_{bat} is the number of parallel strings in the battery pack, $Cost_{ele}(k)$ is the electricity cost, $I_{bat}(k)$ is the average battery current, Q_{loss} (k-1) is the cumulative battery degradation at instant k-1, $P_{SC}(k)$ is the SC power, $P_{bat}(k)$ is the battery power, and L_c is the drive cycle distance. The SC initial voltage is set to 90% of its maximum value. The SC voltage is strictly controlled above 50% of its maximum value because the SC efficiency is poor when the SC voltage is low. It is assumed that the battery cannot be used when its capacity reduces to 80% of its initial value, thus the battery capacity usage is 20% of its capacity, as shown in Eq. (3). The battery degradation cost is proportional to the battery degradation and price, and the car owners should pay for it when they replace the battery pack after it degrades to 80% of its capacity. More detailed information about the DP algorithm is presented in Ref. [17].

As shown in Eq. (3), the battery price is an important parameter which can dramatically influence the optimization result. Thus the effect of battery price should be carefully examined, as lithium battery prices have decreased rapidly in recent years. To be specific, the cost of battery packs used by market-leading EV manufacturers



(a) Battery degradation rates under different temperatures and discharge rates



(b) Experimental verification result

Fig. 3. Battery degradation model verification results.

have declined by 8% annually between 2007 and 2014 [27]. Analysts from McKinsey stated in 2012 that \$200/kW·h could be reached in 2020, and \$160/kW·h could be reached in 2025 [28]. Furthermore,

Table 3
Parameters of the city bus.

Parameter	Value
Vehicle mass	15,500 kg
Vehicle length	12 m
Wheel radius	0.5 m
Gravity acceleration	9.8 m s^{-2}
Air drag coefficient	0.7
Front area	7.5 m^2
Air density	1.29 kg m^{-3}
Motor efficiency	85%
Transmission efficiency	90%
Regenerative braking efficiency	65%
DC/DC converter efficiency	95%

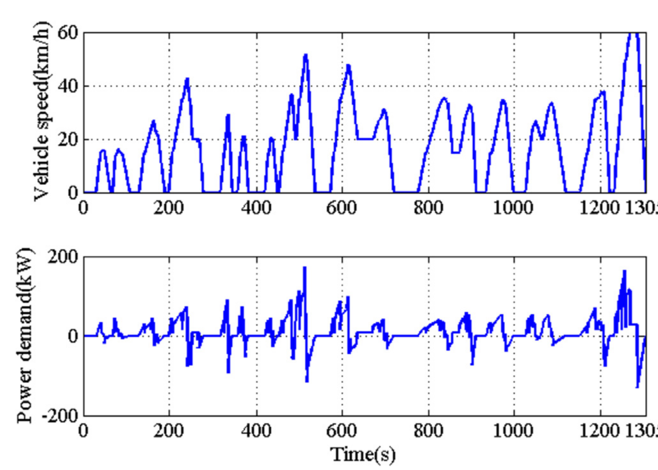


Fig. 4. Speed and power profiles of China Bus Driving Cycle.

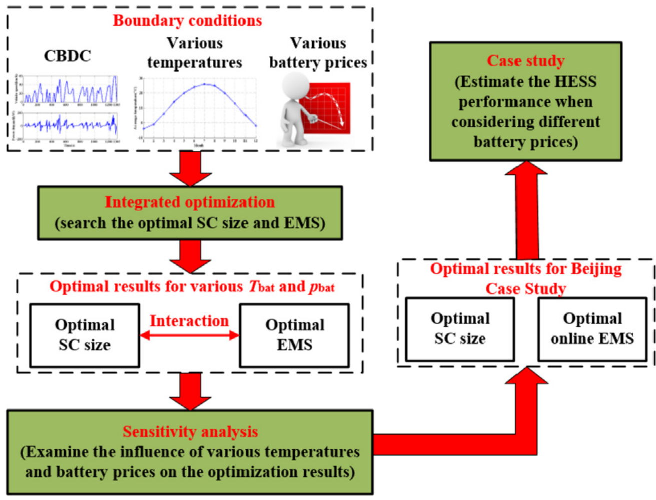


Fig. 5. The process of the case study.

BEVs are commonly understood as becoming cost-competitive with conventional vehicles when the battery price is \$150/kW·h [29]. For now, the cost of a lithium ion battery pack is about \$257/kW·h (1800RMB/kW·h) in China.[1] To present the influence of battery prices on the HESS optimization result, including both the SC sizing and EMS design results, battery prices of \$200/kW·h (1400RMB/kW·h, which is assumed to be realized after 5 years) and \$143/kW·h (1000RMB/kW·h, which is assumed to be realized after 10 years) are also considered in the following analysis. The electricity price is set to \$0.11/kW·h (0.8RMB/kW·h), and the SC price is \$15000/kW·h according to Ref. [30].

In addition, different temperatures are also considered in this study, as temperature significantly impacts the battery degradation cost. The analysis process is depicted in Fig. 5. The influence of various battery prices and temperatures on the optimization result is first investigated. Based on the optimal SC size and optimal online EMS, the benefit of HESS can be accurately analyzed through the case study.

4. Influence of battery price and temperature on HESS optimization results

As mentioned in the sequel, the battery cell number is fixed at 600 based on the minimum mileage requirement while the SC size is optimized using the DP approach. In the SC sizing process, the number of the SC modules in series varies from 1 to 6, and the number of parallel strings varies from 15 to 29. The HESS operating cost of each SC size is minimized using the DP approach, and then the optimal SC size, i.e., the size with the minimum overall operating cost, is determined.

The optimal SC sizing results under different battery prices and temperatures are shown in Fig. 6. It can be seen that the sizing results can be split into two sections, which have a significant difference in their relationship between the SC capital cost and the HESS operation cost. Initially, the operating cost can be rapidly reduced with increasing SC capital cost. When the SC capital cost reaches a certain value, however, the operating cost begins to decrease less rapidly with the increase in SC capital cost. Therefore it is less worthwhile to increase the SC amount. Consequently, the SC cost at the “knee” of the curve can be regarded as the optimal solution [17].

As shown in Fig. 6, the operating cost significantly increases with increases in the battery price and the absolute value of (T_{bat}-T_b). However, the optimal SC size does not change significantly, which means that the SC sizing result is robust to battery price and temperature variations. To be specific, Fig. 6 (a) and Fig. 6 (b) show that the SC sizing results have the same trend when the battery price is constant, and it is validated for different prices. Similarly, Fig. 6 (c) and Fig. 6 (d) show that the SC sizing results have the same trend at one temperature even when the battery price significantly changes. Thus it is verified that the SC sizing result is robust to the variances of battery price and temperature. The optimal SC size can be determined as 50 modules (2-parallel and 25-series configuration), which will be adopted in the following analysis.

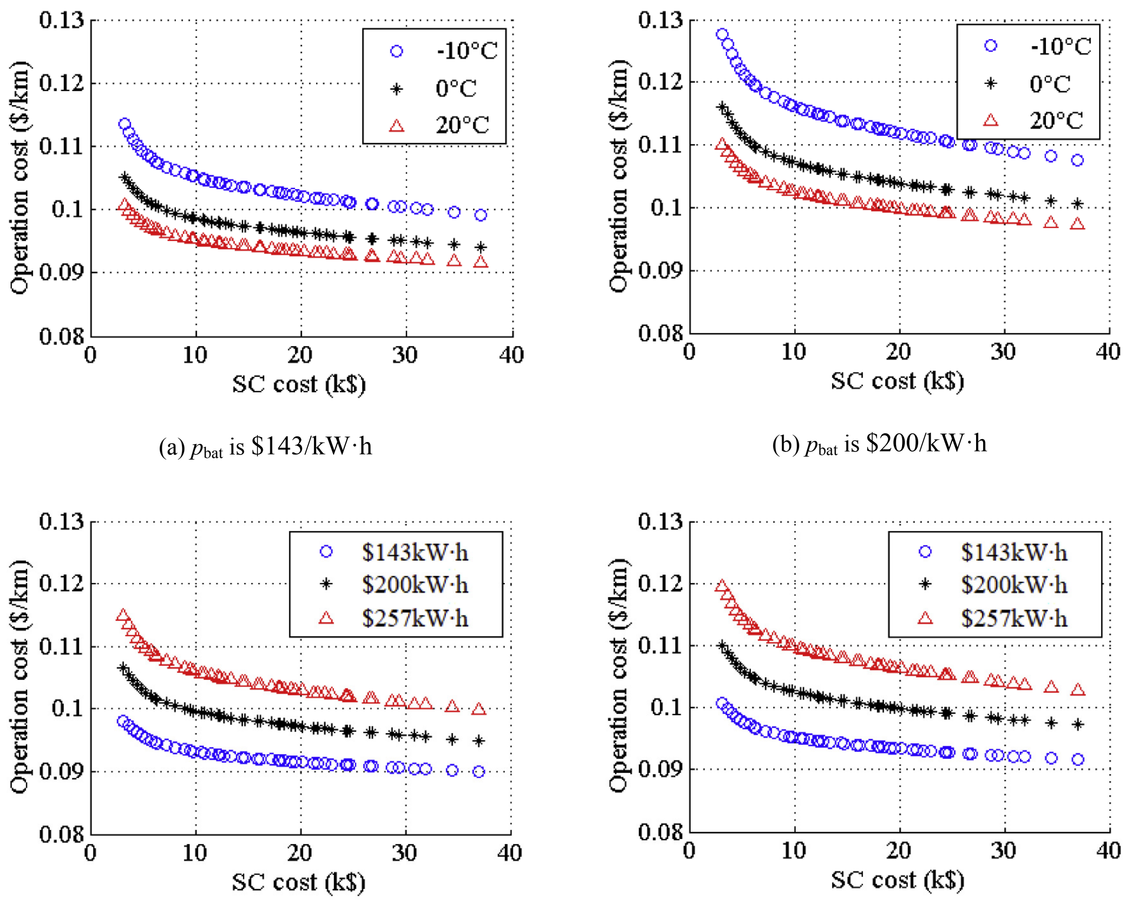
After the SC size optimization the optimal EMS, which can be used in on-line applications, can be determined based on DP results [17]. More specifically, the optimal on-line EMS should be designed for various battery prices and temperatures to ensure that the EMS is robust and optimal under different conditions. The DP results under various battery prices and temperatures are presented in Fig. 7, showing that the relationship between the total power demand P_{demand} and SC power P_{SC} can be divided into three linearized sections. Specifically, under braking conditions, the SC tends to absorb all regenerative energy and the battery tends to be idle. In addition, under traction conditions, the SC does not support any power when P_{demand} is less than a threshold P_{min}. When P_{demand} exceeds P_{min}, the battery tends to output a constant power P_{min}, and the SC supports the remaining power.

It is seen that P_{min} decreases with both decreasing battery price and $|T_{bat}$-$T_b|$, because the battery tends to supply more power to the load when the battery degradation is reduced. The reason is that the efficiency of SC is low when its voltage decreases to a low value. As shown in Fig. 7, P_{min} changes slightly under different battery prices and temperatures. Simulation results show that P_{min} varies from 24 kW to 30 kW when the battery price varies from \$143/kW·h (in 2028) to \$257/kW·h (in 2018) and the temperature varies from −10 °C to 20 °C. Even if P_{min} slightly changes under different conditions, the DP results show the same characteristics under different temperatures and battery prices. As shown in Fig. 7 (a) and Fig. 7 (b), the DP results are similar when the temperature increases. This is also verified in Fig. 7 (c) and Fig. 7 (d) when the battery price increases from \$143/kW·h (in 2028) to \$200/kW·h (in 2018). When comparing the results in Fig. 7 (a), Fig. 7 (c), Fig. (e), and Fig. (f), it can be found that the DP results are similar when the temperature varies from −10 °C to 20 °C. Thus the simulation results in Fig. 7 show that the optimal EMS of HESS is robust to temperatures and battery prices.

Although the DP approach can find the globally optimal solution, it is still difficult to be adopted in practical applications due to its high computational cost and the requirement of future information. Based on the intuitive guidance provided by DP results, however, a near-optimal rule-based EMS, which includes five modes, can be therefore proposed as shown in Fig. 8. In addition to the rules derived from the DP results, another two rules are applied:

1) The battery is required to charge the SC with constant value P_{ch} when the SC voltage V_{SC} is less than half of its maximum voltage $0.5V_{SC,max}$.
2) The energy stored in the SC should be evaluated before assigning power requirement to SC. To be specific, the SC supplies P_{SC} when P_{SC} is less than or equal to its maximum power $P_{SC,max}$, as shown in Eq. (4). Otherwise, the SC supplies as much power as possible and the battery supplies the rest, i.e.:

[1] Throughout this study, all values denominated in \$ are based on 2012 constant US\$, unless otherwise noted.



(a) p_{bat} is \$143/kW·h

(b) p_{bat} is \$200/kW·h

(c) T is 10°C

(d) T is 20°C

Fig. 6. The influence of temperatures and battery prices on SC sizing results.

$$P_{SC,max} = \frac{C_{SC}}{2T_s}\left(V_{SC}^2 - \frac{1}{4}V_{SC,max}^2\right) \geq P_{SC}, \tag{4}$$

where C_{SC} is the capacity of the SC pack. As mentioned above, P_{min} varies from 24 kW to 30 kW in the DP results. Thus its average value of 27 kW is employed in the on-line EMS.

5. Case study

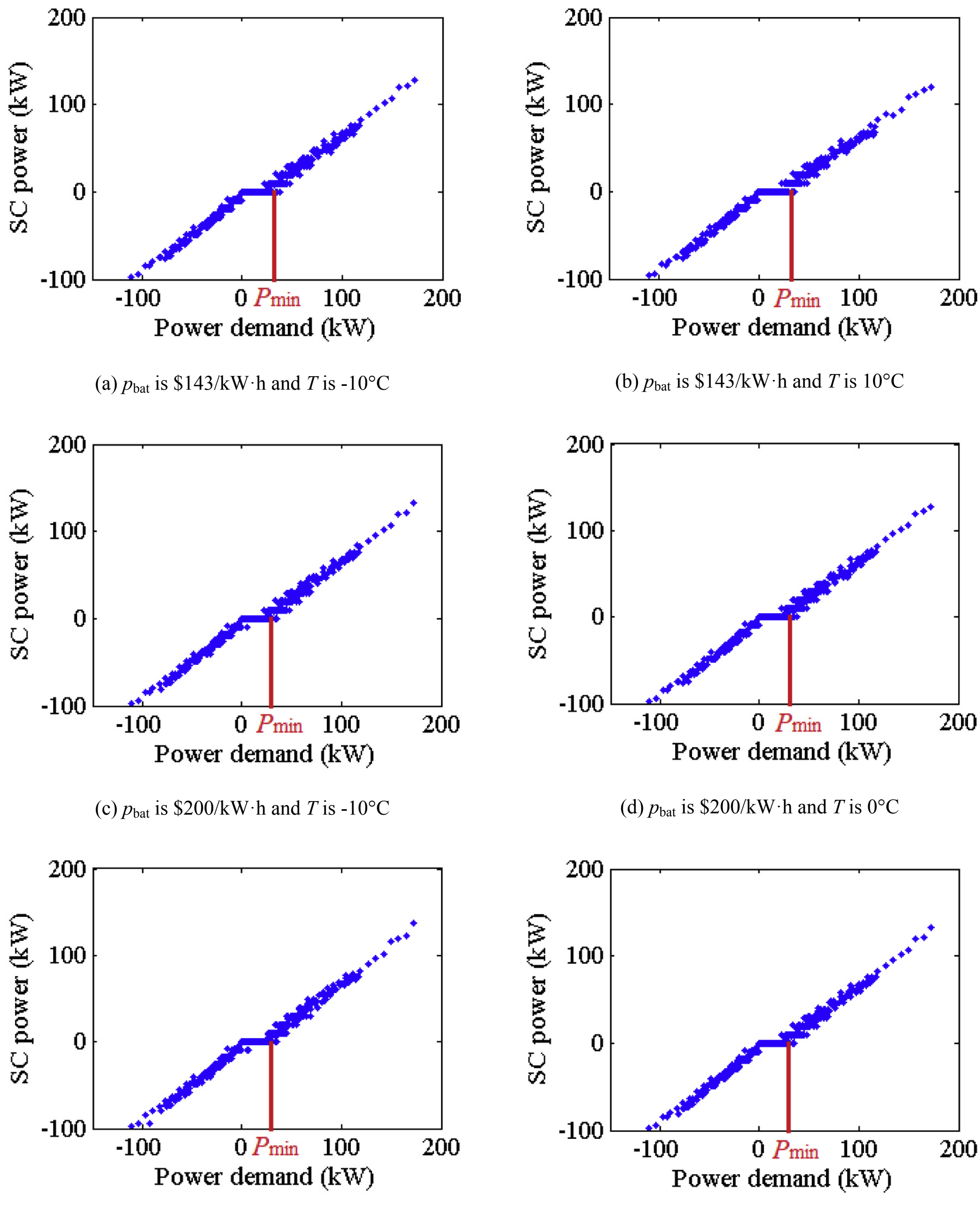
Based on the optimization results presented in Section 4, a case study of Beijing is conducted in this section to comprehensively estimate the HESS benefit in EV applications. The average temperatures of different months in Beijing, as shown in Fig. 9, are considered in the case study. The maximum temperature is 26 °C in July, while the minimum temperature is −4 °C in January. April and October are the best months for the battery in terms of degradation because they have the most appropriate temperatures.

In the case study it is assumed that the electric bus works 365 days a year. The daily mileage of electric buses in China is assumed to be 200 km based on results provided in Ref. [31]. This means that the electric bus runs approximately 34 CBDCs per day. In the case study, the SC is set to its optimal size (2 parallel and 25 series connection), and the optimal on-line EMS shown in Fig. 8 is adopted. Three battery prices, i.e., \$257/kW·h (in 2018), \$200/kW·h (in 2023), and \$143/kW·h (in 2028) are considered.

The overall electricity cost does not change with the battery price, while it changes slightly with temperature. When compared to the battery degradation cost, as shown in Fig. 10, the electricity cost is overall constant and about \$0.08/km. The battery degradation cost is proportional to the battery price, and is significantly influenced by the temperature. For a battery price of \$257/kW·h (in 2018), the battery degradation cost varies from \$0.029/km to \$0.047/km, which is less than the electricity cost. As described earlier, the battery degradation cost achieves minimum values in April and October because of their appropriate temperatures.

HESS was originally developed to reduce the high battery replacement cost. Obviously, the benefits of adopting the HESS in EV applications are weakened as the battery price decreases. Thus the operating cost of HESS should be compared to that of BESS to show the benefits of HESS. As shown in Fig. 11 (a), the electricity cost of BESS is a bit lower than that of HESS, as BESS has a higher efficiency because no DC/DC converter is used. The electricity cost of BESS also changes slightly with temperature because the battery resistance is not constant. As shown in Fig. 11 (b), the battery degradation cost of BESS varies from \$0.066/km to \$0.104/km when the battery price is \$257/kW·h (in 2018), which is significantly higher than that of HESS. Although the electricity cost is slightly increased, the battery degradation cost can be reduced up to by 50% through adopting HESS. It should be noted, however, that the capital cost of HESS is higher.

To comprehensively evaluate the HESS benefit, a 10-year



(a) p_{bat} is \$143/kW·h and T is -10°C

(b) p_{bat} is \$143/kW·h and T is 10°C

(c) p_{bat} is \$200/kW·h and T is -10°C

(d) p_{bat} is \$200/kW·h and T is 0°C

(e) p_{bat} is \$257/kW·h and T is -10°C

(f) p_{bat} is \$257/kW·h and T is 20°C

Fig. 7. The influence of temperatures and battery prices on the EMS optimization results.

scenario is chosen. We assume that the battery should be replaced when its capacity is reduced to 80% of its initial value. Based on the simulation results shown in Figs. 10 and 11, the total costs of HESS and BESS during 10 years are summarized in Table 4. BESS has a higher efficiency in our results, so there is 6% more electricity cost under HESS. In addition, the HESS approach requires 39.4% more initial capital cost than BESS. In the summary presented in Table 4, the total capital cost of the SC and DC/DC converter is assumed to decline by 1% annually, which is conservative when compared to the assumed reduction rates of battery prices in this paper. The HESS benefit is obtained by increasing the time between replacements of the battery pack. For the BESS, the battery pack will be replaced twice during the 10 years, which will significantly increase the cost. In contrast, the original battery packs of the HESS can be still effective after 10 years of operation. Based on current prices the total cost of HESS, including capital cost, electricity cost,

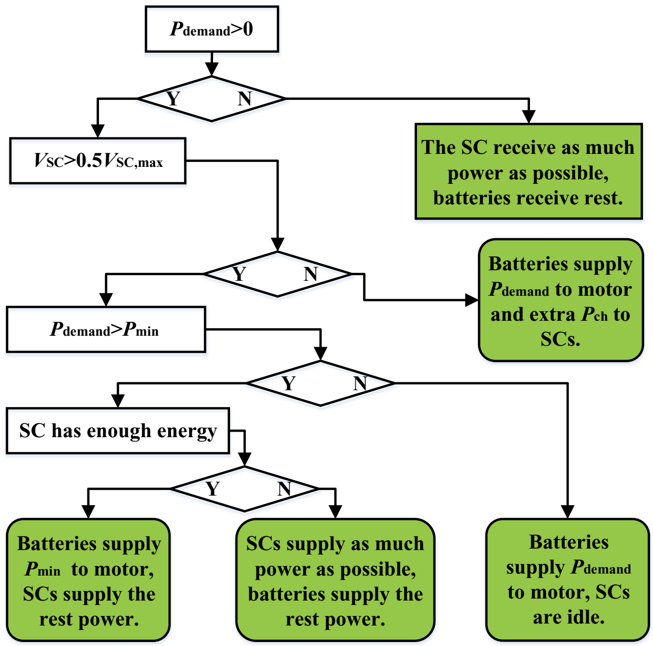


Fig. 8. The rule-based EMS for online applications.

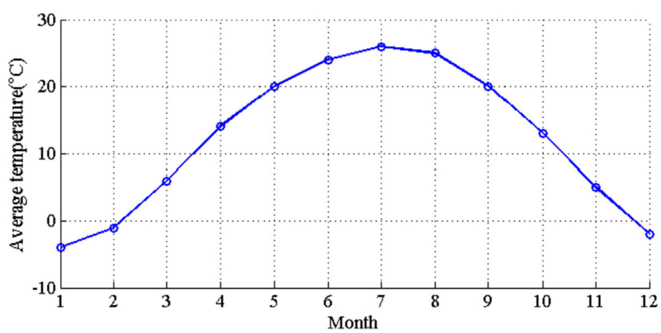


Fig. 9. The average temperatures of Beijing.

and battery replacement cost, is 25.9% less than that of BESS. With the battery price decreasing, the benefit of HESS will be reduced. However, based on these results the HESS should still have potential in future vehicle applications, as the total cost of HESS is predicted to be 12% less than that of BESS when the battery price reduces to $143/kWh (in 2028), which is assumed to be realized 10 years later. Therefore, even though battery prices may decrease

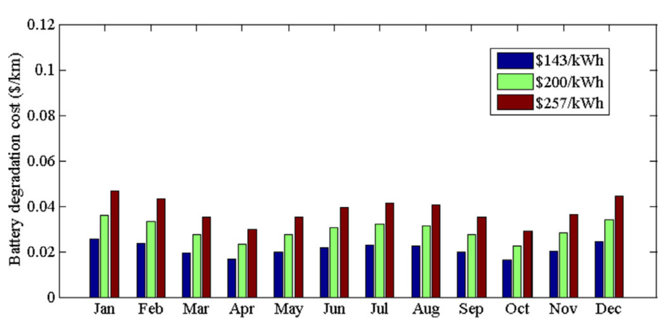


Fig. 10. HESS battery degradation cost in Beijing over the entire year.

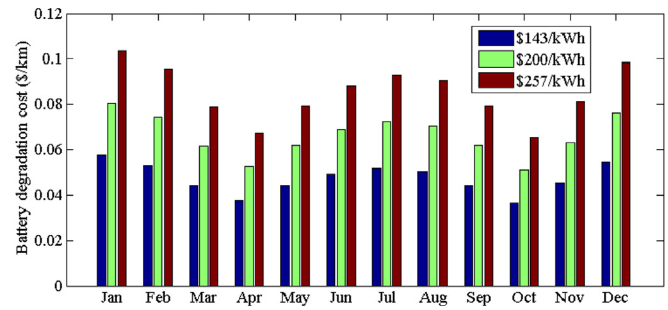


Fig. 11. BESS battery degradation cost in Beijing over the entire year.

Table 4
HESS and BESS cost over 10-year operation in Beijing.

Type	HESS			BESS		
Battery price ($/kWh)	143	200	257	143	200	257
Capital cost (k$)	34.1	41.7	49.2	16.5	23.2	29.8
Electricity cost (k$)	56.4	56.4	56.4	53.2	53.2	53.2
Battery replacement cost (k$)	0	0	0	33.1	46.3	59.5
Total cost (k$)	90.5	98.1	105.6	102.8	122.7	142.5
Cost reduction (%)	12.0	20.1	25.9	NaN	NaN	NaN

quickly in the next 10 years, the HESS will still be effective in EV applications.

The comparison is significantly influenced by the characteristics of the driving cycle. It has been found that actual driving cycles are generally more intense than CBDC [32]. This will increase the HESS benefit because the battery degradation cost will be further increased [17]. The recovery value of HESS and BESS is out of the scope of this paper. The BESS has high recovery value after 10-year operation because the second battery replacement happens in the final stage, indicating that the battery pack is still new when the EV is scrap. In contrast, the battery capacity of HESS is close to 80% after 10-year operation. However, the recovery value of the SC pack is still high because the SC cycle life can be longer than 1,000,000 duty cycles [33]. The power split between battery and SC under CBDC is shown in Fig. 12. It can be seen that fluctuations in the battery power profile are well suppressed due to the effective usage

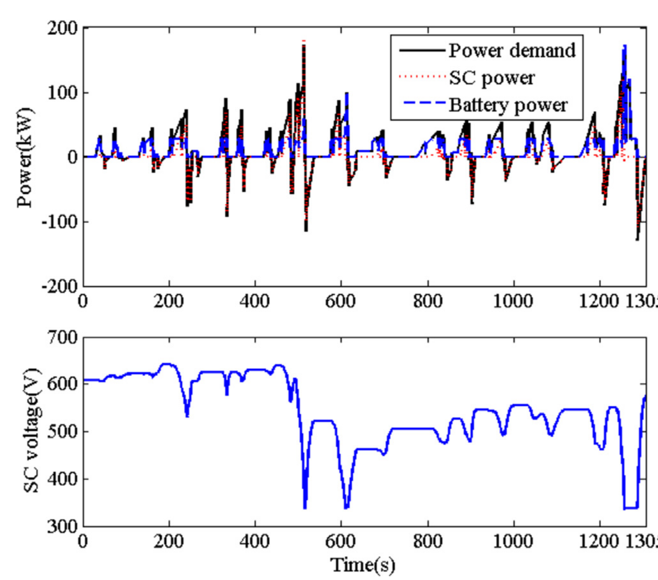


Fig. 12. The power split result and the SC voltage with the proposed on-line EMS.

of SC modules, therefore the battery degradation can be significantly reduced, though the battery power is high at the end of the drive cycle due to the exhaustion of SC. In fact, there is no full cycle for the SC because its voltage is critically controlled. As shown in Fig. 12, in terms of the SC power profile, there are at most two full equivalent cycles. Hence, after 10 years of operation, the SC cycle number is 250,000, a quarter of its life time. This implies that the SC will still be valuable after 10 years of operation.

6. Conclusion

This paper investigates the influence of different battery prices and temperatures on an optimized HESS, including the optimization of SC size and on-line EMS. The sizing result shows that the optimal SC size is robust to variations in battery price and temperature. In addition, DP results under various battery prices and temperature are determined, which also show robustness under different conditions. The relationship between the total power demand and SC power can be divided into three linearized sections, therefore a near-optimal rule-based EMS can be used for on-line implementation.

Based on the above optimization results, a case study of Beijing is conducted to comprehensively evaluate the benefits of HESS when compared to BESS. The simulation results show that the total cost of HESS during a 10-year operation, including capital cost, electricity cost, and battery replacement cost, is 25.9% less than the one of BESS under current battery prices. Furthermore, HESS will still be beneficial in the near future because the total cost of HESS is predicted to be 12% less than that of BESS when the battery price reduces to $143/kWh, which is assumed to be realized 10 years later (in 2028). Therefore, even though the battery price may decrease in the near future, the HESS can still be effective in EV applications.

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