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Optimal design and control of battery-ultracapacitor hybrid energy storage system for BEV operating at extreme temperatures

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ABSTRACT

The battery energy storage system (BESS) is a critical and the costliest powertrain component for battery electric vehicles (BEVs). Extreme operating temperatures distort the battery's electrochemical reactions, causing permanent capacity loss, shortening operational life, and increasing lifecycle costs (LCC). In this work, new methods for optimizing battery and ultracapacitor (UC) hybrid energy storage system (HESS) design and the HESS' energy management strategy (EMS) and thermal management strategies (TMS) are introduced. In addition to altering the batteries' use pattern to extend operational life, this combination also improves battery performance and reduces the impacts on the batteries' operational life under low temperatures. First, performance and degradation data of commonly used lithium-ion (Li-ion) batteries under extreme temperatures and various use patterns are collected to form advanced battery performance, degradation and thermal models to facilitate the HESS's optimal design and energy management for a BEV under different operation conditions. Effective EMS and TMS are introduced to play the batteries and UCs to their strength and to use energy from the UCs to improve the batteries' operating temperature to extend battery life and minimize the BEV's LCC. The optimal sizing of the batteries and UCs and the HESS baseline optimal EMS are simultaneously generated using empirical data-based battery performance and degradation models and the BEV's operation cycle through global design optimization and dynamic programming (DP)-based optimal energy management. The accurate prediction of vehicle propulsion power is made through the extended Kalman filter (EKF) using both statistical and real-time data. The batteries' performance and degradation models are dynamically updated using the online battery voltage data and continuously calibrated state-of-health (SOH) model. These updates enable precise optimal control and EMS through model predictive control (MPC). The optimized battery-UC HESS design and dedicated optimal EMS and TMS extended BEV battery life by 47 %. In addition, the newly introduced real-time control reduced battery degradation by up to 23 %.

1. Introduction

The rapid market growth of electrified vehicles (EVs), particularly battery electric vehicles (BEVs), is driven by a confluence of factors, including heightened environmental awareness, fluctuating gasoline prices, commendable fuel efficiency inherent in EVs, and the compelling need to adhere to evolving pollution standards [1]. Notably, the reduction or absence of tailpipe emissions of EVs and BEVs contributes substantially to enhanced air quality and an overall decrease in the carbon footprint. The superior energy efficiency of EVs, particularly evident in stop-and-go traffic scenarios where regenerative braking enables energy recovery, positions them as pivotal contributors to sustainable transportation. Lithium-ion (Li-ion) batteries are EVs' predominant energy storage system (ESS). Renowned for their high energy density, Li-ion batteries play a critical role in compactly and effectively storing substantial energy, a vital attribute for optimizing the range and performance of BEVs.

Battery energy storage system (BESS) is a critical and the costliest powertrain component for BEVs. Applying Li-ion batteries in BEVs introduces certain challenges related to their limited lifespan based on charge/discharge cycles, susceptibility to charge/discharge current and depth, and vulnerability to extreme temperatures. The BESS's power performance and energy storage capacity depend upon its operating temperature and level of degradation. The degradation rate depends

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upon the battery use pattern and operating temperature. Extreme operating temperatures distort the battery's electrochemical reactions, causing permanent capacity loss, shortening operational life, and increasing lifecycle costs (LCC). At present, considerable efforts have been made to improve the performance and operational life of the batteries through improved materials and manufacturing processes. [2] showed that a high rate of charging and discharging leads to significant degradation of the cells, with the degradation rate linearly declining with the charging/discharging rate. The optimization strategies toward dual-ion battery materials and electrolytes were highlighted in [3], and their energy-related applications were provided. [4] fully exploited the 2D structure of photovoltaic silicon waste, combined with the advantage of controllable depositing layers offered by fluidized bed atomic layer deposition, to achieve high initial Coulombic efficiency and high-rate performance of Si-based anodes. [5] reported a Calcium-ion battery that can work stably at room temperature in a new cell configuration using graphite as the cathode and tin foils as the anode and the current collector. A BEV's operation conditions cannot be improved without the assistance of a secondary power source, such as the engine or hydrogen fuel cell system in a hybrid electric vehicle (HEV).

The battery-ultracapacitor (UC) hybrid energy storage system (HESS) can address these challenges and enhance the longevity of Li-ion batteries. Most research focuses on reducing BESS's dynamic power loads without improving its operating temperature, particularly at cold and hot starts. A HESS incorporating batteries and UC has been explored, using the UC for high-frequency shallow charging and discharging, thereby minimizing the strain on the battery under variable loads and extending its overall service life [6,7]. Effective and economical battery protection within a HESS relies on optimizing the UC size and energy management strategy (EMS) [8]. The early investigations on battery-UC HESS were predominantly directed toward formulating effective control strategies to unlock the full potential of the HESS. These strategies primarily encompass three common control methods: rule-based or reference curves and tables control [9,10], fuzzy logic control [11,12], and closed-loop control [13,14]. Their primary objectives revolved around concurrently addressing the challenges of delivering high energy and high-power output while minimizing the actual number of working cycles endured by the Li-ion batteries. The optimal power control and EMS of the HESS for a specific vehicle and its conditions are aimed at encompassing the optimal solution for all operating scenarios. Dynamic programming (DP) stands out as the most effective solution method, widely employed in developing the optimal EMS for vehicles equipped with HESSs [15] [16,17]. Relying on the optimal HESS configuration, [17] extracts several control rules derived from DP outcomes and introduces a near-optimal rule-based strategy. The efficacy of UC in HESS is evident, showcasing a significant reduction in battery life cycle costs compared to configurations solely reliant on batteries. [18] advocated for adopting optimal control and power allocation strategies of the battery-UC HESSs for plug-in HEVs, introduced a distinctive analytical strategy utilizing DP, and presented a tailored optimization framework. The vehicle operation cycle that may constitute repeated standard driving cycles and typical load profile is a statistical representation of the vehicle use pattern. The DP and statistical operation cycle-based global optimization strategy is ideal for producing the optimal hybrid powertrain system design and generating the benchmark optimal control solution. However, these DP-based methods can only generate the optimal EMS for vehicles that exactly follow the given operation cycle. As real-time vehicle operations always depart from the statistical driving and load cycles, the DP-based static optimal EMS will not lead to the optimal control solution. On the other hand, conventional real-time optimal control methods produce optimal EMS based on instantly acquired vehicle operation data under dynamically changing vehicle operating and environment conditions. These include equivalent consumption minimization strategy (ECMS) [19], Pontryagen minimum principle (PMP) [20,21] and the most recent developments of model predictive control (MPC) [22–24]. ECMS identifies the most energy-efficient hybrid powertrain design and control solution through balanced mechanical and electric power flows. The PMP strategy optimizes the power allocation by minimizing the Hamiltonian function at each instant, making it implementable in real time and related to the co-states. Predictive algorithms leverage weighted Markov processes to forecast propulsion power demands, showcasing real-time control strategies that enhance the operational efficiency of the HESS and facilitate the capture of surplus regenerative energy [25]. [26] introduced a novel, straightforward, and readily optimized mathematical representation of EMS designed for real-time control of the BEV's HESS to minimize energy consumption. [27] established a neural network model trained offline with a dataset derived from wavelet transform decomposition. This model was designed to predict the low-frequency power demand of the battery in real-time, calculate the high-frequency power demand online, and subsequently allocate it to the UCs. These research endeavours rely on static battery performance and degradation models derived from laboratory data, constraining their efficacy in formulating optimal power control and EMS for electrified propulsion systems. However, these real-time optimal control methods can only predict the vehicle power demand over a short period, and they cannot foresee the vehicle operation over the entire vehicle operation cycle. The series of local optima do not necessarily lead to the global optimum. A combination of the DP and statistical operation cycle-based global control optimization and the conventional real-time optimal control methods can potentially minimize the errors caused by the difference between the statistical operational cycle and real-time operation and the inability to predict long-term power demand accurately. This research will introduce a new optimal EMS-generating method to fulfill this need.

Temperature extremes, especially at the lower end of the spectrum, significantly impact the performance and capacity of Li-ion batteries [28–30]. Operational temperatures between 15 °C and 35 °C are deemed optimal, ensuring limited adverse effects on battery performance and capacity [31]. To mitigate the impact of low temperatures, typically ranging from −40 °C to 15 °C, and high temperatures of above 35 °C, active battery thermal management using another onboard power source, such as the engine in a HEV, is employed to bring the operating temperature of the batteries into the desired 15–35 °C window to ensure its performance and avoid rapid degradation. For a BEV with the sole energy source, drawing battery power to warm up cold batteries at low operating temperatures is ineffective due to poor battery performance and is harmful to battery life. Cooling down the hot batteries at high operating temperatures using battery power is also detrimental to battery life.

BESS are typically costly, have limited lifespans, and are sensitive to charge/discharge currents, depth of discharge, and extreme temperatures. In contrast, UCs offer a wide operating temperature range of −40 °C to +65 °C and can deliver peak power performance without degradation, even in cold climates. The battery ESS must be much larger than normally needed to provide high power and avoid fast degradation at extremely low temperatures. Integrating batteries with UCs in HESS can effectively improve ESS performance, avoid the harsh working conditions on the batteries, and extend the service life of lithium-ion batteries. While most HESS research has focused on extending battery life by improving battery use patterns, our work adds active thermal management using energy from the added UCs to improve battery operating temperature, particularly at cold starts. The benefit of this strategy is obvious. However, the lack of comprehensive data on battery performance and degradation at extreme temperatures has hindered the development of effective thermal management strategies (TMS) and optimized HESS designs and control methods. This work explores the expanded function of the UCs in HESS. The UC-enhanced HESS meets the BEVs' high energy and power output requirements, reduces the high current charge and discharge burdens on the batteries, and ensures sufficient energy storage to enhance battery performance during extreme cold/hot starts, reducing long-term capacity degradation. These three objectives are achieved simultaneously through the global minimization of the system LCC.

The core innovation of this work is the optimal thermal management for the batteries using the energy from the UCs in the HESS at cold or hot starts and during operations. The realization of optimal thermal management is embedded into the HESS system design optimization and the HESS optimal EMS. In this context, temperatures around 25 °C represent the ideal operational range, with goals set for the TMS to maintain conditions conducive to prolonged battery life and sustained performance. Considerable efforts have been devoted to collecting Li-ion batteries' performance, temporary and long-term capacity loss, and thermal behaviour data and building their performance, degradation, thermal, and LCC models. These models form the foundations for optimized system design, EMS and TMS of the HESS for a given BEV under a specific operation profile. These vehicles experience diverse operations and extreme starting temperatures, leading to propulsion and operation power demand fluctuations. Particularly, extremely low temperatures significantly impact the aging of Li-ion batteries, temporarily or permanently diminishing the energy they supply, impacting these vehicles' overall capacity and performance. The extremely high environmental temperatures present a similar case without instant battery degradation. Battery chilling, instead of heating, can be used. The topic is beyond the scope of this paper.

The new synchronized optimizations of the battery-UC HESS design, EMS and TMS are introduced to address this overlooked issue, ensuring the BEVs' electric ESS power performance and energy storage capability and minimizing the LCC of the BEV. This optimized HESS design and operation improve the batteries' use pattern and performance under low temperatures and reduce the extreme temperatures' impacts on the batteries' operational life. First, performance and degradation data of commonly used Li-ion batteries under extreme temperatures and various use patterns are collected to form advanced battery performance, degradation and thermal models to facilitate the HESS's optimal design and energy management for a BEV under different operations. Effective EMS and TMS are introduced to play the batteries and UCs to their strength to minimize the BEV's LCC. Secondly, the optimal sizing of the batteries and UCs and the HESS baseline optimal EMS are simultaneously generated, using empirical data-based battery performance and degradation models and the BEV's operation cycle through global design optimization and DP-based optimal energy management. Thirdly, the optimal operation of the HESS in real-time incorporates active battery TMS under different temperatures and extends the baseline optimal EMS and battery degradation models according to the vehicle's and the batteries' instant operation data. The accurate prediction of vehicle propulsion power is made through the extended Kalman filter (EKF) using both statistical and online data. The batteries' performance and degradation models are improved using the continuously updated state-of-health (SOH) model. These rapid updates enable precise control and EMS through MPC. A case study demonstrates the benefits of the newly introduced HESS design and control optimization methods, showcasing the efficiency of the new EKF-MPC real-time optimal control, EMS and TMS.

2. ESS system design and energy management for EVs

The design and EMSs for various types of EVs, including HEVs and BEVs, differ significantly due to their varying propulsion architectures and ESS characteristics.

HEVs feature an internal combustion engine (ICE) and an electric motor/generator, with a smaller battery pack than other EVs. The ESS in HEVs is typically used to supplement the ICE during acceleration and provide regenerative braking capability. Thermal management in HEVs often relies on the engine's waste heat and power to regulate battery temperature. Energy management focuses on optimizing the coordination between the ICE and the electric motor to achieve fuel efficiency while meeting performance demands. (See Fig. 1.)

BEVs feature a significantly larger battery pack than HEVs to provide sufficient range. In the design of BESS, battery usage patterns must be carefully considered to avoid excessive degradation. BEVs rely solely on battery power, making battery performance and longevity critical. Advanced battery management systems (BMS) are necessary to monitor and regulate factors such as charging/discharging rates, depth of discharge, and temperature to optimize battery life. Thermal management is crucial to maintaining optimal battery temperature, often employing active cooling/heating methods. However, under extremely low temperatures, the efficiency of thermal systems is usually limited, especially if the vehicle is not actively being driven or if the temperature remains consistently low for an extended period, which could lead to reduced battery efficiency and capacity, limiting the vehicle's range and overall performance.

The batteries and UCs in HESS-EVs are complementary energy storage technologies, potentially offering improved performance,

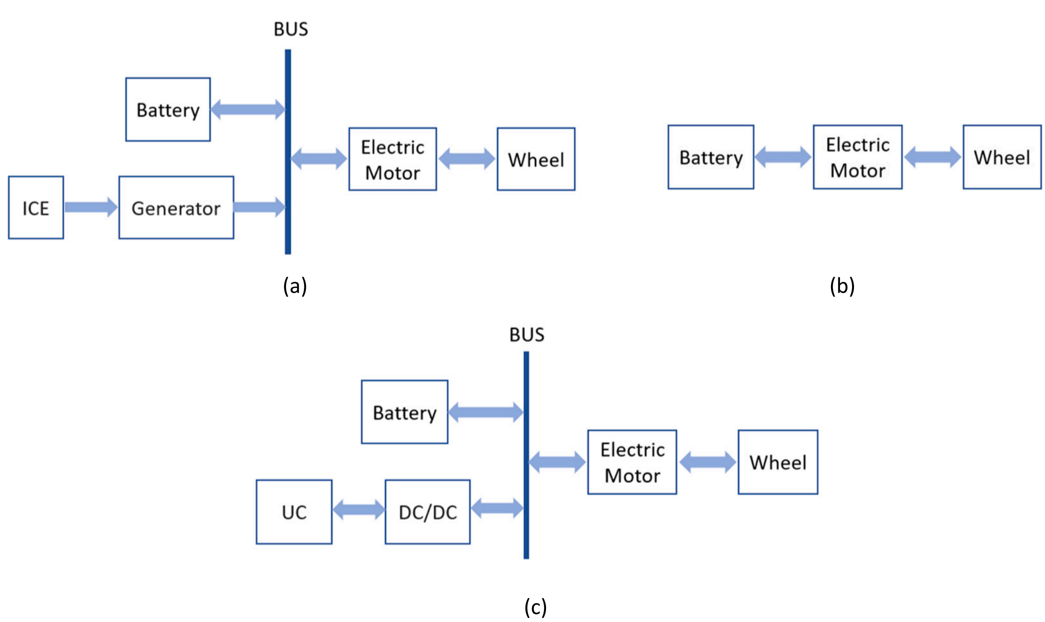


Fig. 1. Energy power diagram for (a) HEV, (b) BEV and (c) HESS-EV.

efficiency, and extended lifetime compared to using either technology alone. By integrating UCs, the ESS can optimize the use of both batteries and UCs, reducing strain on the battery and improving overall efficiency. First, UCs can efficiently handle rapid charge and discharge cycles, making them ideal for capturing energy during braking and providing surged power during high acceleration. UCs can provide bursts of power without significant temperature fluctuations. By sharing the workload with UCs, the battery experiences less stress, which can help regulate temperature impacts and improve battery longevity. Secondly, insensitive to extreme low-starting temperatures, UCs can provide energy to power the batteries' TMS during cold starts to regulate the battery pack's temperature without putting additional strain on the batteries. However, the latter has not yet been systematically studied due to inadequate battery performance/degradation data and models at low temperatures and the effective optimal EMS and TMS. This research adds the second part and integrates both to enhance BEV's efficiency, durability, and usability across various operating conditions.

3. Battery performance and degradation modelling

The main purpose of introducing HESS in this work is to improve the performance and operation life of the Li-ion batteries for the BEVs by changing their working conditions and use. The modelling of Li-ion battery is thus introduced first in this section ahead of the HESS modelling.

3.1. Battery performance model

In contemporary power system design and implementation, the second-order RC network equivalent circuit model is a prevalent choice. This model effectively characterizes the internal resistance of the system, representing ohmic resistance for the resistive component and employing two resistor-capacitor networks (RC networks) to capture the polarization internal resistance. This model adeptly delineates the interplay between load current and terminal voltage during battery operation. Notably, its accuracy is commendable, and the model parameters are easily ascertainable through impedance testing. Consequently, its simplicity renders it a convenient and practical tool for designing and controlling electric propulsion systems. These equations capture the relationships between the model's voltages, currents, and state variables.

$$
\begin{aligned}
V_1(k+1) &= V_1(k) - \frac{1}{R_1C_1}V_1(k)\Delta t + \frac{1}{C_1}I_{cell}(k)\Delta t \\
V_2(k+1) &= V_2(k) - \frac{1}{R_2C_2}V_2\Delta t(k) + \frac{1}{C_2}I_{cell}(k)\Delta t \\
SOC(k+1) &= SOC(k) - \frac{1}{Q_{cap}}I_{cell}(k)\Delta t
\end{aligned}
\tag{1}
$$

where $V_1(k)$ and $V_2(k)$ are the voltage across C_1 and C_2 respectively, $I_{cell}(k)$ is cell current, Δt is the time step between $k+1$ and step k, SOC(k) is the state of charge (SOC), and Q_{cap} is the battery's energy storage capacity.

The battery output voltage V_{cell} is determined by the Kirchhoff's law:

$$V_{cell}(k) = V_{oc}(SOC) - I_{cell}(k)R_i - V_1(k) - V_2(k). \tag{2}$$

3.2. Battery degradation model

Alterations in battery performance induced by temperature fluctuations are, in many cases, reversible. These changes often correspond to temporary shifts in the electrochemical processes and internal reactions. Many of these effects can be mitigated or reversed when the temperature returns to the battery's optimal operating range. Additionally, extreme temperature conditions can cause permanent damage to a battery in certain cases, leading to irreversible degradation.

Changes in battery performance caused by specific usage patterns are generally irreversible. These usage-related changes typically result from the wear and tear that batteries experience over time because of charging, discharging, and cycling. While temperature-related effects can often be reversible when the battery returns to its ideal operating conditions, performance changes tied to usage patterns tend to be cumulative and permanent.

3.2.1. Permanent degradation model

This work's extensive battery testing data were obtained through cycling tests on Liyuan New Energy's 18 Ah Li-ion phosphate/graphite (LFP/C) prismatic battery samples [32]. Extensive battery cycle testing is used to obtain the degradation trend of the battery's maximum charge-holding capacity, and the increased trend of the internal resistance is obtained by fitting the test data using the Particle Swarm Optimization (PSO) global optimization search algorithm, as shown in Fig. 2, suggesting deteriorating overall health.

Battery capacity loss is a function of operating conditions, including working temperature, overall amp-hours, and discharge rate. A semi-empirical performance degradation and operating life model for LFP batteries, following the form in [33], is used in this work.

$$Q_{loss}(k) = A \bullet e^{-\frac{B + C\bullet C_{rate}(k)}{R\bullet Temp}} \bullet (Ah(k))^D, \tag{3}$$

where Q_{loss} is the battery capacity loss with an initial capacity normalized to 1; C_{rate} is the discharge rate; R is the gas constant (J/(mol·K)); $Temp$ the absolute temperature; Ah is the Amp-hour (Ah) throughput; and A, B, C and D are the fitter parameter.

Low temperatures hinder the battery's chemical reactions and lead to reduced battery performance, including lower energy storage capacity, as shown in Fig. 3, lower voltage output, and diminished charge and discharge efficiency. The capacity loss may be reversible to some extent as the temperature increases, but repeated exposure to low temperatures can contribute to permanent capacity loss over time.

The temperature influence on battery performance is shown in Table 1, with an evident downward trend as temperatures decrease. At -20 °C degrees, the battery's performance is significantly halved compared to its original state. Extended exposure to low temperatures exacerbates the issue, contributing to irreversible degradation. This degradation is evident in a decline in capacity, compromised charge retention, and an overall shorter lifespan. As temperatures drop, the battery's attenuation rate accelerates, reaching three times the original rate at -20 °C.

Warming up the batteries can help to improve their performance and mitigate these issues. Using energy in the UCs for the initial heating can reduce BEV performance drop and battery degradation.

3.2.2. Temporary degradation model

The open-circuit voltage (OCV) of the battery changes at different temperatures. The cold temperature slows down the chemical reactions within the battery, reducing the availability of electrons and ions, which results in a lower open-circuit voltage. [34] shows the changes in battery voltage under different C-rates from 40 to −25 °C. The battery voltage changes with time during discharge at various ambient temperatures of −20 °C, −5 °C, 10 °C, 25 °C, and 40 °C at the different discharge rates are shown in Fig. 4.

The figure shows the obvious voltage drop of the battery at low temperatures, and the battery's voltage remains stable at 25 °C. The parameters correct the OCV at different temperatures to:

$$V_{oc}^{tem}(SOC) = V_{oc}(SOC) + \Delta V_{oc}(Temperature, C_{rate}) \tag{4}$$

Using the PSO algorithm to process the data, the regular changes in ΔV_{oc} can be fitted, as shown in Fig. 5.

Studies [35–37] illustrate the temperature-induced variations in battery capacity. The red solid line in Fig. 6 is the fitting result.

Hence, the battery voltage exhibits varying surfaces at different

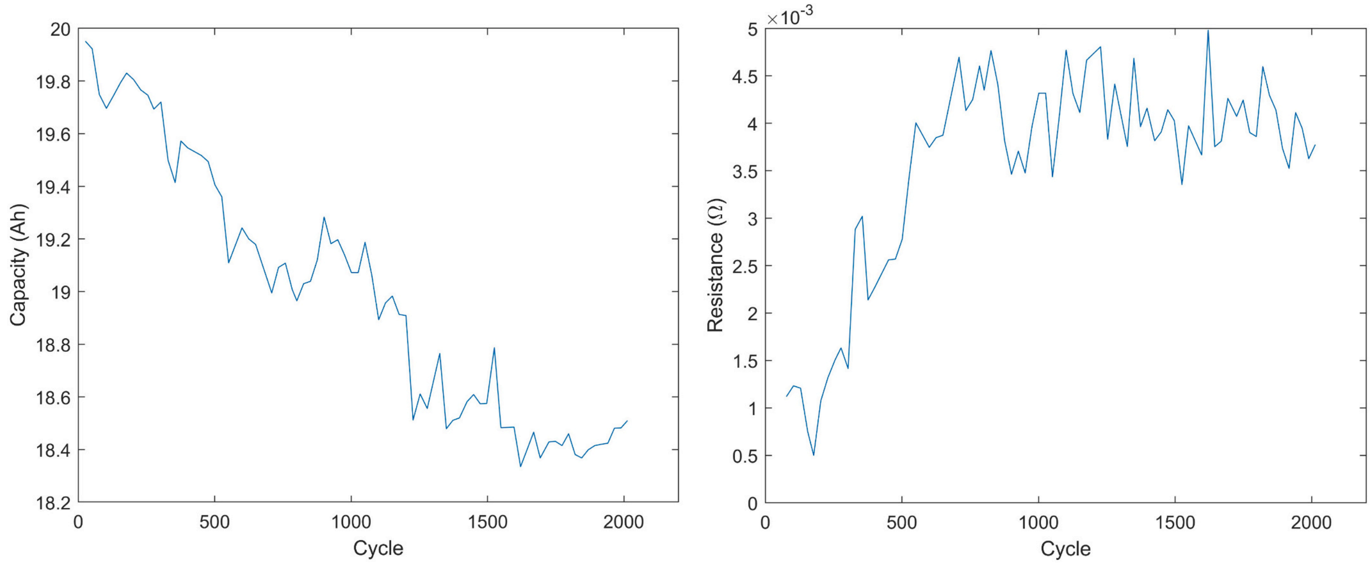


Fig. 2. LFP battery capacity and resistance in different cycles.

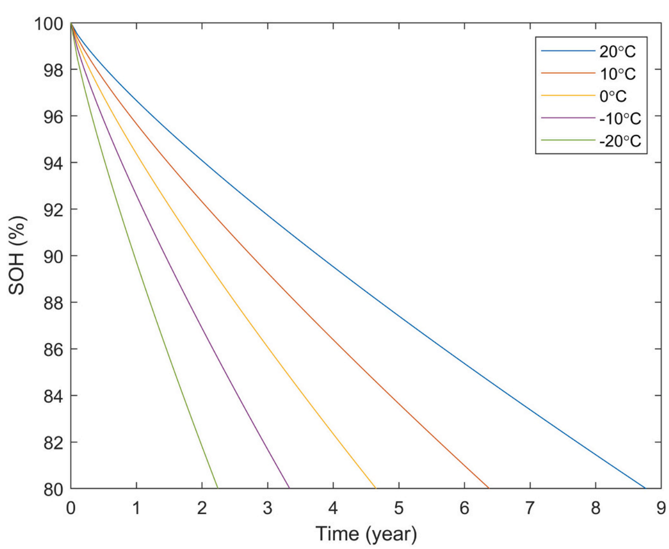


Fig. 3. Battery SOH variation under different temperatures.

Table 1
Battery performance and degradation rate under different temperatures.

Temperature	20 °C	10 °C	0 °C	−10 °C	−20 °C
Performance	100 %	93 %	83 %	68 %	50 %
Degradation rate	100 %	130 %	169 %	222 %	308 %

temperatures, notably demonstrating a conspicuous decline as temperature decreases, as shown in Fig. 7.

These valuable data were obtained and reformatted through an extensive search of numerous related literature to support this work. The values illustrated in this work provide guiding directions and scope for battery laboratory testing.

3.3. Battery thermal model

Operating temperature plays a pivotal role in determining battery degradation rate, and gaining a thorough comprehension of the temperature fluctuations induced by heat generation during battery charge and discharge is essential for precise capacity loss prediction. For this purpose, [38] proposed and validated the thermal-electrochemical model, which simplifies the internal heat generation during standard charge/discharge operations as follows:

$$\dot{Q}_{cell} = I_{cell}\left(V_{oc} - U_{cell}^{avg}\right) + I_{cell}T_{cell}\frac{\partial U_{cell}^{avg}}{\partial T_{cell}} \tag{5}$$

Considering the heating device, the complete battery thermal model is described as [33]:

$$n_s n_p C_{cell}\frac{dT_{cell}}{dt} = P_{heat}\eta_{heat} - h_{cell}(T_{cell} - T_{env}) + n_s n_p \dot{Q}_{cell} \tag{6}$$

where C_{cell} is the thermal capacity of the battery cell, P_{heat} is the heat power, h_{bat} is the heat transfer coefficient, η_{heat} is the heating efficiency and T_{env} is the ambient temperature.

Heating of the batteries at low temperatures is done through active heating using the energy from the UCs in the HESS and by the self-generated heat from the battery use, as described in the following sections.

4. Modelling of HESS and its other components

4.1. Li-ion battery-UC HESS

Battery-UC HESSs have three different energy management strategies: passive, active and semi-active. The semi-active HESSs are currently used in most applications due to the balance between system performance and complexity, as shown in Fig. 8. Here, a bidirectional DC/DC converter is used to adapt to the wide range of voltage changes when the UC works and control the energy flow between the battery and the UC.

4.2. UC model

As UCs are increasingly used in different applications, their modelling is essential for system design, condition monitoring, and performance analysis. Many UC models have been reported in the literature, and the UC model is shown in Fig. 9.

UC packs are organized into groups using n_s^{uc} series and n_p^{uc} parallel connections:

$$C_{uc} = \frac{n_p^{uc} C_M}{n_s^{uc}} \tag{7}$$

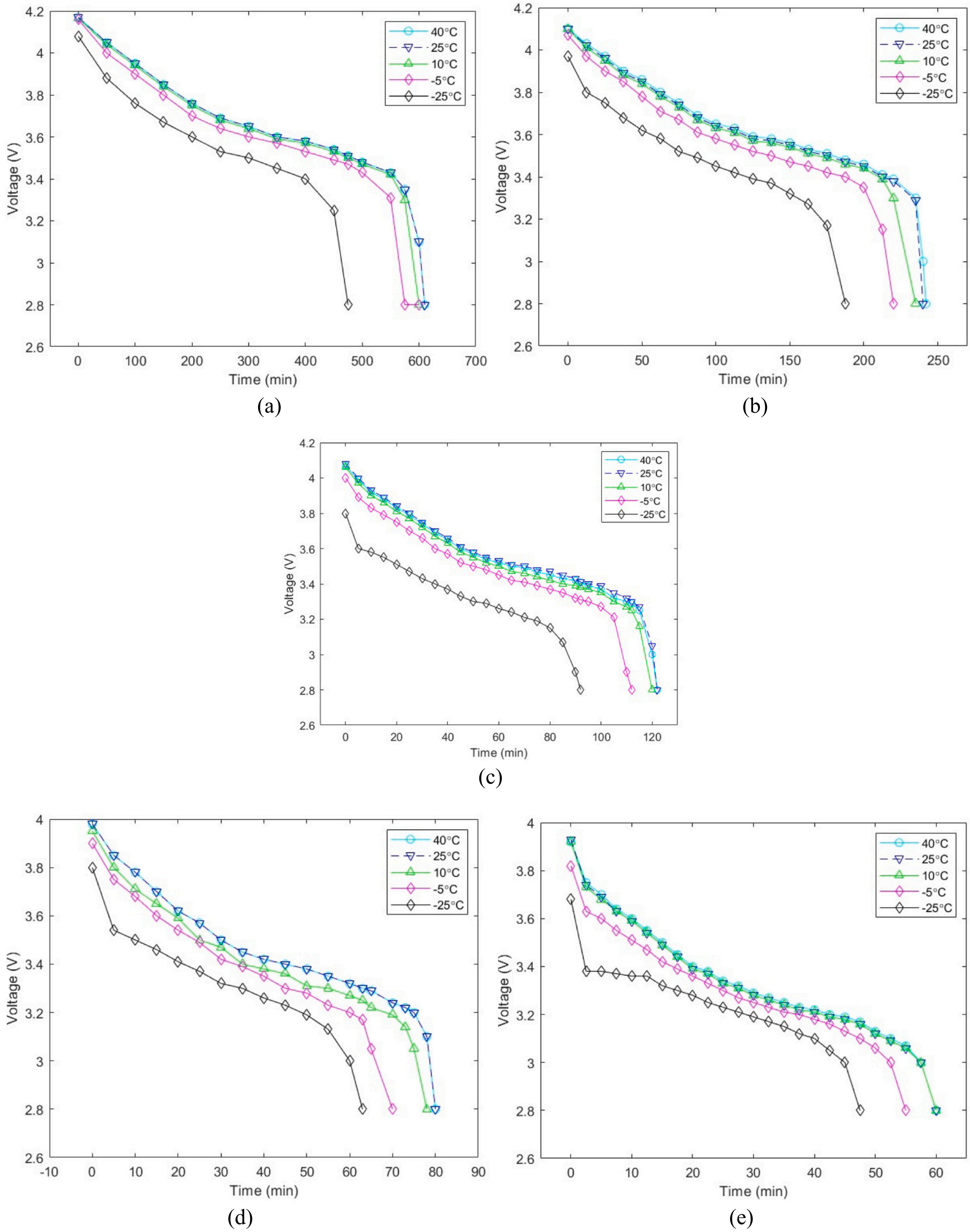


Fig. 4. Discharge voltage change curve: (a) 0.1C discharge rate; (b) 0.25C discharge rate; (c) 0.5C discharge rate; (d) 0.75C discharge rate; (e) 1C discharge rate [34].

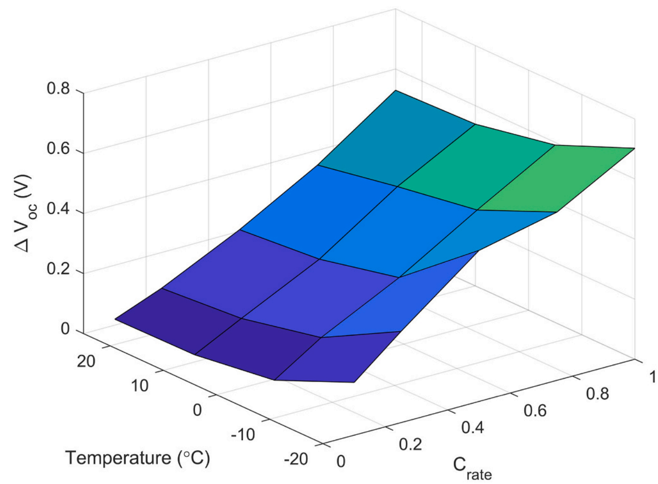


Fig. 5. ΔV_{oc} changes in different temperature and C_{rate}.

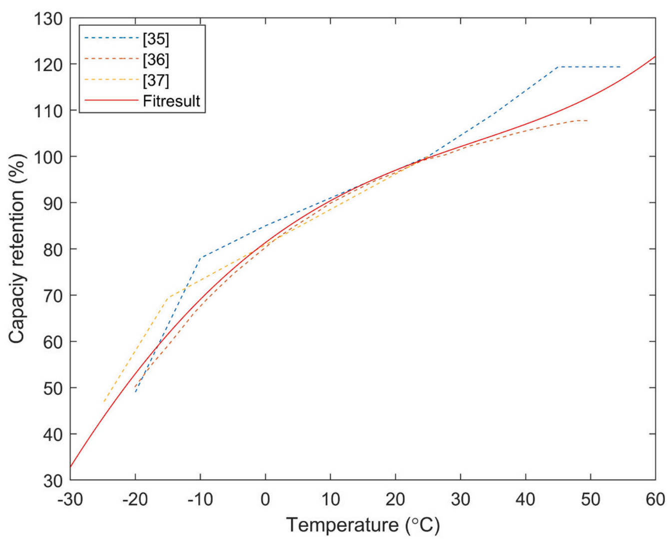


Fig. 6. Effect of temperature on Li-ion battery capacity.

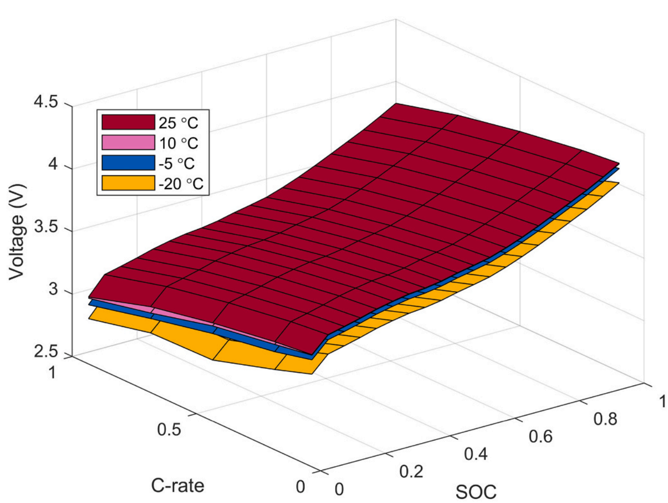


Fig. 7. Voltage surfaces in different temperatures.

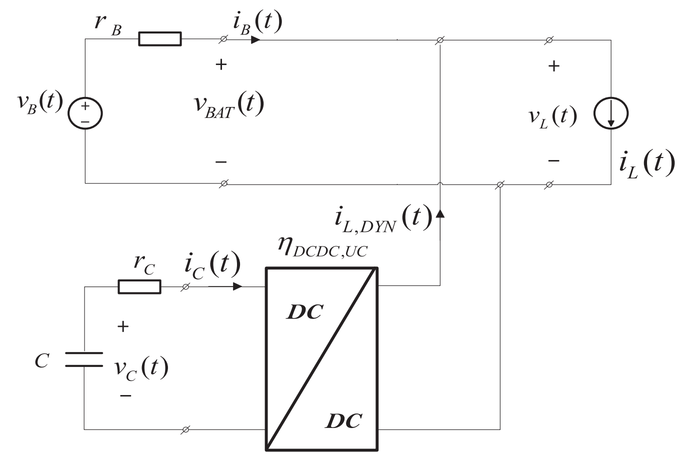


Fig. 8. Composite electric energy system structure of Li-ion battery-UC.

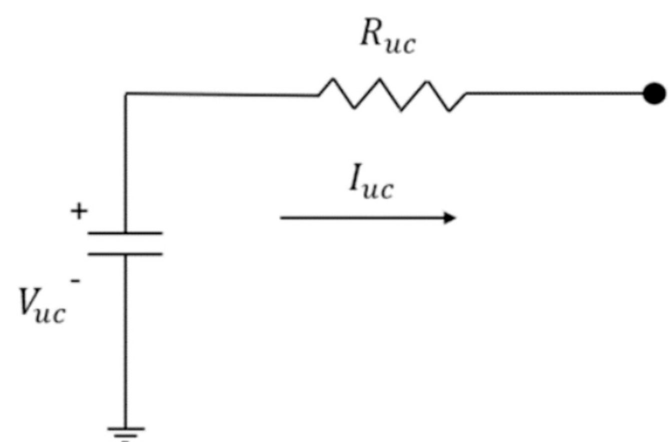


Fig. 9. UC equivalent circuit model.

$$V_{uc} = V_{uc}^{ocv} n_s^{uc} \tag{8}$$

where C_{uc} is the capacity of the UC pack, C_M is the capacity of UC cells. V_{uc}^{ocv} is the open circuit voltage of the UC module, and V_{uc} is the OCV of the SC pack.

The SOC of the SC is linearly proportional to V_{uc} as follows:

$$SOC_{uc} = \frac{V_{uc}}{V_n} \tag{9}$$

$$E_{uc} = 0.5 C_{uc} V_n^2 \left(1 - SOC_0^2\right) \tag{10}$$

where V_n is the UC voltage under fully charged conditions, E_{uc} is the released energy of the UC when its SOC drops to SOC_0.

Since a simplified UC model is used, the slight influence of temperature is not considered for C_{uc}. Eq. (8) shows that when the power in the UC drops from 100 % to 50 %, the UC can release 75 % of its stored energy. The feasible SOC of the UCs is normally between 50 and 100 %. Given the long cycle times of UCs of over 500,000 cycles, their capacity loss is not considered in the model.

4.3. DC/DC converter model

A generic modelling tool for a DC/DC converter, with its example efficiency map shown in Fig. 10, has been introduced in our earlier research [39] to predict power loss under different operation conditions. The performance and energy efficiency influences of possible DC/DC converters in the electric powertrain and ESS charge systems will be

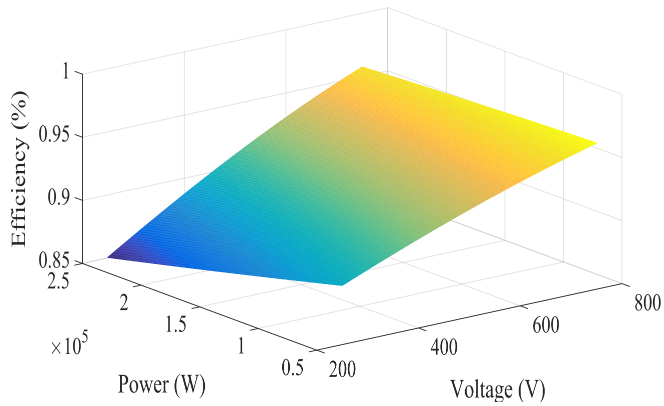


Fig. 10. DC/DC converter efficiency map model [39].

captured using this tool.

5. Battery-UC HESS design and baseline optimal EMS

UCs and batteries, distinct yet complementary energy storage technologies, allow the HESS to surpass their individual energy storage capabilities to meet a BEV's power demand and improve battery performance and life, which is unique to this work.

The optimal sizing of the batteries and UCs within the HESS and the baseline optimal EMS are based on the specific BEV and its driving characteristics, represented by the standard driving cycle from statistical operation data. We use a typical BEV with an average payload and the standard driving cycle to derive the vehicle power load profile to be met by the new integrated HESS design and EMS optimizations. The battery TMS is part of the HESS EMS, extending its function beyond providing propulsion power to the BEV as in the conventional strategies.

A new and more accurate real-time optimal control method is introduced based on instant vehicle and battery operation data for dynamically coordinating battery-UC their charge and discharge.

5.1. A typical commercial BEV and its powertrain system model

In this study, we built a vehicle simulation model in the MATLAB/Simulink environment based on the parameters of a typical light-duty truck (LDT) (Table 2, Fig. 11). The comprehensive setup encompasses battery ESS, propulsion motors, final drive, wheels, vehicle dynamics, power converters, and electrical accessories.

A backward-facing, MATLAB-based, vehicle-level DP model was used to perform the energy analysis of the BEV. This high-level model captures the vehicle's longitudinal dynamics and propulsion power demand. The model calculates the propulsion force due to air drag, tire resistance and grade force during uphill/downhill driving.

Table 2
Vehicle design parameters of electric light-duty truck (LDT).

Vehicle	Curb mass/kg	2212
	GVWR/kg	3495
	Wheelbase/mm	3030
	Top speed/km/h	131.3
	Tire radius/m	0.3012
Final drive	Ratio/1	5
Motor	Rated power/kW	150
	Maximum speed/r/min	8000
	Maximum efficiency	0.9
Battery	Cell nominal voltage/V	3.7

$$T_{wheel} = F_{wheel} {}^{*} r_{wheel} \tag{11}$$

$$\begin{aligned} F_{wheel} = &\ F_{roll} + F_{cd} + F_{grade} + ma \\ = &\ \alpha + \beta v + \gamma v^2 + m\,g \times sin(\theta) \\ &+ \alpha_{cd} A v \times sin(\theta) + ma\# \end{aligned} \tag{12}$$

where α, β, γ are the tire friction coefficient, v is the vehicle speed, m is the mass of the vehicle, a_{cd} is the air drag coefficient, A is the vehicle frontal area, and a is the acceleration. T_{wheel}, F_{wheel}, and r_{wheel} are the torque, total force and the radius of the wheel. As shown in Fig. 12, the optimal power control codes are embedded in the controller model.

The United Nations Economic Commission developed the Worldwide Harmonized Light Vehicles Test Cycles (WLTP) for Europe (UNECE), which is a series of standardized test procedures and driving cycles designed to assess the fuel consumption and emissions of light vehicles, such as passenger cars and light commercial trucks. (See Figs. 13 and 14.)

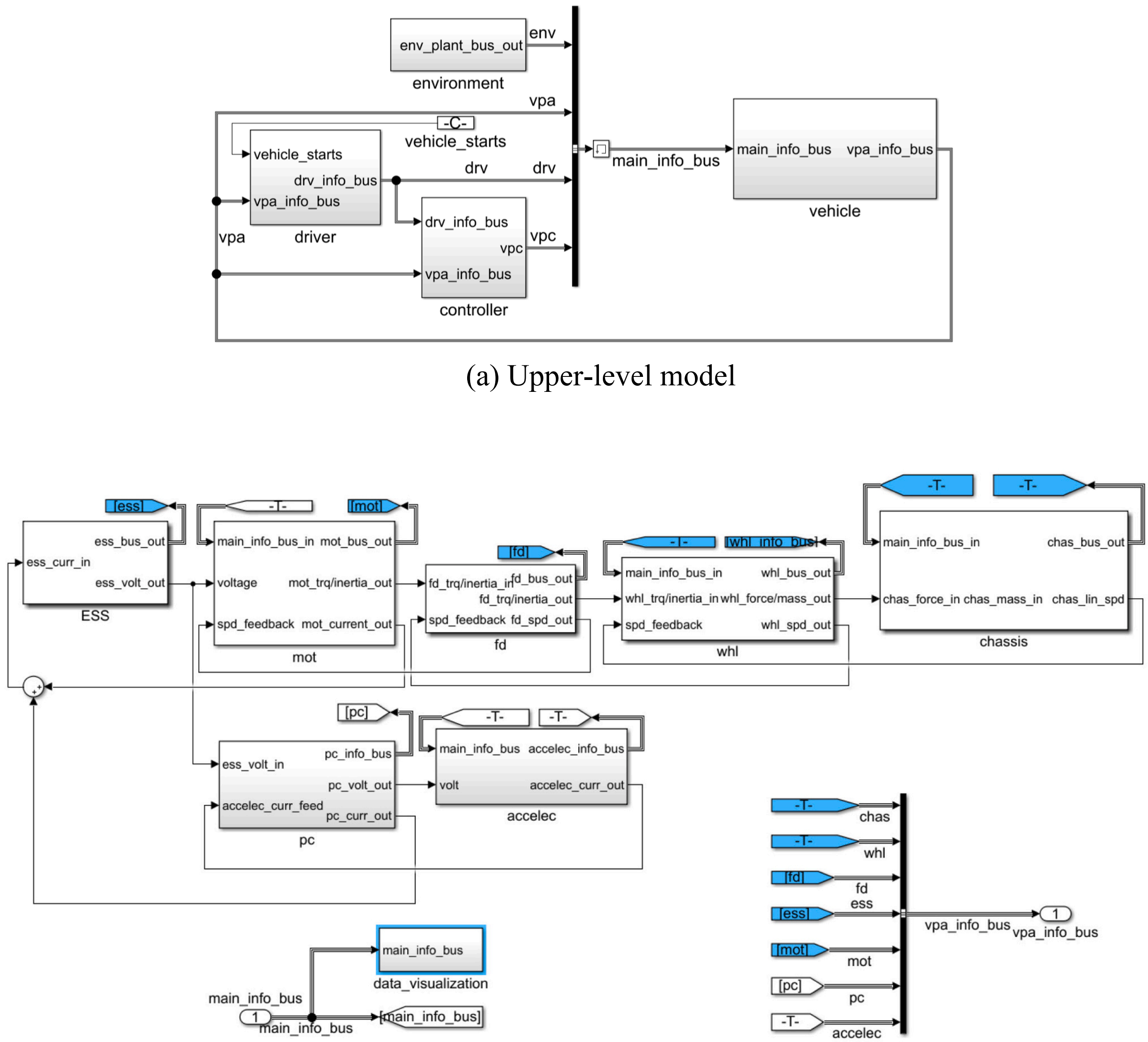
5.2. Typical power load profiles for an electric ESS

The power demand was obtained using vehicle operation simulations under the WLTC driving cycle.

6. Optimal sizing of battery and UC for minimum LCC

The design of the HESS and its EMS/TMS are inseparable. The global minimization of the HESS' LCC involves the optimal sizing of the batteries and the UCs and the optimal EMS and TMS of this optimally sized HESS. This formulation leads to a nested, two-level global optimization problem. The problem consists of the top-level global optimization of the HESS sizing parameters and the bottom-layer optimal EMS and TMS searches using DP over all feasible control operations. These optimizations' objective and constraint functions are based on the numerical simulations of the vehicle performance, energy consumption, system investment costs and battery end-of-life replacement cost using the BEV's MATLAB/Simulink models.

Fig. 11. A typical electric MDT.



(a) Upper-level model

(b) Vehicle plant model.

Fig. 12. Vehicle simulation model.

6.1. Optimal sizing of battery and UC for minimum LCC

The optimal sizing of batteries and UCs in a HESS incorporates various considerations. First and foremost, it aims to fulfill the BEV's functional requirements, ensuring simultaneous compliance with the high-energy and high-power output demands of the vehicle power system. Utilizing UCs involves taking over or shunting frequent shallow and rapid charging and discharging, thereby diminishing the actual working cycles of the battery in each application. Additionally, leveraging the power stored in UCs enhances electric vehicle battery performance during cold starts or extremely high temperatures. These requirements dictate the minimum size of UC cells in the HESS. However, this sizing must align with overall ESS constraints such as size, weight, and costs. These requirements and constraints are contingent upon the specific application. Simultaneously, achieving the lowest LLC of the system is imperative. Investing and incorporating UC units into the ESS prolongs the battery's service life and reduces costs.

Minimizing LLC determines the optimal size of the HESS and devises effective energy management and power allocation schemes for the BEV's powertrain. Overly large HESS, including their UC units, can result in substantial investment costs and added weight for electric vehicles, lowering energy efficiency. Conversely, inadequately sized systems may compromise vehicle performance and lead to more costly battery replacements. Striking an optimal balance among competing LCC contributing factors, including UC and battery investment costs, powertrain energy efficiency, and battery life extension, is crucial for achieving an optimal and cost-effective BEV's ESS solution. The LCC model includes capital and operating costs:

$$LCC = \omega_1 \left(UC_{cap} + Batt_{cap}\right) + \omega_2 Q_{cycle} \tag{13}$$

$$UC_{cap} = S_{UC} \bullet P_{UC} \bullet E_{UC\,cell} \tag{14}$$

$$Batt_{cap} = S_{batt} \bullet P_{batt} \bullet E_{batt\,cell} \tag{15}$$

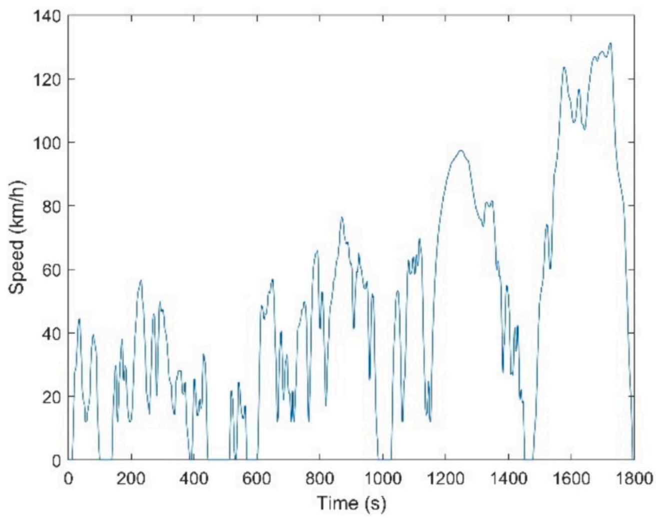


Fig. 13. Vehicle speed of WLTC cycle.

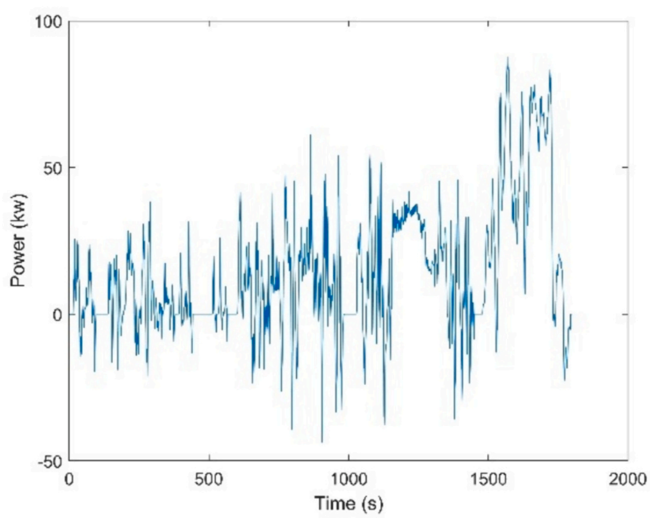


Fig. 14. Vehicle propulsion power demand based on the WLTC cycle.

$$Q_{cycle} = \sum_{i=1}^{N} Q_{loss(i)} \tag{16}$$

where UC_{cap} and $Batt_{cap}$ are the capital costs of UC and battery, respectively, S_{UC}, P_{UC}, S_{batt}, P_{batt} are the number of UC/battery cells in series and parallel, E_{UCcell} and $E_{battcell}$ are the cost of UC and battery cells, respectively. Q_{cycle} is the total Q_{loss} in a cycle, which covers the costs related to system efficiency loss.

6.2. Optimal HESS power control and baseline EMS using DP

The DP is widely applied to solve the problem of EMS for HESS-based vehicles [15–17]. The strategy identifies the global optimal control solution for power allocation and sharing between the batteries and the UCs in the HESS over the entire BEV's power demand cycle or a trip between ESS grid charges. The optimization of HESS baseline EMS is crucial for enhancing the performance and longevity of BEVs. This optimization encompasses three key aspects, each designed to maximize efficiency, extend battery life, and improve overall vehicle performance.

- Optimizing HESS Energy Efficiency: Our optimization strategy focuses on achieving the best possible energy efficiency for the HESS. By precisely matching the energy demand cycle of BEVs with the capabilities of the HESS, we aim to minimize energy wastage and ensure optimal utilization of available resources.
- Extending Battery Life with Improved Usage Patterns: Prolonging the lifespan of BEV batteries is crucial for reducing operational costs and environmental impact. Utilizing UC, we can efficiently manage large and shallow charge/discharge loads, reducing strain on the battery cells.
- Extending Battery Life Using Active Heating at Cold Start: Cold weather conditions present significant challenges to battery performance, particularly during startups. By utilizing the energy stored in the UC to power the battery thermal management system, we can efficiently heat the battery to a more suitable operating temperature. This strategy could minimize cold-start-related degradation, extending its lifespan and improving long-term reliability.

The formulation of the DP-based EMS optimization consists of the objective function and constraints listed in Eqs. (17) and (18). As the DP search is based on the statistical data-based standard driving cycle, the optimal EMS serves the baseline optimal EMS, which needs to be extended for the BEV's real-time operations, as discussed in the following section.

$$min\sum_{k=1}^{T} \omega_E E(k) + \omega_Q Q_{loss}(Ah(k), C_{rate}(k), Temp(k)), \tag{17}$$

$$\begin{aligned} P_{dmd}(k) &= P_{cycle}(k), k \in [1, T] \\ SOC_{UC} &\in [SOC_{UC_L}, SOC_{UCH}] \\ SOC_{UC0} &= SOC_{UCend} \\ I_{BT} &\in [0, I_{BTmax}] \\ P_{UC} &\in [P_{UCmin}, P_{UCmax}] \end{aligned} \tag{18}$$

where E is the energy consumption of the ESS, P_{dem} is the power demand, P_{cycle} is the total power of the driving cycle, $SOC_{UCL}$and SOC_{UCH} are the lower and upper limits of the SOC_{UC}, is the initial SOC_{UC} value, SOC_{UCend} is the end SOC_{UC} value, $SOC_{UC_{min}}$ and $SOC_{UC_{max}}$ are the minimal and maximal power of the UC pack, and I_{BTmax} is the maximal discharge current of the battery pack.

The power of the battery and UC needs to satisfy the power demand shown in Eq. (19), where P_{BT} and P_{UC} represent the actual output power of the battery and UC packs after considering the efficiency of the DC/DC converter:

$$P_{dem}(k) = P_{BT}(k) + P_{UC}(k) \tag{19}$$

During vehicle operation, the battery's performance is influenced by two key factors. Firstly, temperature fluctuations impact the battery's V_{oc}, with lower temperatures resulting in lower V_{oc}. Additionally, battery aging occurs with usage, leading to diminished SOH, elevated resistance, and reduced capacity. An effective battery degradation model continually monitors performance during usage and adjusts parameters to refine the battery model.

Since low temperatures accelerate battery degradation, prompt temperature elevation is crucial, although the battery gradually generates heat and warms up during operation. UCs, whose performance remains largely unaffected by temperature, are pivotal in providing reliable heating energy. Leveraging UC energy, especially when battery temperatures haven't risen, safeguards both the thermal management system and vehicle power supply, augmenting the battery's function.

A crucial step in designing a DP model and search is specifying state and control variables. State variables (such as SOC and temperature) are chosen to maintain consistency throughout the driving cycle. In contrast, the control variable (such as the power split rate between different power sources) is determined to influence the vehicle state at the proceeding step. The state vector, X, is calculated by iterating through the values of each state variable and driving cycle. The control vector, U, is formed by repeating this process. The indices in the respective vectors are used to relate to each distinct state and control.

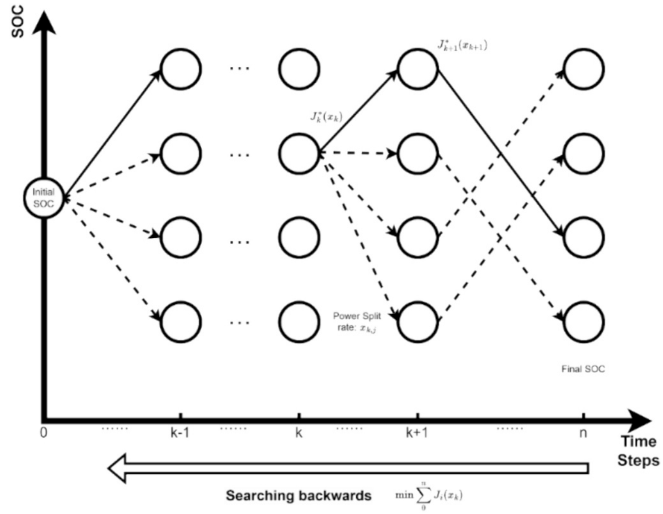


Fig. 15. DP algorithm.

Finally, the DP algorithm can be summarized in Fig. 15.

6.3. Advantages of HESS and comparison

BEVs rely solely on batteries as their primary energy source, and the battery SOC can exhibit significant fluctuations during a driving cycle. This SOC fluctuation is due to the varying energy demands on the battery as the vehicle accelerates, decelerates, and encounters different driving conditions. These fluctuations can impact the overall efficiency and performance of the vehicle.

Integrating a UC as an auxiliary energy source in the BEV's electrical system can help stabilize the battery SOC. UCs are energy storage devices that can quickly store and discharge electrical energy to rapidly provide bursts of power, making them well-suited for smoothing out the power demands on the battery in dynamic driving situations.

UCs can absorb and release electrical energy rapidly. When the vehicle goes through a quick acceleration and deceleration with propulsion and braking-recovery power surges, the UC can provide and absorb the excess energy, reducing strain on the battery with fewer SOC fluctuations and large discharge and charge currents. During regenerative braking, energy generated during deceleration is typically captured and stored. UCs excel in this scenario, quickly absorbing the excess energy and preventing battery overcharging. These UCs mitigate stress on lithium batteries, reducing their charge-discharge cycles and currents, reducing battery degradation, and extending battery operational lifespan, thus lowering the overall LLC.

Moreover, UCs operate efficiently at lower temperatures to warm up cold batteries and provide propulsion power initially, improving electric ESS performance and efficiency, extending battery operational lifespan, and lowering the overall LLC.

Fig. 16 depicts a DP-based control strategy. Initial parameters are set with the battery's SOC at 0.95, the UC's SOC at 1, and both battery and

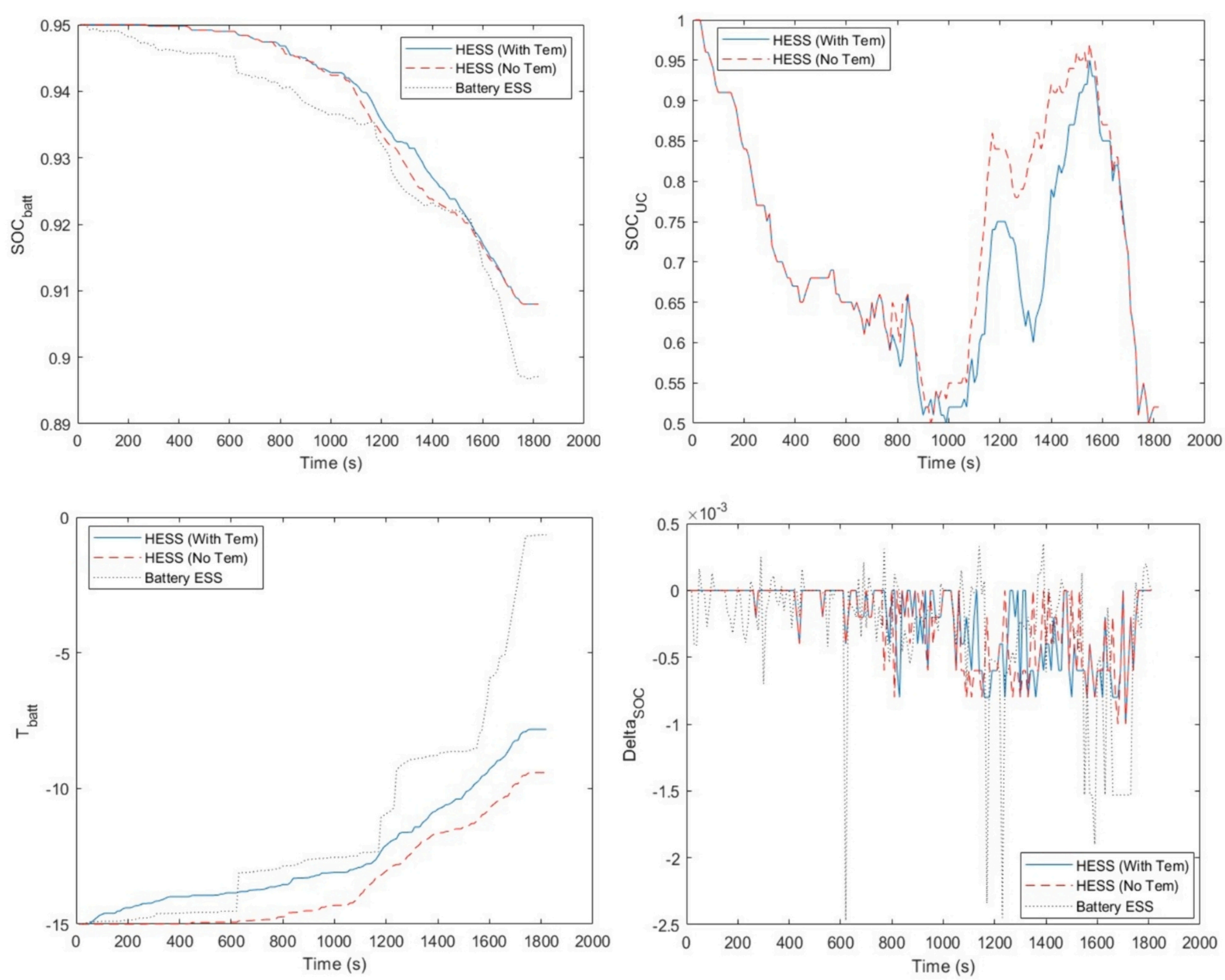


Fig. 16. Battery SOC, UC SOC, battery temperature and delta SOC of both HESS and BESS.

ambient temperatures at −15° Celsius. When factoring in an initial low temperature of −15 °C and employing UCs for battery heating, optimizing energy management within the composite electric ESS undergoes significant changes. This results in distinct operational states for two design configurations: HESS with no temperature consideration (No Temp) and HESS with low startup temperature consideration (With Temp).

The impact on the lithium battery's storage capacity loss and the equivalent charge-discharge cycles over a half-hour period is detailed in the table below. (See Table 3.)

By adjusting the temperature and reducing the depth of discharge on the battery, adding UCs can help extend the battery's overall lifespan by 42.86 % and reduce the number of battery cycles by 45 % in one cycle. Considering low temperatures, the lifespan was extended by another 2.92 % in addition to improved ESS power performance. Integrating a UC as an auxiliary energy source in a BEV can improve energy management and contribute to a more efficient and durable vehicle.

6.4. Solution of the nested global optimization problem

Solving this complex, computation-intensive, black-box global optimization problem requires an efficient global optimization search algorithm. Our test examples compare the commonly used Genetic Algorithms (GA) with our innovative Multi-Start Space Reduction (MSSR) algorithm, leveraging a Kriging-based agent model, multi-start scheme, and alternating sampling in global, medium, and local spaces. Table 4 shows the total computation time and the number of computationally demanding DP calculations for both algorithms over 50 iterations. Notably, the MSSR algorithm reduces total time consumption to just 10 % of the commonly used GA, primarily due to a significant reduction in DP calculations. This reduction is crucial, given the time-intensive nature of the DP algorithm. The MSSR algorithm's computation time reduction by an order of magnitude makes the solution of the formulated optimization problem viable on a regular Windows PC workstation. This efficiency paves the way for rapid and effective optimization iterations, ensuring a streamlined strategy to achieving the best system design and control integration solution.

The LCC minimization formulation ascertained optimal HESS sizes and initial EMS/power allocation schemes for the HEV propulsion system, as shown in Table 5. (See Table 6.)

7. Real-time optimal control of HESS

The standard driving cycles, like WLTC, define representative vehicle speed variation patterns, serving as the foundation for powertrain system design and performance analysis. However, real vehicle speed differs considerably in operations due to varying traffic, road and weather conditions, and driver behaviour, as illustrated in Fig. 17. Accurately predicting vehicle speeds is essential for estimating the coming propulsion power demand and optimizing energy management.

The HESS's real-time optimal power control and energy management are based on the vehicle speed, battery temperature, and voltage measured under the instant battery operating parameters. The vehicle speed from the standard driving cycle, the baseline optimal EMS and the statistical battery degradation model are used as long-term prediction guides to improve the prediction accuracy over the entire driving cycle.

Table 3
Comparison of BESS, HESS (No Temp) and HESS (With Temp).

	BESS	HESS (No Temp)	HESS (With Temp)
Q_{loss}	11.60e-6	8.12e-6	7.89e-6
Equivalent charge-discharge cycles	1.45	1	1

Table 4
Comparison of two algorithms.

Algorithms	Total time	Times of DP Searches
GA	37.5 h	1000
MSSR	3.7 h	98

Table 5
Parameters of energy storage components.

Battery	Cell nominal capacity/Ah	40
	Number in series	125
	Number in parallel	10
UC	Nominal capacity/F	140
	Number in series	10
	Number in parallel	15

A baseline optimal EMS-guided MPC method is introduced to enhance the real-time optimal power control and EMS, as shown in Fig. 18.

As discussed earlier, the UCs and batteries in the HESS supply the BEV with instant propulsion power. The optimal power distribution between the two is determined by minimizing the LLC of the BEV and HESS, considering the entire vehicle operation cycle. The energy loss of UC and battery charges and discharges, the battery efficiency loss and operation life loss during fast charges/discharges and low-temperature operation, and the gain of active battery heating using energy from the UCs are considered jointly, using the objective function, $J(x)$, similar to Eqs. (17) and (18).

Instead of DP, MPC generates real-time optimal power control and energy management solutions for each time step instead of DP. The MPC is carried out by more accurately predicting the vehicle propulsion power at each time instance using the EKF with both driving cycle and real-time vehicle speed data. The difference between the projected vehicle speed from the statistical driving cycle, which produces the baseline optimal EMS, and the actual sensed vehicle speed at each time instance during the BEV's operation is used to correct the needed propulsion power prediction for the coming states in MPC.

In addition, based on the instantly measured battery voltage under the instant C-rate, SOC and temperature, the "effective" cycle number of the battery degradation model shown in Fig. 7 is calculated to reflect the actual SOH of the batteries rather than using the fixed, statistical degradation model parameters and cycle count. By adjusting the battery temperature in real-time, the instant energy supply capacity and degradation rate of the Li-ion batteries are determined, serving as critical control inputs for subsequent time steps in the BEV's operation cycle.

The MPC algorithm manages the entire vehicle operation cycle in real time, ensuring optimal energy allocation at each time step. This strategy enables dynamic adaptation and optimization of the HESS EMS, enhancing overall vehicle efficiency and battery longevity. The comparisons were made over the same duration of the WLTC driving cycle to show the improvements.

8. Result discussions

During this research, we used a large amount of battery laboratory experimental data and in-vehicle operation data, which were obtained over an extended period of time. Some of these data were used to test and validate the models and the newly introduced methods. This study introduced a new and innovative strategy departing from the previous research and demonstrated the efficiency and benefit of the new strategy. We are building a prototyping system for testing and obtaining operational data. However, it will take considerable testing time to get accurate data from the slow degradation of the batteries. This work contributes to the new methodology, the new battery low-temperature performance and degradation models, the integrated HESS design, TMS and EMS optimizations, and the realization of real-time optimal

Table 6
Minimum overall LCC measure results under different vehicle operations.

Q_{loss}(%) / SOH \ Operations	Without speed changes		With speed changes	
	DP-based	MPC-based	DP-based	MPC-based
New	7.89e-6	8.45e-6	13.27e-6	10.85e-6
Old	9.98e-6	9.11e-6	14.61e-6	11.85e-6

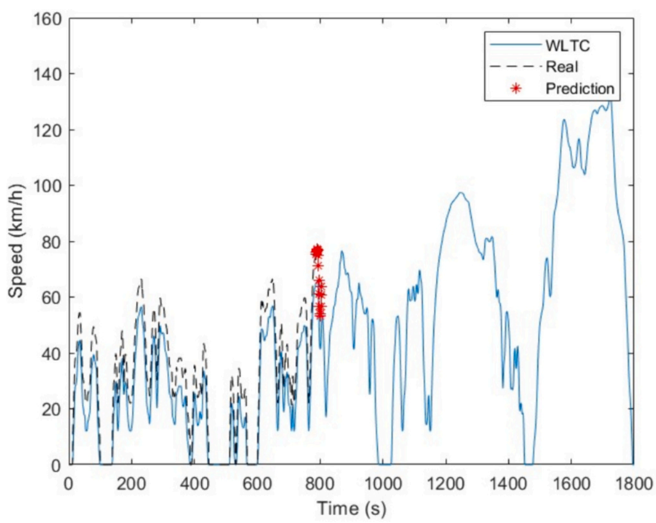


Fig. 17. Vehicle speed variation pattern and real-time speed prediction.

control of the HESS.

A comprehensive comparison between the newly introduced MPC-based real-time control and the baseline optimal EMS derived from the speed change-free DP method is shown using results illustrated in Fig. 19, and compared to the baseline optimal EMS, battery degradation based on real-time EMS increased by 7.10 %.

This finding underscores the efficiency of real-time control strategies in mitigating battery degradation. Unlike traditional strategies such as DP, which rely on static control strategies, real-time control continuously adapts to changing conditions and battery states. When the battery undergoes degradation over time due to usage, the real-time control system dynamically adjusts the battery parameters to optimize performance and extend its lifespan.

Adding the critical battery cold-start issue addressing mechanism, combining electric ESS design, EMS and TMS optimizations, and more accurate real-time optimal control schemes, make this newly introduced strategy fundamentally different from the traditional electric BESS strategies, such as the DP-based, offline optimal EMS methods reported in present researches.

For instance, the present fixed and offline DP-based strategy may lead to unintended consequences, such as accelerating the battery's degradation. When the battery's power output declines, the control system often compensates by demanding more from the battery, whether through higher current draws or more frequent charging and discharging cycles. This increased demand can exacerbate the battery's wear and tear, leading to faster degradation of its capacity and overall health. As the battery ages, several factors contribute to its degradation. The battery's internal resistance increases, causing greater energy losses during charging and discharging. Moreover, the battery's SOC is adjusted more frequently to compensate for its reduced capacity. Over time, these factors can lead to a significant reduction in the battery's remaining useful life.

We introduced adaptive control strategies that respond to the battery's health in real time to address these challenges. Such strategies might gradually reduce the power demand on the battery as its health declines, shifting more load to the UCs by optimizing the power-sharing dynamics between the battery and the UC, ensuring that the battery is not overworked and that its remaining capacity is preserved for as long as possible. Active thermal management also ensures batteries operate within safe temperature limits, further extending their lifespan.

By proactively adapting the control strategy based on the battery's condition, the overall longevity and performance of the HESS can be significantly improved. The collective effect not only enhances the reliability of the ESS but also reduces the total cost of ownership by delaying the need for battery replacement. Implementing real-time control strategies represents a significant advancement over

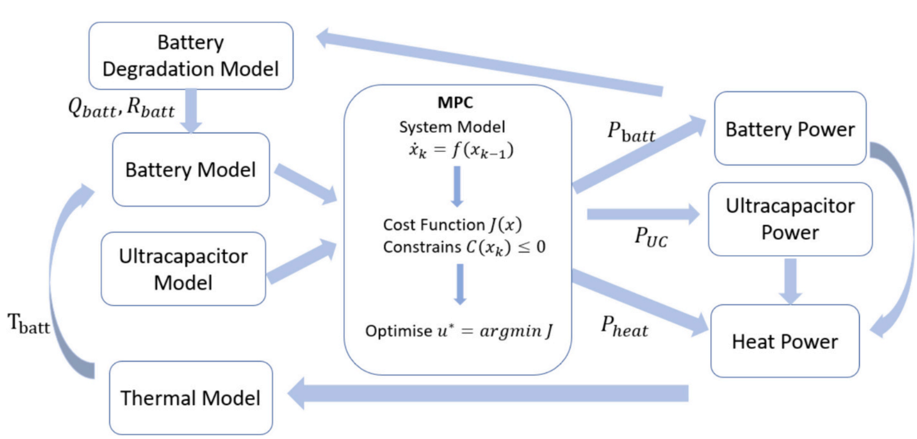


Fig. 18. The novel adaptive MPC method.

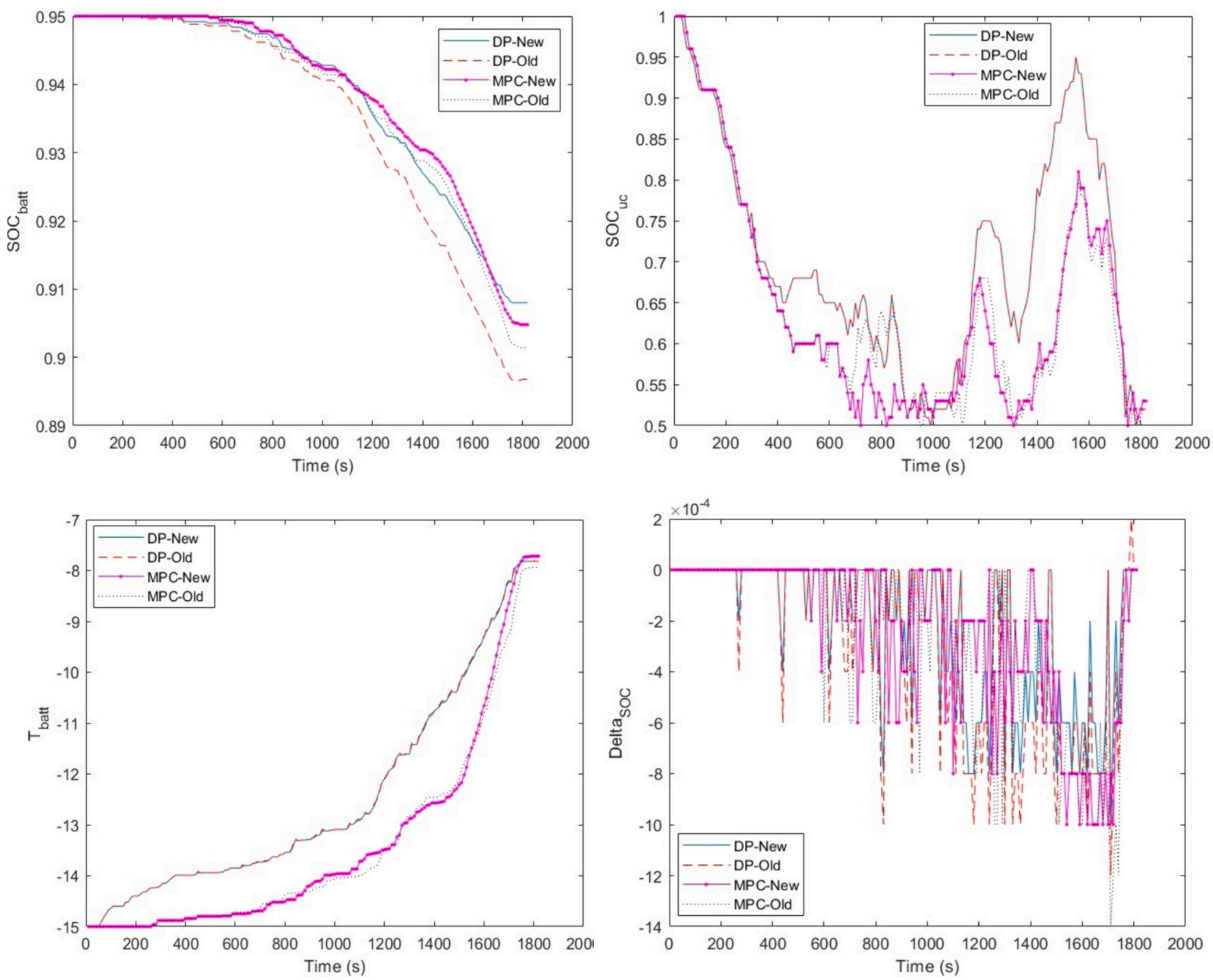


Fig. 19. Battery SOC, UC SOC, temperature and delta SOC based on different methods and different SOH.

traditional DP strategies. Real-time control mitigates battery degradation and enhances overall system performance by continuously optimizing the charging and discharging profiles, managing temperature fluctuations, and adapting to varying usage patterns. The 9.55 % reduction in battery degradation observed in our research highlights the potential of real-time control to improve the longevity and reliability of energy storage systems, ultimately leading to lower operational costs and more sustainable energy solutions.

Utilizing the UC within the baseline optimal EMS introduces a fundamentally static strategy, particularly when the vehicle's speed experiences fluctuations. In such a system, the control strategy for the UC remains fixed, leading to a reliance on the battery to meet any additional energy demands that arise during these perturbations. While this method ensures that immediate power needs are met, it highlights a significant limitation: the system's inability to adapt dynamically to changing conditions. This limitation becomes especially problematic compared to the flexibility of real-time control algorithms.

Fig. 20 starkly illustrates the shortcomings of this static UC usage, particularly in scenarios where significant current fluctuations occur. Under these conditions, the UC, constrained by its static control parameters, struggles to replenish power effectively. As a result, the battery is forced to take on an increasing share of the load, leading to high-current discharges. This increased burden accelerates the battery's degradation as it is subjected to stress beyond its optimal operating range.

The consequences of this static strategy are twofold. Firstly, the high-current discharges place considerable strain on the battery's internal components, leading to a more rapid degradation in its capacity and overall health. Secondly, the heightened activity within the battery generates additional heat. While a certain heat level can improve battery performance by reducing internal resistance, excessive temperatures can have the opposite effect, exacerbating the degradation process. This paradox highlights a critical flaw in relying solely on static UC usage within the EMS: the system inadvertently accelerates the degradation it aims to prevent.

In contrast, real-time control strategies offer a dynamic and adaptive solution that effectively mitigates these issues. Unlike the static strategy, real-time control continuously monitors the battery's condition and the system's operating environment, allowing for on-the-fly adjustments to the UC and battery's roles. By optimizing charging and discharging profiles in real-time, the system can ensure that the battery operates within its ideal parameters, thereby minimizing the stress that contributes to degradation.

Our Analysis has shown that employing real-time control strategies can lead to a substantial 22.30 % reduction in battery degradation compared to the conventional DP algorithm. This improvement is particularly significant as the battery undergoes natural wear over time. Real-time control demonstrates its efficiency in the immediate reduction of degradation and its ability to slow the overall degradation rate by an impressive 23.29 %.

The implications of this research extend beyond just prolonging battery life. By mitigating battery degradation, real-time control

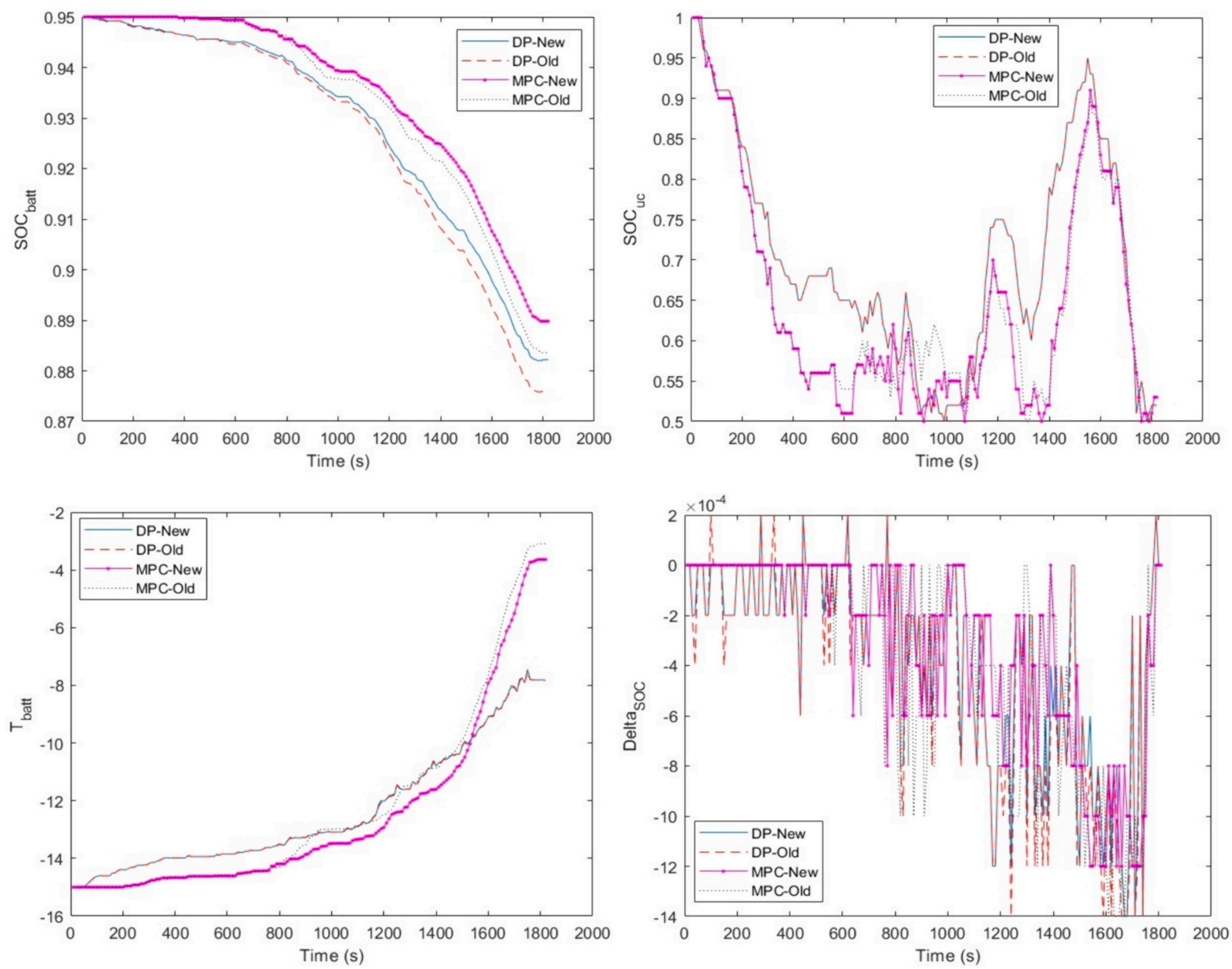


Fig. 20. Battery SOC, UC SOC, temperature and delta SOC based on different methods and different SOH considering speed changes.

strategies also enhance the overall efficiency and reliability of the ESS. This reduces maintenance and replacement costs and improves the system's performance in demanding applications, such as electric vehicles, renewable energy storage, and industrial power systems.

9. Conclusion

This study presented a novel strategy to enhance the resilience of battery systems to extreme temperatures, thereby prolonging battery life and improving overall energy storage efficiency. We demonstrated significant battery performance and longevity advancements by integrating UCs into an HESS and implementing advanced EMS and TMS. Using DP and advanced modelling techniques, our optimized HESS design effectively mitigated the detrimental effects of extreme temperatures on battery health. By strategically leveraging the UC's fast charge/discharge capabilities and thermal adaptability, we achieved a remarkable battery life extension by 47 %. We reduced the number of battery cycles within a single cycle by 45 %. Furthermore, the integration of the EKF and MPC enables real-time monitoring and precise management of the ESS. This strategy ensured optimal performance under varying conditions and reduced battery degradation rates by up to 23 %. The battery performance data under extreme temperatures in this study is relatively limited. To address this issue, future research needs to cover battery testing across a broader range of temperature variations and usage scenarios. This expansion will help develop more comprehensive and accurate models of temperature impact on battery performance and degradation, providing deeper insights into how extreme temperatures impact battery performance.

CRediT authorship contribution statement

Bo Pang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Haijia Zhu:** Validation, Software, Formal analysis, Data curation. **Yuqi Tong:** Data curation. **Zuomin Dong:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data availability

Data will be made available on request.

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