Energy management strategies comparison for electric vehicles with hybrid energy storage system

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HIGHLIGHTS

• Different control strategies compared for battery/supercapacitor hybrid energy systems.
• A dynamic battery degradation model is adopted to evaluate the battery capacity loss.
• Fuzzy-logic and rule-based controllers perform better along certain driving cycles.
• The comparison result is validated by the dynamic programing result.
• The system life cycle cost is dramatically reduced when supercapacitors are adopted.

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ABSTRACT

This paper deals with the real-time energy management strategies for a hybrid energy storage system (HESS), including a battery and a supercapacitor (SC), for an electric city bus. The most attractive advantage deriving from HESSs is the possibility of reducing the battery current stress to extend its lifetime. To quantitatively compare the effects of different control strategies on reducing battery degradation, a dynamic degradation model for the LiFePO4 battery is proposed and validated in this paper. The battery size is optimized according to the requested minimal mileage, while the size of SC is optimized based on the power demand profile of the typical China Bus Driving Cycle (CBDC). Based on the optimized HESS, a novel fuzzy logic controller (FLC) and a novel model predictive controller (MPC) are proposed and compared with the existing rule-based controller (RBC) and filtration based controller (FBC), after all the controllers are tuned to their best performance along the CBDC. It turns out that FLC and RBC achieve the best performance among the four controllers, which is validated by the DP-based result. Furthermore, about 50% of the HESS life cycle cost is reduced in comparison with the battery-only configuration. In addition, the controllers are also compared along the New European Driving Cycle (NEDC), which represents another normalized driving cycle. The results show that the RBC, MPC, and FLC achieve a similar performance, and they reduce about 23% of the HESS life cycle cost when compared to the battery-only configuration. The RBC and FLC are regarded as the best choices in practical applications due to their remarkable performance and easy implementation.

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1. Introduction

Energy storage systems (ESSs) have a crucial role in hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and all-electric vehicles (EVs) [1–3]. Each vehicle application has a unique set of requirements on the battery, but a common thread among them is long life cycle [4]. EV applications stress the battery more than the PHEV and HEV applications do because they use a large fraction of the available energy (~80% for an EV, ~50% for a PHEV, but ~10% for a HEV) [5]. In addition, batteries used in EVs often encounter instantaneous power demand, thus they tend to perform frequent charge and discharge operations, which have an adverse effect on battery life [6–8]. This is one of the main reasons that discourage people from using EVs, therefore it is important to seek solutions to extend battery lifetime.

One possible solution is to use hybrid energy storage systems (HESSs), which combine the functionalities of supercapacitors (SCs) and batteries. Here, the SC will absorb regenerative energy
and assist the battery during discharge. This technology utilizes the unique advantages of SCs that offer relatively high power density, yet low energy density, when compared to LiFePO4 batteries. Generally, HESSs can be classified into three major types: passive, semi-active, and fully-active. In passive HESSs, the battery and SC packs are connected in parallel and directly coupled to the DC bus [9,10]. In a fully-active HESS, two DC/DC converters and an additional control circuit are involved to decouple the battery and SC with the DC bus [11,12]. The passive HESS is the least-cost topology; however, the SC cannot be used effectively to achieve a satisfactory performance. The fully-active HESS achieves the best control effect due to its flexibility. Nonetheless, this topology demands compromise in terms of cost, weight volume, efficiency, and simplicity. The semi-active HESS, which only employ one DC/DC converter, has a good balance of performance and system cost [13,14]. Therefore, a semi-active HESS, in which a bi-directional DC/DC converter is used to interface the SC with battery/DC bus, is applied in this study.

The main purpose of using an HESS is to extend the battery lifetime and decrease the life cycle cost of the ESS. However, most of the past work on the control strategy optimization for HESSs only considered several simple indexes, such as, the root mean square and the peak values of the battery current, to evaluate the battery capacity loss. Thus, a dynamic battery capacity degradation model, based on the Arrhenius degradation model, is proposed and employed in this study. The parameters in this model have been calibrated via experimental data by using the genetic algorithm.

A variety of controllers for HESSs have been designed and discussed in the literature. For instance, Allègre et al. [15] presented a “bang-bang” control strategy, which uses the SC when its state of charge (SOC) is above a definite value, and the battery is only used when the SC is discharged. Similarly, Trevão et al. [16] performed a rule based controller (RBC) to simultaneously consider the total power demand and the SOCs of the battery and SC. Meanwhile, Jaafar et al. [17] used a filtration based controller (FBC) to separate the power demand of the EV traction system into low-frequency and high-frequency components, with the high-frequency component supplied by the SC to keep the battery current profile smooth. A model predictive controller (MPC) is proposed and experimentally verified by Hredzak et al. [18]. The MPC limits the rate of change of the battery current to extend its lifetime. Ferreira et al. [19] introduced a fuzzy logic controller (FLC) for the HESS to reduce the peak current of the battery. Moreno et al. [20] proposed a very efficient energy-management system for HEVs, using neural networks.

However, a direct estimation of battery life extension due to the adoption of SCs is still missing. Santucci et al. [21] proposed a MPC and a dynamic programming (DP) algorithm including a simplified battery aging model. In addition, Vinot and Trigui [22] used Pontryagin’s minimum principle to reduce the root mean square (RMS) of the battery current. Definitely, the DP algorithm and the Pontryagin’s minimum principle can find the global optimization solution to extend the battery life. However, these methods can only be used in off-line simulation (where the driving cycle is known in advance). Moreover, it is difficult to employ these methods in practical applications due to their large computational cost and complex calculation processes, and only the simplest strategies can be adopted for on-line uses [23,24].

There is therefore currently no quantitative comparison of different real-time energy management strategies adopted in the HESS on the battery lifetime extension. Based on a dynamic battery degradation model, the novel FLC and MPC implementations are proposed in this paper. Applied on an electric city bus, the proposed controllers are compared with existing RBC and FBC implementations along a typical China Bus Driving Cycle (CBDC) under the premise that all controllers have been well tuned. The results show that RBC and FLC achieve the better performance, and the adoption of the SC reduces up to 50% of the HESS life cycle cost in comparison with the battery-only configuration. In addition, the controllers are also compared along the New European Drive Cycle (NEDC), which represents another normalized driving cycle. It will be shown that the FLC achieves the best performance and reduces about 23% of the HESS life cycle cost compared to the battery-only configuration.

This paper is organized as follows: In Section 2, the theoretical model of the HESS is illustrated, and the optimum sizing of the HESS is introduced. Section 3 presents a detailed description of the proposed FLC and MPC. In addition, the RBC and FBC are also presented. In Section 4, the simulation results of different controllers are compared and analyzed. The conclusions are presented in Section 5.

2. HESS modeling and sizing

The topology of the HESS applied in this paper is shown in Fig. 1, in which a bidirectional DC/DC converter is used to interface the SC with the DC bus, thereby allowing flexible operation of the SC [13]. This topology has sufficient degrees of freedom to implement different control strategies. In addition, a good tradeoff between the performance and the circuit complexity and price is achieved because only one DC/DC converter is used.

2.1. SC model

The relationship between the discharge/charge resistances $R_{SC, disch}/R_{SC, ch}$ of the SC module, and the discharge/charge currents were determined by measuring the SC voltage drops when it is discharged at different currents, as shown in Fig. 2. In the sizing process, the series/parallel numbers $N_{SC}/M_{SC}$ of the SC module within the SC pack will be determined. Accordingly, the following equations can be deduced:

$$C_{SC} = M_{SC} C_M/N_{SC},$$
$$R_{SC, ch} = N_{SC} R_{SC, M, ch}/M_{SC},$$
$$R_{SC, disch} = N_{SC} R_{SC, M, disch}/M_{SC},$$
$$V_{SC} = V_{SC, M} N_{SC}.$$

where $C_M$ is the capacity of the module, $C_{SC}$ is the capacity of the SC pack, $R_{SC, ch}/R_{SC, disch}$ are the charge/discharge resistances of the SC pack, $V_{SC, M}$ is the open circuit voltage (OCV) of the module, and $V_{SC}$ is the OCV of the SC pack. The SOC of the SC pack is linearly proportional to $V_{SC}$ as follows:

$$SOC_{SC} = \frac{V_{SC}}{V_{SC, max}} \in [0, 1],$$

where $V_{SC, max}$ is the maximum voltage of the SC pack. The SC SOC is strictly controlled above 0.5 because the efficiency of power conversion becomes poor when the SC voltage is low.

![Fig. 1. Configuration of the HESS employed in this paper.](image-url)
This paper focuses on the HESS performance over a prolonged time range (~22 min for one CBDC, and ~20 min for one NEDC). Therefore, the $R_{\text{int}}$-Capacity model shown in Fig. 3(a) was adopted to represent the responses of the SC pack, primarily due to its simplicity and sufficient accuracy.

2.2. Battery model

LiFePO$_4$ batteries are preferred in EV applications owing to their high voltage, exceptional specific capacity, and long cycling life [25]. The main parameters of the LiFePO$_4$ cell used in this study are listed in Table 1.

The $R_{\text{int}}$ model shown in Fig. 3(b) is adopted to represent the battery behavior. The charge/discharge resistances $R_{\text{bat,cell,charge}}/R_{\text{bat,cell,discharge}}$ of the cell are measured under different temperatures and SOCs through Hybrid Pulse Power Characterization test, which are shown in Fig. 4.

If the battery pack in the HESS is grouped by battery cells via $N_{\text{bat}}$ series and $M_{\text{bat}}$ parallel connection, the following relationship establishes,

$$
C_{\text{bat}} = M_{\text{bat}}N_{\text{bat}}C_{\text{bat,cell}}; \\
R_{\text{bat,charge}} = N_{\text{bat}}R_{\text{bat,cell,charge}}/M_{\text{bat}}; \\
R_{\text{bat,discharge}} = N_{\text{bat}}R_{\text{bat,cell,discharge}}/M_{\text{bat}}; \\
V_{\text{bat}} = V_{\text{bat,cell}}N_{\text{bat}},
$$

where $C_{\text{bat}}$ is the capacity of the battery pack, $R_{\text{bat,charge}}/R_{\text{bat,discharge}}$ are charge/discharge resistances of the battery pack, and $V_{\text{bat}}$ is the battery pack OCV.

2.2.1. Dynamic battery degradation model

The most important motivation of developing HESS in EV applications is to prolong the lifetime of the battery and decrease the life cycle cost of the ESS. Thus a dynamic battery capacity degradation model has been proposed based on a semi-empirical life model [26]. The effect of four parameters: time, temperature, depth of charge, and discharge rate, are considered within the model. As shown in Eq. (4), the original formula of the semi-empirical model is based on the Arrhenius degradation model.

$$
Q_{\text{loss}} = A e^{\left(\frac{E_a}{R T_{\text{bat}}} \frac{C_{\text{Rate}}}{\text{Ah}}\right)} (A_0)^7,
$$

where $Q_{\text{loss}}$ is the percentage of battery capacity loss, $A$ is the pre-exponential factor, $E_a$ is the activation energy (J), $R$ is the gas constant (J/(mol K)), $T_{\text{bat}}$ is the absolute temperature (K), $A_0$ is the Ah-throughput, $C_{\text{Rate}}$ is the battery discharge rate, and $B$ is the compensation factor of $C_{\text{Rate}}$. 

### Table 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{\text{bat,cell}}$ Cell nominal voltage (V)</td>
<td>3.2</td>
</tr>
<tr>
<td>$C_{\text{bat,cell}}$ Cell capacity (Ah)</td>
<td>60</td>
</tr>
<tr>
<td>Cell stored energy (kW h)</td>
<td>0.192</td>
</tr>
<tr>
<td>Cell mass (kg)</td>
<td>~2</td>
</tr>
<tr>
<td>Discharging temperature range (°C)</td>
<td>20 to 55</td>
</tr>
<tr>
<td>Charging temperature range (°C)</td>
<td>0–45</td>
</tr>
<tr>
<td>Recommended SOC usage window (%)</td>
<td>10–90</td>
</tr>
</tbody>
</table>

Fig. 2. Resistance of the SC module.

Fig. 4. Charge and discharge resistances of the LiFePO$_4$ cell.
We assume that the capacity fade model of the LiFePO4 battery shown in Eq. (4) can also be used for predicting battery dynamic degradation according to the cumulative damage theory [27]. The discrete formula of the dynamic degradation model can therefore be determined:

\[ Q_{\text{loss},p-1} - Q_{\text{loss},p} = \Delta A_p A e^{-\frac{1}{2} H_p (\Delta A_p)^2} Q_{\text{loss},p} \]  
\[ (5) \]

where \( Q_{\text{loss},p} \) and \( Q_{\text{loss},p-1} \) are the accumulated battery capacity loss at instants \( t_p \) and \( t_{p-1} \), and \( \Delta A_p \) is the Ah-throughput from \( t_p \) to \( t_{p-1} \), which is defined as follows:

\[ \Delta A_p = \frac{1}{3600} \int_{t_p-1}^{t_p} |I_{\text{bat}}| dt. \]  
\[ (6) \]

Finally, the dynamic model is verified by experiments on the LiFePO4 cell, and the parameters in the model are calibrated. Throughout the experiments, the battery was charged at 0.3C-rate, and discharged at 1.5C-rate. The cell was discharged from 100% SOC to 0% SOC at 1.5C-rate, once again followed by a standing time of 20 min. The experiment cycle repeats as illustrated above. The ambient temperature during the experiment was changed between 5 °C and 45 °C after every 90 cycles. Based on Eq. (5), the various parameters, including \( A \), \( B \), \( E_0 \), and \( z \), are calibrated using genetic algorithm. The verification result shown in Fig. 5 reveals that the accuracy of the dynamic battery degradation model is satisfactory under different C-rates and temperatures.

\[ Q_{\text{loss}} = 0.0032e^{-\left(\frac{15126-15126}{5} \Delta A_p \right)} (A_h)^{0.824}. \]  
\[ (7) \]

2.3. HESS sizing

The HESS sizing problem includes calculating the number of battery cells and SC modules, which is based on the requirement of minimal mileage and the continuous high power demand in CBDC, respectively. The parameters of the city bus modelled in this study are listed in Table 2, and the vehicle dynamic model is given as [25]

\[ mg f r \cos \alpha + 0.5 C_p \rho v^3 + m v \frac{dr}{dt} + mg v \sin \alpha = P_{\text{demand}} \eta_1 \eta_{\text{Hess}}, \text{ for } P_{\text{demand}} > 0, \]
\[ mg f r \cos \alpha + 0.5 C_p \rho v^3 + m v \frac{dr}{dt} + mg v \sin \alpha = P_{\text{demand}} \eta_1 \eta_{\text{Hess}}, \text{ for } P_{\text{demand}} < 0, \]  
\[ (8) \]

where \( m \) is the EV mass, \( g \) is the gravitational acceleration, \( f \) is the rolling resistance coefficient, \( v \) is the vehicle velocity, \( \alpha \) is the climbing angle, \( C_p \) is the air drag coefficient, \( A \) is the front area, \( \rho \) is the air density, \( P_m \) is the input electric power of the DC/AC power inverter required by the electrical machine, \( \eta_1 \) is the transmission efficiency, \( \eta_2 \) is the average efficiency of the regenerative braking process, and \( \eta_{\text{Hess}} \) is the efficiency of the electrical machine. Thus the following equation can be deduced

\[ P_m = (P_{\text{bat}} + P_{\text{SC}} \eta_{\text{DC/DC}}) \eta_{\text{Hess}}, \text{ for } P_{\text{demand}} > 0, \]
\[ P_m = (P_{\text{bat}} + P_{\text{SC}} / \eta_{\text{DC/DC}}) \eta_{\text{Hess}}, \text{ for } P_{\text{demand}} < 0, \]  
\[ (9) \]

where \( P_{\text{bat}} \) is the output power of the battery pack, \( P_{\text{SC}} \) is the output power of the SC pack, \( \eta_{\text{Hess}} \) is the average efficiency of HESS, and \( \eta_{\text{DC/DC}} \) is the average efficiency of the DC/DC converter which is set to 85% in this paper [28]. The minimal mileage \( L \) of more than 100 km, obtained at a constant cruising speed \( v_0 \) (50 km/h) on a flat road, is the boundary condition used to determine the battery usage. In the HESS, the energy stored in the SC is much less than that stored in the battery. Thus the SC can be neglected here, and we get:

\[ \left( \frac{C_p A p v_0^2 + mg f}{2} \right) \frac{L}{\eta_1 \eta_{\text{Hess}}} \frac{1}{3600 \bar{V}_{\text{bat, cell}}} \bar{V}_{\text{cell}} \leq N_{\text{bat}} M_{\text{bat}}. \]  
\[ (10) \]

According to Eq. (10), the number of battery cells should be equal or more than 605. As a result, 600 battery cells are used which are appropriate for grouping. Considering the operating range of the DC bus voltage required by the electrical machine, \( N_{\text{bat}} \) and \( M_{\text{bat}} \) are set to 120 and 5.

In the HESS, the SC is used to protect the battery from supplying continuous high power. Hence the 75% energy stored in the SC (considering the SWC work range) should be large enough to supply the power pulses in the CBDC. This problem can be formulated as

\[ 0.75 N_{\text{SC}} M_{\text{SC}} \left( \frac{C_m V_0^2}{2} \right) \eta_{\text{DC/DC}} \geq \int_{t_0}^{t_f} P_{\text{demand}}(t) dt, \]  
\[ (11) \]

where \( P_{\text{demand}}(t) \) is the power demand from \( t_0 \) to \( t_f \).

Assuming that the average efficiency of the electrical machine is 0.85, and the average efficiency during the regenerative braking process is 0.65, the city bus speed and the power demand profiles along the CBDC are shown in Fig. 6.

As shown in Fig. 6, the SC is required to supply the continuous power demand in the red box from 455 s to 510 s. The calculation result indicates that the number of the SC module should be more than 49, thus \( N_{\text{SC}} \) and \( M_{\text{SC}} \) are set at 25 and 2 in this study.

3. EMSs design

To fairly compare the performance of different controllers under CBDC, two common control rules are included in all controllers.

(1) The SC voltage is strictly controlled between \( 0.5 \bar{V}_{\text{DC, max}} \) and \( \bar{V}_{\text{SC, max}} \). As a consequence, a hysteresis control algorithm is included in all the following controllers to avoid frequent start/stops of the DC/DC converter. The control scheme is
3.1. Rule based controller [16]

The flowchart of the RBC is shown in Fig. 8 [16], in which the SC voltage hysteresis controller is incorporated. The power split strategy depends on the power demand $P_{\text{demand}}$, the battery power threshold $P_{\text{min}}$, and the charging power sending from battery to SC $P_{\text{ch}}$. Hence these parameters should be carefully tuned based on the specific type and size of the vehicle, as well as the specific driving cycle.

The relationship between the cycle-related battery capacity loss, $P_{\text{min}}$, and $P_{\text{ch}}$ along the CBDC is shown in Fig. 9. Apparently, the battery capacity loss is significantly influenced by $P_{\text{min}}$ and a minimal loss is achieved when $P_{\text{min}}$ is 34 kW. However, the impact of $P_{\text{ch}}$ on the controller performance is not obvious and can be neglected. As a result, $P_{\text{min}}$ and $P_{\text{ch}}$ adopted in this study are set to 34 kW and 10 kW.

3.2. Filtration based controller

The second strategy, namely, the FBC, uses a filter to split the demanded power into low-frequency and high-frequency components. The low frequency power is supplied by batteries, while the SC supplies the high frequency power. The battery operating condition can be improved with the decrease of the cut-off fre-

![Fig. 6. Speed and power demand profiles for the city bus along the CBDC.](image)

![Fig. 7. Hysteresis controller for the SC high/low voltage protection.](image)

![Fig. 8. Rule based controller flow-chart.](image)

![Fig. 9. Rule based controller optimization ($P_{\text{min}}$ and $P_{\text{ch}}$ tuning results).](image)
quency $f_e$ in the filter. However, when $f_e$ decreases to a low value, the battery will charge the SC even if $P_{demand}$ is zero, as shown in Fig. 11 (from 660 to 782 s). This is caused by the filter phase delay, and this phenomenon should be avoided from the standpoint of efficiency. A good trade-off for $f_e$ is represented by 0.016 Hz, therefore this value is selected for the following simulations. In order to avoid the early appearance of the SC support, a SC voltage control process is added in this study when compared to the original FBC, as shown in Fig. 10. The SC voltage controller can maintain the SC voltage above a certain value otherwise the SC will discharge at initial processes and its voltage will stay in a low range. This phenomenon indicates that the SC will be ineffective when the high demanded power pulses occur. The SC voltage reference $V_{SC_{ref}}$ is set to 0.9$V_{SC_{max}}$. Furthermore, the SC voltage compensation factor $K_c$ is set to 30, which brings the best comprehensive performance.

3.3. Model predictive controller

As shown in Fig. 12, three steps are included in the MPC:

1. Prediction of the future outputs over the optimization horizon (5 s in this study), using the linearized system model.
2. Evaluation of the quadratic programing problem for the future outputs of the system.
3. Selection of the control variables which bring the minimal cost based on the calculation result of the quadratic programing solver.

In Matlab/Simulink, the system plant can be automatically linearized by the MPC toolbox [29]. The model has to predict the system response with good accuracy, while keeping a low computational cost, thus a reduce-order model of the HESS components is adopted. The simplified battery and SC models are represented by Eqs. (12)–(14), based on the equivalent circuits shown in Fig. 3 [18].

\[
P_{bat} = V_{bat}I_{bat} - R_{bat}I_{bat}^2,
\]

\[
P_{SC} = V_{SC}I_{SC} - R_{SC}I_{SC}^2.
\]  

\[
I_{bat} = \frac{V_{bat} - \sqrt{V_{bat}^2 - 4R_{bat}P_{bat}}}{2R_{bat}},
\]

\[
I_{SC} = \frac{V_{SC} - \sqrt{V_{SC}^2 - 4R_{SC}P_{SC}}}{2R_{SC}}.
\]  

\[
SOC_{bat} = \frac{I_{bat}}{C_{bat}} = \frac{V_{bat} - \sqrt{V_{bat}^2 - 4R_{bat}P_{bat}}}{2R_{bat}C_{bat}},
\]

\[
SOC_{SC} = \frac{V_{SC}}{V_{SC_{max}}} = \frac{I_{SC}}{C_{SC}V_{SC_{max}}} = \frac{V_{SC} - \sqrt{V_{SC}^2 - 4R_{SC}P_{SC}}}{2R_{SC}C_{SC}V_{SC_{max}}}.
\]  

Within the MPC, the continuous-time domain state-space model of the HESS components can be derived and expressed by Eqs. (15) and (16)

\[
\dot{x} = \begin{bmatrix} A_{bat} & 0 \\ 0 & A_{SC} \end{bmatrix} x + \begin{bmatrix} B_{bat} & 0 \\ 0 & B_{SC} \end{bmatrix} u + \begin{bmatrix} K_{bat} \\ K_{SC} \end{bmatrix},
\]

\[
y = \begin{bmatrix} C_{bat} & 0 \\ 0 & C_{SC} \end{bmatrix} x + \begin{bmatrix} D_{bat} & 0 \\ 0 & D_{SC} \end{bmatrix} u + \begin{bmatrix} K_{bat} \\ K_{SC} \end{bmatrix},
\]

where

\[
x = \begin{bmatrix} SOC_{bat} \\ SOC_{SC} \end{bmatrix}, \quad u = \begin{bmatrix} P_{bat} \\ P_{SC} \end{bmatrix}, \quad y = \begin{bmatrix} I_{bat} \\ V_{SC} \end{bmatrix},
\]

and $K_{bat}$, $K_{SC}$, and $K_{bat}$ are constant matrices derived from the system linearization. In this case, the manipulated variables are $P_{bat}$ and $P_{SC}$, the measured outputs are $I_{bat}$ and $V_{SC}$. The MPC action at instant $k$ is obtained by minimizing the cost function, which is a core part of the MPC and empirically chosen as shown in Eq. (17).

\[
J = \sum_{i=1}^{p} \left[ w_1|I_{bat}(k+i)|^2 + w_2 \left( \frac{dP_{bat}(k+i)}{dt} \right)^2 + w_3|V_{SC}(k+i) - V_{SC_{ref}}|^2 \right].
\]  

where $(k+i)$ denotes the value predicted for time $(k+i)$ based on the information available at instant $k$, $p$ is the prediction horizon ($p$ is 5 s, while the control horizon is 2 s in this study), $V_{SC_{ref}}$ is the SC reference voltage and is set to 0.9$V_{SC_{max}}$ to keep the consistence with the FBC. The positive values of the weight parameters $w_1$, $w_2$, and $w_3$ determine the weighing of different parts in the cost function. In fact, a trade-off relationship regarding sharing power between the battery and SC is reflected in the cost function. When the SC voltage is low, the third term of the cost function plays a leading role. Therefore the battery tends to supply more power to
loads, and the SC tends to be charged by the battery when the SC voltage is extremely low. In contrast, the battery tends to be idle and the SC tends to supply more power when \( V_{SC} \) or \( I_{bat} \) is high. In summary, a good trade-off for \( w_1, w_2, \) and \( w_3 \) is represented by 10, 10/3, and 15, consequently, these values are selected in the following simulations.

An estimator used for predicting future power demand is helpful to improve the MPC performance, as developed by Hredzak et al. [18]. However, in most practical applications, the action of the driver is random and hard to predict, thus no estimator is included in the proposed MPC to ensure an impersonal evaluation.

### 3.4. Fuzzy logic controller

The FLC has been widely used in energy management applications of EVs and HEVs due to its convenience [19,30,31]. An algorithm that can convert the linguistic control strategy based on expert knowledge into an automatic control strategy is provided by FLC [32]. The FLC used in this study includes three inputs: \( V_{SC} \), \( P_{demand} \), and battery \( C_{Rate} \), and one output: the power-split ratio \( \alpha_0 \) between the battery power demand \( P_{bat\_demand} \) and \( P_{demand} \), which is defined in Eq. (18). The membership functions of the input and output are shown in Fig. 13.

\[
\alpha_0 = \frac{P_{bat\_demand}}{P_{demand}}.
\]

The rules for the proposed FLC are listed in Table 3. The numeric value of each rule indicates a weight of the rule. In fact, Rules 1–15 have no dependency on \( C_{Rate} \), which is an auxiliary input. The relationship between \( V_{SC}, P_{demand} \), and \( \alpha_0 \) shown in Fig. 14(a) reveals that the SC tends to supply more power when \( V_{SC} \) and \( P_{demand} \) are high, while the battery tends to discharge when \( V_{SC} \) or \( P_{demand} \) is low. In addition, Rules 16–17 indicate that the battery power will be slightly suppressed when \( C_{Rate} \) is high, as shown in Fig. 14(b). We note that the maximum value of \( \alpha_0 \) is 1.1 (slightly more than 1), which means that the SC will be charged by the battery when \( V_{SC} \) is too low.

### 4. Simulation results

#### 4.1. Comparison of different controllers

In order to examine the performance of the different controllers mentioned in Section 3, a series of simulation studies were executed in the Matlab/Simulink environment. In the following simulations, the initial SOC of the battery and SC are set to 70% and 90%, and the constant ambient temperature is 15°C, which is also regarded as the operation temperature of the battery. The same size battery pack is adopted in the battery-only configuration.

The battery current profiles for the different controllers along the CBDC are reported in Fig. 15. Although two peak values occur in the MPC result at around 510 and 1250 s due to the low \( V_{SC} \) and high \( P_{demand} \), it is still believed that the short duration high current will not damage the battery severely. In addition, it is worth noticing the difference between the FBC and other controllers under the regenerative braking condition, under which the FBC recharges the battery, while the other controllers assign all the regenerative power to SCs.

The SC voltage for the different controllers along the CBDC is represented in Fig. 16. The FLC and RBC use the SC in a similar way, while the MPC uses the SC more effectively. The Hysteresis controller uses the SC as a buffer, while the Quasilinear controller uses the SC to supply power when the battery cannot meet the demand.
manner, and the SC voltage varies in a wide range when compared to the FBC, which means an effective use of SCs. Among all controllers, the MPC uses the SC in the widest range. However, the cost is that the battery should additionally recharge the SC when the SC voltage drops to a low value. This will increase the working pressure of the battery. The SC voltage operating range is narrow in the FBC, and this causes the "empty storage" and the insufficient support when $P_{\text{demand}}$ is high (e.g., from 800 s to 1100 s). Fig. 17 presents the SC current profile for different controllers. It is typical for most solutions based on LiFePO4 chemistry that cycle life deteriorates significantly if high currents (above 0.5C) are forced [19]. In the RBC and FLC, the SC works appropriately because SCs tend to discharge when $P_{\text{demand}}$ is high. As a result, the possibility of the battery discharging at high rate is decreased.

As mentioned above, RBC and FLC use the SC effectively, therefore achieve the smooth battery current profiles which contain less transient fluctuations. In order to validate the effectiveness of the HESS, the battery only configuration with the same size battery is also compared in this paper. As shown in Fig. 18, the results reveal that the average and peak values of the battery current are suppressed when the SC is incorporated in the ESS. Furthermore, the battery cycle-related capacity loss for the different controllers along the CBDC is shown in Fig. 19. As expected, RBC and FLC achieve the better performance, and reduce almost 50% of the battery capacity loss compared to the battery-only configuration. The performance of RBC, MPC, and FLC are better than the performance of FBC. Beyond that, the effectiveness of adopting the SC in the ESS is also validated.

### Table 3
The rules in the FLC.

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<th>No</th>
<th>$V_{SC}$</th>
<th>$P_{\text{demand}}$</th>
<th>$C_{Rate}$</th>
<th>$\alpha_0$</th>
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<tr>
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<tr>
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<tr>
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</table>

In order to explain the above comparison result, the DP-based result is also given in this paper. Actually, the authors have solved the integrated optimization problem for deriving the best HESS sizes by using the DP approach, and the detailed DP approach development is provided in [33]. In the DP process, the cycle-related battery degradation is minimized. The DP result is shown
in Fig. 20, in which the same size battery and SC are adopted ($N_{SC}$ and $M_{SC}$ are set to 25 and 2, while $N_{Bat}$ and $M_{Bat}$ are set to 120 and 5). As shown in Fig. 20, the battery profile of the DP approach is similar to the profiles related to RBC and FLC. Thus it can be found that RBC and FLC operate in the optimal manner when compared to the global optimal EMS obtained by the DP approach. The reason for which RBC and FLC achieve the better performance among all strategies is therefore gained.

4.2. Life cycle cost analysis

In this section, a quantitative analysis of the HESS life cycle cost is given. The cost of energy storage devices are supported as 1600 USD kW h$^{-1}$ for the LiFePO$_4$ battery, 15,000 USD kW h$^{-1}$ for the SC, and 50 USD kW$^{-1}$ for the DC/DC converter [34]. We assume that the battery cannot be used when its capacity reduces to 80% of its initial value. The driving distance during one CBDC is 5.84 km, the peak power of the SC $P_{SC,max}$ is 200 kW. Finally, the equivalent life cycle cost of the HESS is determined from Eq. (19).

$$\text{Cost}_{\text{HESS}} = 15000 \cdot \frac{25}{Q_{\text{loss}}^{\text{CBDC}}} + 600 \cdot \frac{0.192 \times 1600}{5.84} + 200 \cdot 0.84,$$

(19)

Although the future drive cycle information is not adopted in the controllers mentioned above, the parameters are tuned based on the CBDC. In order to compare the different controllers in practical applications, the performance of the same controllers along the NEDC, which is shown in Fig. 21, is also examined.

The battery cycle-related capacity loss for the different controllers along NEDC is shown in Fig. 22. It can be found that the reduction of the battery capacity loss is not as significant as the CBDC in Fig. 20.
5. Conclusion

In this paper, the battery-SC HESS for electric city bus is designed, and the size of batteries is optimized according to the requested minimal mileage, while the size of SCs is optimized based on the power demand profile of the CBDC. Given the optimized HESS and the proposed dynamic battery degradation model, the proposed MPC and FLC are compared with the existed RBC and FBC after all the controllers have been tuned to their best performance along the CBDC. RBC and FLC achieve the better performance among all the controllers, and reduce more than 50% of the battery capacity loss along the CBDC compared to the battery-only configuration. The analysis of HESS cycle-related cost indicates that the adoption of SC reduces about 50% of the HESS life cycle cost in comparison with the battery-only configuration. In addition, all the controllers studied in this paper are also compared along the NEDC, which represents another normalized driving cycle. In this case, the FLC achieves the best performance and reduces about 23% of the life cycle cost compared to the battery-only configuration. Thus it is further verified that the energy hybridization brings the economic benefit.

Among the four controllers, RBC and FLC have distinct advantages along certain driving cycles because they are flexible and easily tuned, which is also validated by the DP-based result. In terms of NEDC, the performance difference between RBC, FLC, and MPC turns out to be minimal. They all perform better than FBC. In summary, the RBC and FLC are preferred in practical applications due to their easy implementation and satisfactory performance.

The recommended future developments are: (i) to use the dynamic programming (DP) algorithm to obtain the global optimization solution along the certain driving cycle, and (ii) to extract a set of rules from the DP algorithm result to improve the performance of the on-line controller.

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