A Finite-Set Model-Based Predictive Battery Thermal Management in Connected and Automated Hybrid Electric Vehicles

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***Abstract*—The connected and automated hybrid electric vehicles (CAHEVs) have the potential to improve safety by mitigating traffic accidents. A crucial problem of the CAHEVs is that the Lithium-ion batteries are highly temperature-sensitive and may be premature aging at high working temperatures. Consequently, an effective and efficient battery thermal management (BTM) system is required with the minimum possible cooling energy consumption. To achieve the multiple objectives, a finite-set model-based (FSMB) predictive control strategy for the BTM in a CAHEV is presented, in which an improved cost function is proposed for better performances. Based on the predictive model of battery temperatures, the optimum cooling approach is determined with consideration of the future road information and battery charge/discharge power. The hardware-in-the-loop (HIL) test based on a Toyota Prius HEV model and the UDDS road cycle is conducted, and the results demonstrate the effectiveness of the proposed BTM strategy in both temperature control and energy saving.**

Keywords—connected and automated hybrid electric vehicles (CAHEVs), battery thermal management, model predictive control, energy saving.

I. Introduction

Hybrid electric vehicles (HEVs) are more energy efficient and cleaner than conventional vehicles [1]. Recently, the implementation of connected and automated driving system has been applied to HEVs to further reduce fuel consumption with the improvement of safety and traffic congestion [2, 3]. However, CAHEVs involve several technical challenges. Among them the battery thermal management (BTM) is crucial because battery packs have to operate within a certain temperature range to ensure safety, optimum performance, and long service life [4-7].

To maintain optimum working temperatures, the BTM solutions for Lithium-ion battery packs are usually based on air cooling and liquid cooling systems. Since the implementation of cooling systems contributes to a further decrease in vehicle autonomy, optimal control methods are urgent for effective and efficient BTM. The widely implemented strategy is to simply use two PID controllers to regulate the air and liquid cooling power separately, combined with a state-machine mechanism to determine whether the liquid cooling should be cut in or off according to predefined battery temperature levels [8]. Although this classical method can effectively maintain the battery temperature to a reasonable range, the controllability of the consumed energy is unavailable due to the single degree of freedom of the PID controller. Therefore, the conventional BTM method is hard to realize the energy optimization.

Compared to the classical scheme of using PID controllers and finite-state machines, some advanced strategies exploit their potentials with multiple-object optimization on both battery temperature control and energy saving. Ref. [9-11] utilize the dynamic programming (DP) method to calculate the global optimized input variables of the BTM system at each time stamp, achieving the required battery temperature with the minimum BTM system energy cost. However, the global optimization of DP method is based on the entire road profile of the driving cycle, which is unavailable and not practical for CAHEVs. Also, the tremendous computational burden of the DP method reduces its feasibility in real-time applications. Model predictive control (MPC) strategy is implemented on BTM system to solve the real-time application issue by using the receding horizon optimization [11, 12]. The proposed MPC strategies neglected the thermoelectric dynamics of the battery cells, leading to a considerable error in a long prediction horizon. Meanwhile, the future driving cycle information of the CAHEV is not sufficiently utilized in the MPC strategy, which decreases the potential performance of the BTM system.

In this paper, a finite-set model-based predictive control strategy is proposed to improve the efficiency of the BTM for CAHEVs. A thermoelectric model of Lithium-ion battery pack is first established with consideration of parameter dynamics. Then, predictive equations for battery temperature concerning two cooling systems are obtained, in which future information of the CAHEV is fully considered. Based on the predictive model, an improved cost function is proposed to evaluate the finite possible solutions, leading to an optimum approach for BTM. Hardware-in-the-loop (HIL) test results validate the effectiveness and efficiency of the proposed BTM method.

II. Model of the BTM System in HEVs

A. System Configuration

The heat transfer approaches in BTM system of HEVs can be seen in Fig. 1. The battery internal heat Q_{gen} is generated due to the charge/discharge current, resulting in the temperature rising. Meanwhile, the ambient temperature also

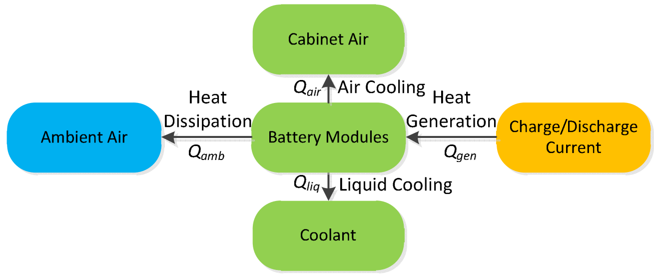


Fig. 1. Structure and dimensions of the integrated magnetic coupler

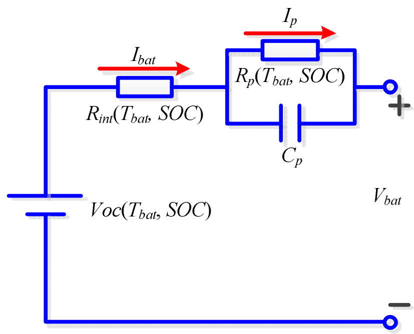
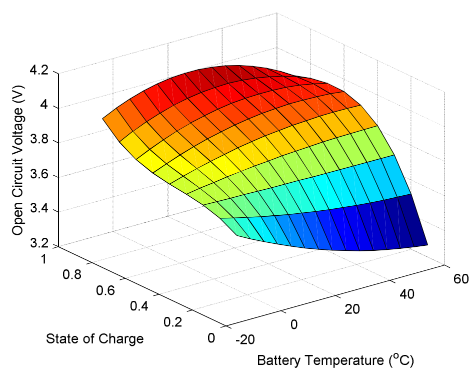
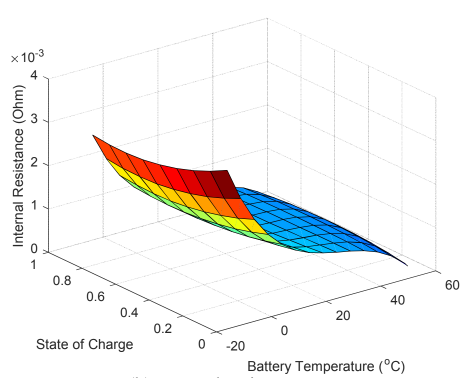


Fig. 2. Equivalent circuit model of the battery in HEVs



(a) Open circuit voltage V_{oc}



(b) Internal resistance R_{int}

Fig. 3 Test-data-based model of the battery parameters

has an effect on the battery temperature, providing a non-negligible heat Q_{amb} transferred to the battery. The purpose of the BTM system is to keep the battery modules in the temperature range that assure safety and reduce aging. With the BTM system containing both air and liquid cooling equipment, the heat Q_{air} and Q_{liq} can be dissipated to the air and coolant flow to maintain an acceptable battery temperature. It should be noted that the air flow in the air cooling system is from the cabinet whose temperature is different from the ambient.

B. *Equivalent Circuit Model of the Battery*

The thermoelectric model in this study is an equivalent circuit model using a combination of voltage sources, resistances, and capacitors to determine the Lithium-ion battery voltage under current solicitations [13, 14]. As shown in Fig. 2, V_{oc} and V_{bat} denote the open circuit voltage and output voltage of the battery, respectively. R_{int} denotes the internal resistance of the Lithium-ion battery, while R_p and C_p describe the polarization effect of the battery. According to the electrochemistry characteristics, these parameters are variants on the state of charge (SOC) and the battery temperature T_{bat}.

As the SOC and the battery temperature are varied during the driving cycle, their effects on the electrical and thermal performances of the battery module cannot be neglected. One of the effective approaches to is to obtain the equivalent electrical parameters through offline test under different SOCs and temperatures, and then proper curve fitting methods can be used for establishing the function. In this study, a test-data based parametric model of the power battery module in the Prius HEV is built according to the experimental results provided by The Idaho National Laboratory [15], as shown in Fig. 3. Through a 4th-order polynomial curve fitting methods, the parametric model of the battery module can be obtained to calculate the charge/discharge current I_{bat} and output voltage V_{bat} used in the HEV battery thermal model under different scenarios.

C. *Thermal Model of the Battery*

A lumped parameter thermal model is chosen for its effectiveness on representing the temperature dynamics without too much computational efforts in real-time applications. In the battery thermal model, both the Joule effect and the entropy should be taken into account for heat generation. Thus, the heat generation rate Q_{gen} of the battery can be presented as:

$$Q_{gen} = I_{bat}\left(V_{oc} - V_{bat}\right) - I_{bat}T_{bat}\frac{\partial V_{oc}}{\partial T_{bat}}\left(SOC\right) \qquad (1)$$

where $\partial V_{oc}/\partial T_{bat}$ denotes the coefficient of the heat generated in the chemical reactions, which is related to the SOC and also can be obtained through experimental test.

The heat dissipation model can be established using the theory of uniform wall [16]; thus the three approaches of heat transfer can be expressed as

$$Q_{air} = C_{p1}m_1 \cdot \left[T_{bat} - T_{cab}\right]\left(1 - e^{-\tau_1}\right) \qquad (2)$$

$$Q_{liq} = C_{p2}m_2 \cdot \left[T_{bat} - T_{liq}\right]\left(1 - e^{-\tau_2}\right) \qquad (3)$$

$$Q_{amb} = C_{pb}m_b \cdot \left[T_{bat} - T_{amb}\right]\left(1 - e^{-\tau_3}\right) \qquad (4)$$

where C_{p1}, C_{p2}, and C_{pb} denote the equivalent heat capacities of the air, the coolant, and the battery pack, respectively. m_1 and m_2 are equivalent thermal mass flow of the air flow and the coolant, while m_b represents the thermal mass of the battery body. τ_1, τ_2, and τ_3 are heat transfer time constants and are expressed by (5)-(7):

$$\tau_1 = h_1 A_1 / C_{p1} m_1 \tag{5}$$

$$\tau_2 = h_2 A_2 / C_{p2} m_2 \tag{6}$$

$$\tau_3 = h_3 A_3 / C_{pb} m_b \tag{7}$$

where h_1, h_2 denote the equivalent heat transfer coefficient from the battery pack to the air flow, the coolant, and the ambient respectively. A_1, A_2, and A_3 denote the corresponding heat dissipation areas. Note that the time constants are determined by the thermal mass rates of the air and coolant flow m_1 and m_2, which are defined as the control variants of the BTM system.

$$T_{bat} = \frac{1}{C_{pb} m_b} \int_0^t \left[Q_{gen}(\tau) - Q_{liq}(\tau) - Q_{air}(\tau) \right] \left(1 - e^{-\tau_b t}\right) d\tau \tag{8}$$

Based on the law of thermodynamics, the temperature of the battery pack can be expressed by (8), in which the time constant τ_b describes the heat transfer between the battery internal and shell. The thermoelectric model of the battery pack in HEVs is described by (1)-(8) in time domain, in which the input variables m_1 and m_2 can be controlled by the BTM system for optimum temperature with reduced energy cost.

III. Finite-Set Model-Based Predictive Battery Thermal Management

A. Battery Temperature Prediction

According to the battery thermal model presented by (8), a discrete prediction model for battery temperature in CAHEVs can be built, as shown in (9).

$$\begin{aligned} T_{bat}(k+1) = {} & \frac{T_s^2 \left[Q_{gen}(k+1) - Q_{liq}(k+1) - Q_{air}(k+1) - Q_{amb}(k+1) \right]}{(\tau_b + T_s) C_{pb} m_b} + \\ & \left(1 + \frac{\tau_b}{\tau_b + T_s}\right) T_{bat}(k) - \frac{\tau_b T_{bat}(k-1)}{\tau_b + T_s} \end{aligned} \tag{9}$$

Performing a simple 1st-order approximation on (9), the temperautre prediction funciton can be presented as

$$\begin{aligned} T_{bat}(k+1) = {} & \frac{T_s^2 \left[Q_{gen}(k) - Q_{liq}(k) - Q_{air}(k) - Q_{amb}(k) \right]}{(\tau_b + T_s) C_{pb} m_b} + \\ & \left(1 + \frac{\tau_b}{\tau_b + T_s}\right) T_{bat}(k) - \frac{\tau_b T_{bat}(k-1)}{\tau_b + T_s} \end{aligned} \tag{10}$$

In (10), the generated heat $Q_{gen}(k)$ can be estimated by the future charge/discharge power of the battery according to (1):

$$Q_{gen} = \frac{P_{bat}(k)}{V_{bat}(k)} \left\{ V_{oc}(k) - V_{bat}(k) + T_{bat}(k) \frac{\partial V_{oc}}{\partial T_{bat}} \left[SOC(k) \right] \right\} \tag{11}$$

where the battery electrical parameters are all related to the battery temperature and the state of charge. Based on the integral estimation method, the SOC of the battery can be predicted as

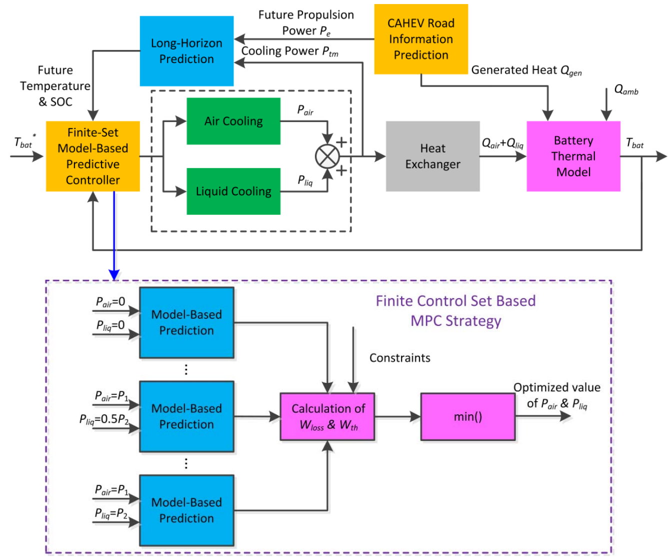


Fig. 4. Proposed FSMPC scheme for BTM system in CAHEVs

$$SOC(k) = SOC(0) - \sum_{i=1}^{k} \frac{V_{oc}(i) - \sqrt{V_{oc}^2(i) - 4 P_{bat}(i) R_{bat}(k)}}{2 C_{bat} R_{bat}} \tag{12}$$

The dissipated heat rates $Q_{air}(k)$ and $Q_{liq}(k)$ depend on the BTM system inputs $m_1(k)$ and $m_2(k)$; thus they can be directly calculated by (2)-(7).

From (9)-(12), it is concluded that the battery temperature at the next time step is determined by the ambient temperature, output power of the cooling system (air cooling, liquid cooling, or both). For CAHEVs, there is an outstanding feature that the future information of the drive cycle can be obtained from the intelligence ECU in advance. Therefore, the future propulsion power of the vehicle can be used for predicting the potential charge/discharge battery power considering the optimized powertrain system, then $Q_{gen}(k)$ can be easily predicted by the proposed thermoelectric model. Consequently, a long prediction horizon for the BTM system in CAHEVs, e.g. 30 seconds or even 1 minute, is able to be implemented to significantly improve the system efficiency. The battery temperature and consumed cooling power during the prediction horizon are available by using the proposed prediction functions (9)-(12).

B. Finite-Set Based Control Strategy

It should be noted that the liquid cooling system is more powerful than the air cooling system and can cool the battery pack within reduced time, though more electric power is consumed. To achieve reasonable battery temperature ranges with minimum consumed power, the optimized combination of the air and liquid cooling system is of vital importance.

As the BTM model described by (1)-(8) is a nonlinear system, it is not applicable for directly solving the optimum values. Thus, a finite-set based control strategy is proposed in this study, in which complicated resolving process can be avoided. As the mass rates of the air and liquid flow are linearly related to the corresponding cooling power, it is reasonable to choose several combinations of the air and liquid cooling powers to a finite solution set with some constraints.

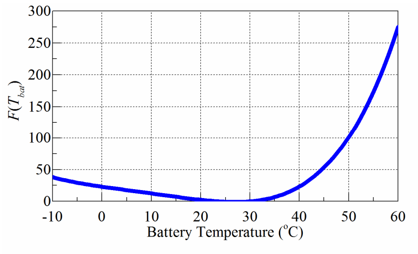


Fig. 5. Battery temperature punishment function

Then, each solution is substituted in the long-horizon prediction model to predict the battery temperature at the destination. Then, a suitable cost function is used to evaluate the related performances of these possible solutions, in which the optimized combination of the cooling powers are selected for improving both the battery temperature and energy saving.

The control structure of the proposed finite-set model-based BTM prediction control is shown in Fig. 4. Unlike the dynamic programming method, the state variable $T_{bat}(k)$ is able to be predicted at each time interval in the prediction horizon. Therefore, the gridding and interpolation of the state variable $T_{bat}(k)$ are no longer required at each prediction interval, in which the computational burden is greatly released. Moreover, for better adaption in the real-time application, further simplification method is applied in the proposed scheme. Due to the large time constant, the battery temperature change slowly during a prediction horizon, such as 30 seconds. Therefore, the constant cooling mass rates of m_1(k) and m_2(k) are assumed within the prediction horizon. This reasonable assumption can reduce the iteration times to only 30n (n is the number of the possible solutions in the finite set) in each control period. In addition, a basic rule is considered in the BTM system, which is that the liquid cooling system only operates after the full power of the air cooling system turns on. This common rule can reduce the number of solutions in the finite set, .which further alleviate the computational burden of the ECU for BTM system.

C. Improved Cost Function

In order to obtain the optimum battery temperature with the minimum required energy cost, a cost function should be used to evaluate the performances of the possible solutions in the finite set. Since the battery temperature and the energy saving are both the control targets, these two facts should be considered in the cost function at the same time.

As the high temperatures accelerate the aging of the battery cells, the cost function should provide the punishment against high temperature values. Meanwhile, under the low temperatures such as the subzero, the battery capacity is severely deteriorated, resulting in the limited output power. Thus, the cost function should also provide the punishment against low temperature values. Considering the critically high or low temperature values have irreversible effects on the battery cells, the BTM system should recover the battery temperature from these critical scenarios as soon as possible. In the proposed strategy, a temperature punishment function is set up based on the aging parameters provided by the battery manufacturers, which is presented as

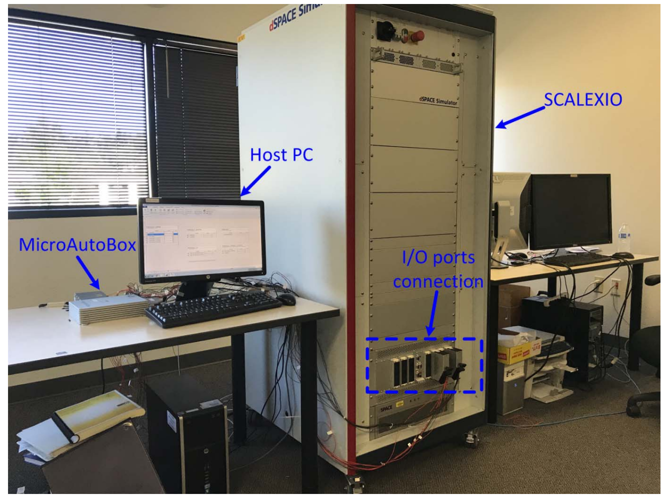


Fig. 5. HIL test bench for the BTM system development in CAHEVs

$$F = \alpha_0 - \alpha_1 T_{bat}(k) + \alpha_2 T_{bat}^2(k) - \alpha_3 T_{bat}^3(k) + \alpha_4 T_{bat}^4(k) \qquad (13)$$

where α_0, α_1, α_2, α_3, and α_4 are aging coefficients. The aging curve against battery temperature is shown in Fig. 4. It is obvious the punishment function can effectively exclude the critically high or low battery temperatures for better aging performance, while the optimum operating temperature range between 20 and 35°C is acceptable.

As to the energy consumption, a very simple and straight evaluation approach is to calculate the consumed SOC. Consequently, the cost function for the FSMPC is derived as

$$J = \min \sum_{k=k_0}^{k_0+H} \left\{ F(k) + \beta \left[1 - SOC(k) \right] \right\} \qquad (14)$$

where H is the prediction horizon. From (14), it is concluded the proposed cost function can effectively evaluate both the battery temperature and the energy cost, which is applicable for the proposed FSMPC method for BTM system in CAHEVs.

IV. Hardware-in-the-Loop Test Results

A. Test Configuration

The HIL simulation test bench for the BTM system development is constructed, as shown in Fig. 5. The real-time optimized BTM strategy obtained above is implemented in a dSPACE MicroAutoBox, which is utilized as the core of the real ECU. The dSPACE SCALEXIO hardware is used to emulate the physical model of the BTM system in a real-time HEV environment. The HIL simulation for the BTM strategy verification is implemented through the analog I/O ports of the hardware and bidirectional communication between the virtual HEV and the real ECU, where a simulation step size of 0.2 s is utilized. Moreover, the generation and flow of the signals of the HIL simulation system are exactly the same as those of the real HEV.

B. HIL Simulation Test Results

HIL simulation test is proposed to validate the effectiveness of the proposed strategy. The UDDS drive cycle shown in Fig. 6 is implemented as the test drive cycle, and the Toyota Prius

TABLE I. SIMULATION PARAMETERS OF BTM SYSTEM FOR CAHEV

C_{p1}	1005 J/(kg•K)	A_2	5 m^2
C_{p2}	3140 J/(kg•K)	A_3	1 m^2
C_{pb}	1350 J/(kg•K)	m_b	40 kg
h_1	32 W/(m^2•K)	τ_b	100 s
h_2	25 W/(m^2•K)	T_{cab}	25 ºC
h_3	10 W/(m^2•K)	T_{liq}	25 ºC
A_1	1 m^2	T_{amb}	40 ºC

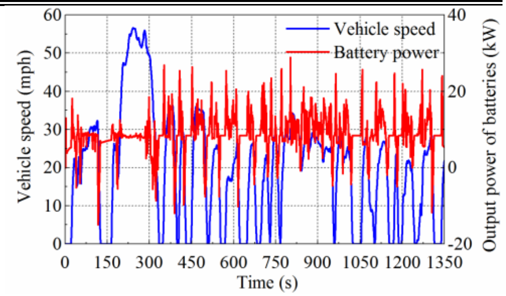


Fig. 6. UDDS cycle

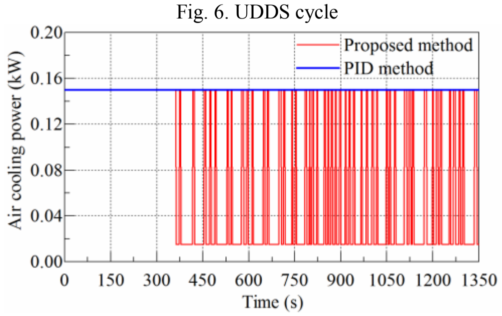


Fig. 7. Simulated results of air cooling powers

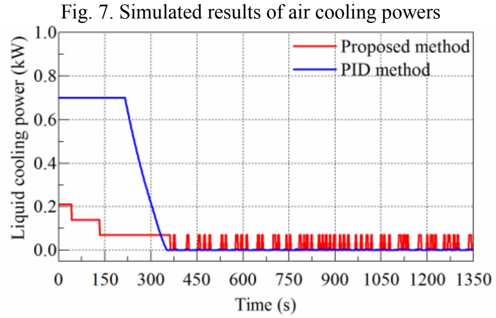


Fig. 8. Simulated results of liquid cooling powers

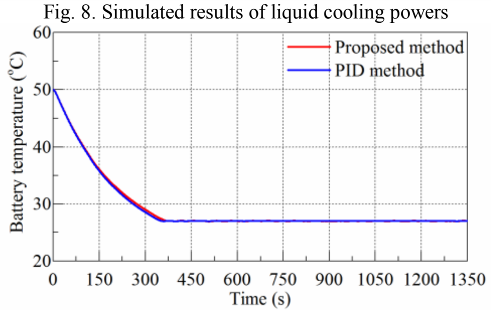


Fig. 9. Simulated results of battery temperatures

2010 HEV model is selected as the test vehicle model. The related parameters in simulation are listed in Table I.

The full powers of the air and liquid cooling systems are 150 W and 700 W, respectively. The standard PID control strategy is also simulated to provide the comparison. The initial battery temperature is set to 50 ºC and the ambient temperature is set to 40 ºC. The simulation results shown in Figs. 7-10

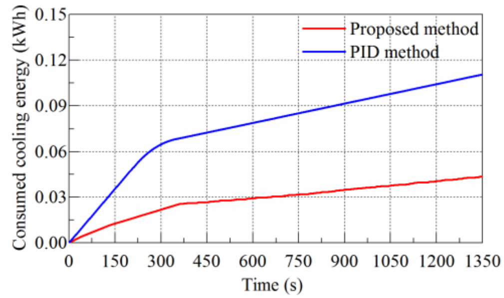


Fig. 10. Simulated results of energy cost for BTM system

present the proposed finite-set model-based predictive BTM strategy provides similar battery temperature dynamical and steady-state performances to the PID method. Meanwhile, the consumed cooling power of the proposed strategy is reduced to 45% compared to the conventional method. The simulation results validate the BTM system for CAHEVs becomes more efficiency by using the proposed predictive control strategy.

V. CONCLUSION

A finite-set model-based predictive strategy for CAHEVs is proposed in this paper to improve the efficiency of the BTM system without any performance degrades. A simplified approach is utilized to reduce the number of solutions in the finite set to reduce the computational burden for better implementation in real-time system. Meanwhile, an improved cost function is proposed to balance the evaluation of the battery temperature and the energy cost. The HIL simulation test is conducted on a Prius HEV under the USDD driving cycle. The test results show the implementation of the FSMPC can achieves 55% cooling energy reduction compared to the conventional method, which is suitable for the BTM system in CAHEVs.

REFERENCES

[1] D. W. Gao, C. Mi, A. Emadi, "Modeling and Simulation of Electric and Hybrid Vehicles," *Proceedings of the IEEE*, pp. 729-745, Apr. 2007.

[2] D. Bevly, X. Cao, M. Gordon, G. Ozbilgin, D. Kari, B. Nelson, J. Woodruff, M. Barth, C. Murray, A. Kurt, K. Redmill, and U. Ozguner, "Lane Change and Merge Maneuvers for Connected and Automated Vehicles: A Survey," *IEEE Trans. Intell. Veh.*, vol. 1, no. 1, pp. 105-120, Mar. 2016.

[3] R. J. Torres and A. A. Malikopoulos, "A Survey on the Coordination of Connected and Automated Vehicles at Intersections and Merging at Highway On-Ramps," *IEEE Trans. Intell. Trans. Sys.*, vol. 18, no. 5, pp. 1066-1077, May 2017.

[4] C. Mi, B. Li, D. Buck, N. Ota, "Advanced Electro-Thermal Modeling of Lithium-Ion Battery System for Hybrid Electric Vehicle Applications," *Vehicle Power and Propulsion Conference*, pp. 107-111, 2007.

[5] A. A. Hussein, "Experimental Modeling and Analysis of Lithium-Ion Battery Temperature Dependence," *IEEE Applied Power Electronics Conference* (*APEC*), pp. 1084-1088, 2015.

[6] X. Gong, C. Mi, "Temperature-Dependent Performance of Lithium Ion Batteries in Electric Vehicles," *IEEE Applied Power Electronics Conference* (*APEC*), pp. 1065-1072, 2015.

[7] J. Jaguemont, L. Boulon, Y. Dube, F. Martel, "Thermal Management of a Hybrid Electric Vehicle in Cold Weather," *IEEE Trans. Energy Conv.*, vol. 31, no. 3, pp. 1110-1120, Sep. 2016.

[8] Q. Peng, Y. Fang, X. Zeng, "Battery Thermal Management System Design and Control Strategy Study for Electric Vehicles," *Proc. IEEE Conf. Expo Transp. Electrific. Asia-Pacific*, pp. 1-4, 2014.

[9] X. Tao, J. Wagner, "Cooling Air Temperature and Air Flow Rate Control for Hybrid Electric Vehicle Battery Thermal Management",

Proc. ASME Dynamic Systems and Control Conf. (*DSCC*), pp. 1-10, 2014.

[10] R. Johri, W. Liang, and R. McGee, “Hybrid Electric Vehicle Energy Management with Battery Thermal Considerations Using Multi-Rate Dynamic Programming”, *Proc. ASME Dynamic Systems and Control Conf.* (*DSCC*), pp. 1-10, 2013.

[11] F. Altaf, B. Egardt, M. L. Johannesson, “Load Management of Modular Battery Using Model Predictive Control: Thermal and State-of Charge Balancing,” *IEEE Trans. Control Sys. Tech.*, vol. 25, no. 1, pp. 47-62, Jan. 2017.

[12] J. L. Sanz, C. O. Martinez, J. A. Florez, M. M. Eguilaz, J. Kalmus, M. Graeber, G. Lux, “Nonlinear Model Predictive Control for Thermal Management in Plug-In Hybrid Electric Vehicles,” *IEEE Trans. Veh. Tech.*, vol. 66, no. 5, pp. 3632-3644, May 2017.

[13] J. Yang, B. Xia, Y. Shang, W. Huang, C. Mi, “Improved Battery Modeling Approach Considering Operating Scenarios for HEV/EV Applications,” *IEEE Applied Power Electron. Conference* (*APEC*), pp. 1216-1222, 2017.

[14] C. Zhang, K. Li, J. Deng, S. Song, “Improved Realtime State-of-Charge Estimation of $LiFePO_4$ Battery Based on a Novel Thermoelectric Model,” *IEEE Trans. Ind. Electron.,* vol. 64, no. 1, pp. 654-663, 2017.

[15] “2010 Toyota Prius VIN 0462 Hybrid Electric Vehicle Battery Test Results,” Idaho Nat. Lab., Idaho Falls, ID, USA, Rep. INL/EXT-13-28025, Jan. 2013.

[16] M. J. Moran, H. N. Shapiro, “Fundamentals of Engineering Thermodynamics: 5th Edition,” Wiley: New York, 2006.