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Zone Model Predictive Control for Battery Thermal Management including Battery Aging and Brake Energy Recovery in Electrified Powertrains

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Abstract: This paper proposes a detailed battery thermal management system for electrified powertrains. A battery aging model consisting of capacity fade and power fade sub-models is built to adjust state of charge estimation and heat generation. The trade-off between the benefit of recuperating braking energy and the cost of additional cooling power is investigated. It is found that the recovery ratio depends on the efficiency of the air conditioning system and the intensity and density of the available braking power. A zone model predictive control approach is developed to maintain the battery temperature within its optimal operating range with minimum power consumption. Remarkable energy consumption reduction can be achieved comparing to traditional controllers.

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Keywords: Electrified powertrains, Battery thermal management, Battery aging, Brake energy recovery, Zone model predictive control.

1. INTRODUCTION

Electrified powertrains are emerging to meet unprecedented emissions regulations and energy shortage. A battery, as an energy storage system, which stores energy from other sources and exchanges energy with the driven load, plays a crucial role in achieving these goals. It is widely acknowledged that battery lifetime is one of the most influencing factors that affect battery performance and durability. Therefore, of particular importance is to design an energy-efficient battery thermal management system (BTMS) to maintain the battery temperature at its optimal operating temperature.

To facilitate the development of BTMS, an accurate battery model is essential. Currently, most studies represent a battery’s electrical behavior by using an equivalent circuit model, Tao and Wagner (2016). This model, however, does not consider the impact of battery aging, which is an inherent phenomenon in a battery during charging and discharging. Battery aging, measured by state-of-health (SOH), results in a reduction in the ability to store energy, related to capacity loss, and deliver power, associated with power loss due to resistance increase, Serrao et al. (2011). These would influence the state of charge (SOC) estimation and heat generation. Furthermore, as far as braking energy is concerned, it is usually regarded as free energy and can be recuperated as much as possible in previous research, Sundstrom et al. (2011). Evidently, brake energy recovery (BER) leads to battery degradation and an increase in the battery temperature, which would request extra cooling power. Hence, a trade-off exists between the benefit of braking energy harvesting and the pay of additional energy consumption, which has not been investigated. In addition, in terms of controlling the battery temperature, earlier works mostly focused on tracking a reference, i.e., keeping the temperature at a setpoint, Tao and Wagner (2016). In practice, however, the cycle life of a battery depends on an ideal working temperature range, as a narrow temperature window indicates wasteful thermal management, Park (2011). Therefore, some control schemes built earlier fail to provide an economic solution in this case. Some researchers implemented on-off strategies to keep the battery temperature inside its suitable range, Pham et al. (2013). Since on-off control is in the class of rule-based approaches, the solution obtained is far from optimal, resulting in excess power consumption. Thus, it is imperative to use more advanced controllers. Model predictive control (MPC), a control scheme belonging to the family of optimal control-based methods, which is good at handling multi-variable systems, complicated dynamics and constraints, has been widely adopted. More importantly, zone MPC (zMPC), Xu and Zhao (2004), is an extension of trajectory tracking MPC, where a constraint-oriented slack variable is utilized to adjust the associated penalties of the cost function, enabling range control. zMPC has yet to be applied to battery thermal management in electrified powertrains.

Motivated by the above analysis, this paper originally proposes a zMPC approach for battery thermal management considering battery aging and BER to maintain the battery temperature within an optimal working range with minimum power consumption. The rest of this paper is structured as follows. System modeling is described in Section II. Controller design is given in Section III. Section
IV presents the simulation results. Finally, conclusions are drawn in Section V.

2. SYSTEM MODELING

The BTMS under consideration is illustrated in Fig. 1. The battery cooling medium driven by a fan removes heat from the battery. When the battery temperature is lower than a predefined threshold, the battery is cooled down with a radiator (\( u_r \)). When the battery temperature is higher than the predefined threshold, it is chilled down by using an evaporator (\( u_e \)) in the air conditioning (AC) system. Furthermore, a reversing valve is added so that the AC system can also work as a heat pump, providing heating power, as they share the same mechanism. The battery considered is a lithium-ion type battery with 96⋅3 = 288 cells and its capacity is 6.4kWh. It is assumed that all battery cells have the same performance. Hence, this research focuses on a single cell. The structure of the battery model is shown in Fig. 2, which contains three sub-models, namely the electrical, thermal and SOH models. The SOH model is derived based on, Arenas et al. (2015). It comprises two sub-models: capacity fade model, which is used to adjust SOC estimation, and power fade model, which is utilized to update heat generation.

![Fig. 1. Battery thermal management system.](image)

![Fig. 2. Battery model structure.](image)

2.1 Electrical model

The electrical part is represented by using an equivalent circuit model with one RC branch from Simscape. It uses an open-circuit voltage \( U_{soc} \), an ohmic resistance \( R_0 \) and a RC branch (with resistance \( R_1 \) and capacitance \( C_1 \)) to predict battery voltage. The SOC of the cell is defined as

\[
SOC = SOC_{init} - \frac{C_{ext}(Ah)}{C_{batt}(Ah)}
\]

where \( SOC_{init} \) is the initial SOC. \( C_{ext} \) is the extracted capacity from the battery, which is the sum of the extracted capacity \( C_{ext,init} \) and the total ampere-hour throughput \( Ah \), i.e.,

\[
C_{ext}(Ah) = C_{ext,init} + \int_0^t I_{batt}(\tau)d\tau
\]

where \( I_{batt} \) is the battery current.

2.2 Capacity fade model

Because of battery aging, the battery capacity \( C_{batt}(Ah) \) is governed by

\[
C_{batt}(Ah) = C_{nom} \cdot (1 - C_{loss}(Ah))
\]

where \( C_{nom} \) is the nominal capacity. \( C_{loss}(Ah) \) is the capacity loss, which is identified by using capacity characterization data, given by

\[
C_{loss}(Ah) = f_{cf}(SOC_{min}, Ratio_{cd}, T_c) \cdot Ah^z
\]

where \( f_{cf} \) is a nonlinear function of the aging factors: \( SOC_{min}, Ratio_{cd} \) and \( T_c \). \( SOC_{min} \) denotes the predefined minimum SOC. \( Ratio_{cd} \) the fraction of time spent in charge depleting over the total operation time, and \( T_c \) the battery core temperature. The coefficients \( f_{cf} \) and \( z \) are the fitting parameters from experiments. The effect of each aging factor on the capacity fade is investigated. The Arrhenius relation is adopted when studying the dependence on the temperature:

\[
f_{cf} = s_{cf}(SOC_{min}, Ratio_{cd}) \cdot \exp \left(-\frac{E_{acti,cf}}{R_g T_c}\right)
\]

where \( s_{cf} \) is the capacity severity factor, \( E_{acti,cf} \) the cell activation energy for the capacity fade process and \( R_g \) the universal gas constant. In order to investigate the influence of temperature, experiments are performed at different temperatures with the same \( Ratio_{cd} \) and \( SOC_{min} \). For analytical purpose, Equation (5) is rearranged in logarithmic scale as

\[
\ln(f_{cf}) = \ln(s_{cf}) - \frac{E_{acti,cf}}{R_g T_c}
\]

Finally, \( E_{acti,cf} \) can be calculated by

\[
\ln \left(\frac{f_{cf}(T_{c,1})}{f_{cf}(T_{c,2})}\right) = -\frac{E_{acti,cf}}{R_g} \left(\frac{1}{T_{c,1}} - \frac{1}{T_{c,2}}\right)
\]

where \( f_{cf}(T_{c,1}) \) and \( f_{cf}(T_{c,2}) \) are the optimal coefficients obtained from curve fitting. To study the effect of the \( Ratio_{cd} \), experiments are carried out at different ratios with the same temperature and \( SOC_{min} \). The experimental severity factor values are fitted to:

\[
s_{cf}(SOC_{min}, Ratio_{cd}) = r_1 + r_2 \cdot (Ratio_{cd})^{r_3}
\]

where \( r_1, r_2 \) and \( r_3 \) are quantified from the data curve fitting. Experiments are conducted at different values of \( SOC_{min} \) with the same temperature and \( Ratio_{cd} \) so as to investigate the dependence of capacity fade on \( SOC_{min} \). The experimental severity factor values are fitted to:

\[
s_{cf}(SOC_{min}, Ratio_{cd}) = s_1 + s_2 \cdot (SOC_{min} - SOC_0)^{s_3}
\]

where \( SOC_0 \) and \( s_3 \) are predetermined constant values. \( s_1, s_2 \) are the identified constants. Therefore, the capacity loss can be expressed as
2.3 Thermal model

Considering the uneven temperature distribution between the battery core and the battery surface, a two-state thermal model is developed with the following dynamics,

\[
\begin{align*}
C_e \frac{dT_e}{dt} &= P_{\text{batt,loss}} - \frac{T_e - T_s}{R_e} \\
C_s \frac{dT_s}{dt} &= -\frac{T_s - T_{\text{cmo}}}{R_s} + \frac{T_e - T_s}{R_e}
\end{align*}
\]

where \(C_e\) represents the heat capacity of the battery core, \(T_s\) the battery surface temperature, \(R_e\) the thermal resistance between the battery core and the battery surface, \(C_s\) the heat capacity of the battery surface and \(T_{\text{cmo}}\) the cooling medium outlet temperature. \(R_s\) is the thermal resistance between the battery surface and the battery cooling medium, which is obtained by, Tao and Wagner (2016)

\[
\begin{align*}
R_s &= \frac{1}{h_{\text{conv}} \cdot A_{\text{conv}}} \\
h_{\text{conv}} &= \frac{\overline{Nu}_D}{D_c} \\
\overline{Nu}_D &= 0.262 \cdot Re_{\text{D,max}}^{0.85} \cdot Pr^{0.36} \cdot \left(\frac{Pr}{Pr_s}\right)^{0.25} \\
Re_{\text{D,max}} &= \rho_c \cdot V_{\text{cm, max}} \cdot D_c \\
V_{\text{cm, max}} &= \frac{\dot{m}_{\text{cm}}}{\rho_c \cdot A_{\text{cross}}} \cdot D_{\text{ctc}}
\end{align*}
\]

where \(h\) denotes the convective heat transfer coefficient, \(A_{\text{conv}}\) the convective heat transfer area, \(\overline{Nu}_D\) the Nusselt number for cooling medium flow across the tube bundles, \(k_{\text{air}}\) the thermal conductivity of air, \(D_c\) the diameter of a cell, \(Re_{\text{D,max}}\) the Reynolds number, \(Pr\) the Prandtl number, \(Pr_s\) the Prandtl number of the surface, \(\rho_c\) the density of the cooling medium, \(V_{\text{cm, max}}\) the maximum flow velocity of the cooling medium, \(\mu_{\text{cm}}\) the dynamic viscosity of the cooling medium, \(\dot{m}_{\text{cm}}\) the mass flow rate of the cooling medium, \(A_{\text{cross}}\) the cross sectional area of the tube and \(D_{\text{ctc}}\) the centre-to-centre distance between two adjacent cells. \(P_{\text{batt,loss}}\) is the battery power loss, computed by

\[
P_{\text{batt,loss}} = I_{\text{batt}}^2 \cdot (R_0 + R_1)
\]

2.4 Power fade model

The internal resistance \(R_{\text{batt}}\), including \(R_0\) and \(R_1\), due to battery degradation, is updated by

\[
R_{\text{batt}}(Ah) = R_{\text{nom}} \cdot (1 + R_{\text{incr}}(Ah))
\]

where \(R_{\text{nom}}\) is the nominal resistance and \(R_{\text{incr}}\) is the internal resistance increase, given by

\[
R_{\text{incr}}(Ah) = f_{\text{pf}}(SOC_{\text{min}}, CR, T_e) \cdot Ah
\]

where \(f_{\text{pf}}(\cdot)\) is a nonlinear function of the aging factors: \(SOC_{\text{min}}, CR\) and \(T_e\). \(CR\) is the ratio between current and C-rate. Similar to the approach described in the capacity fade process, the power fade model can be expressed as

\[
\begin{align*}
R_{\text{incr}}(Ah) &= s_{\text{pf}}(SOC_{\text{min}}, CR) \cdot \exp\left(\frac{-E_{\text{act},pf}}{R_g \cdot T_e}\right) \cdot Ah \\
s_{\text{pf}}(SOC_{\text{min}}, CR) &= p_1 + p_2 \cdot (SOC_{\text{min}} - SOC_0)^{p_3} + c_1 \cdot \exp\left[c_2 \cdot (CR - CR_0)\right] + c_4 \cdot (SOC_{\text{min}} - SOC_0)
\end{align*}
\]

where \(E_{\text{act},pf}\) is the cell activation energy for the resistance increase process and \(s_{\text{pf}}\) is the resistance severity factor. Parameters \(p_1, p_2, p_3, c_1, c_2\) are obtained from curve fitting.

2.5 Coolant circuit model

The interaction between the battery and its cooling medium is described by

\[
C_f \frac{dT_{\text{cmo}}}{dt} = \rho_c \cdot \theta_c \cdot c_c \cdot (T_{\text{cmi}} - T_{\text{cmo}}) + \frac{T_s - T_{\text{cmo}}}{\frac{R_{\text{cm,a}}}{R_s}} - \frac{T_{\text{cmo}} - T_{\text{amb}}}{R_{\text{cm,a}}}
\]

where \(C_f\) is the heat capacity of the cooling medium surrounding the battery, \(\rho_c \cdot \theta_c \cdot c_c\) the heat capacity rate of the cooling medium, \(T_{\text{cmi}}\) the cooling medium inlet temperature, \(T_{\text{amb}}\) the ambient temperature and \(R_{\text{cm,a}}\) the thermal resistance between the cooling medium and the ambient air. For the radiator path, there holds

\[
C_f \frac{dT_{\text{cmi}}}{dt} = -\rho_c \cdot \theta_c \cdot c_c \cdot (T_{\text{cmi}} - T_{\text{cmo}}) - P_a
\]

where the radiator cooling power \(P_a\) can be calculated by

\[
P_a = \rho_c \theta_c c_c (T_{\text{cmo}} - T_{\text{amb}}) \] with \(\rho_c \theta_c c_c\) the heat capacity rate of air. For the evaporator path, the heat exchange between the cooling medium and the AC refrigerant can be described as

\[
C_f \frac{dT_{\text{cmi}}}{dt} = -\rho_c \theta_c c_c (T_{\text{cmi}} - T_{\text{cmo}}) - P_{\text{active}}
\]

where \(P_{\text{active}}\) is the required optimal power, which is obtained from the control strategy.

2.6 AC model

The temperature difference between the cooling medium and the refrigerant gradually decreases to zero, yielding

\[
T_{\text{ref,o}} = T_{\text{cmo}}
\]

where \(T_{\text{ref,o}}\) is the refrigerant outlet temperature. Hence, based on the \(P_{\text{active}}\), the refrigerant inlet temperature \(T_{\text{ref,i}}\) can be calculated by

\[
C_r \frac{dT_{\text{ref,i}}}{dt} = \rho_c \theta_c c_r (T_{\text{ref,o}} - T_{\text{ref,i}}) - \frac{P_{\text{active}}}{\eta_{\text{ref,cm}}}
\]

where \(C_r\) and \(\rho_c \theta_c c_r\) are the heat capacity and heat capacity rate of the refrigerant, respectively. \(\eta_{\text{ref,cm}}\) is the heat exchange efficiency between the refrigerant and the cooling medium, which is computed by using the effectiveness-NTU method, giving, Mathworks (2018).
where $NTU$ is the number of transfer units, $U_{ht}$ the overall heat transfer coefficient, $A_{ht}$ the heat transfer area, $C_{r,min}$ the minimum heat capacity rate of the refrigerant, $\dot{m}_r$ the flow rate of the refrigerant, $c_{ref}$ the reference specific rate, $x_w$ the mixture water vapor mass fraction, $c_{da}$ the dry air specific heat, $c_w$ the saturated water vapor specific heat, $k_r$ the thermal conductivity, $A_p$ the port area and $L_p$ the diameter of the port. Given the refrigerant temperature, the enthalpy at the evaporator outlet and inlet, respectively. Finally, the power consumption by the AC system can be obtained by

$$P_{ac} = w_{comp} \cdot T_{comp} \quad (25)$$

### 2.7 Model validation

Parameter identification and model validation are carried out using measurement data from AMESim and an optimization toolbox in Matlab. For a given current input, a good congruence between Simulink model and AMESim model is visible, as shown in Fig. 3. The key model parameters are listed in Table 1.

### 3. CONTROLLER DESIGN

Since the AC system can provide either cooling power or heating power, the active path is divided into three modes:

$$P_{active} = \begin{cases} > 0, & \text{Cooling mode}, \\ = 0, & \text{Idle mode}, \\ < 0, & \text{Heating mode}. \end{cases} \quad (26)$$

Idle mode implies that the heat generation from the battery is small and the ambient air is capable of removing the heat. Combining the thermodynamics of the battery and the cooling medium, the system is represented by:

$$\dot{X} = A \cdot X + B \cdot U \quad (27)$$

where

$$A = \begin{bmatrix} 1 - \frac{\rho_c \theta_{ccc}}{\gamma_T} & 0 & 0 \\ \frac{\rho_c \theta_{ccc}}{\gamma_T} - 1 & 0 & 0 \\ 0 & \frac{\rho_c \theta_{ccc}}{\gamma_T} & 0 \end{bmatrix}$$

$$X = \begin{bmatrix} T_{c,k} \\ T_{c,k} \\ T_{emo,k} \end{bmatrix} \quad (29)$$

$$U = \begin{bmatrix} \rho_{att,loss} I_{rec}R_{att} + P_{active} \end{bmatrix} \quad (32)$$

where $I_{rec}$ is the charging current during BER and $I_{rec}^2R_{att}$ is the additional heat generation caused by BER. A zMPC is developed to determine an appropriate mode and keep the battery core temperature $T_c$ within its operating temperature range by finding the optimal control input $P_{active}^*$ and the optimal recovered power $P_{rec}$, which will be described in the sequel. A constraint-oriented slack variable $e$ is introduced, given by

$$e_{i[k]} = \begin{cases} x_{i[k]} - x_{upper}, & x_{i[k]} > x_{upper}, \\ 0, & x_{i,k} \leq x_{i[k]} \leq x_{lower}, \\ x_{i[k]} - x_{lower}, & x_{i[k]} < x_{lower}. \end{cases} \quad (33)$$

The cost function of the zMPC is expressed as

$$J(x_{0[k]}, U_k) = e_{N[k]}^T P e_{N[k]} + \sum_{i=0}^{N-1} \left( e_{i[k]}^T Q e_{i[k]} + u_{i[k]}^T R u_{i[k]} \right) \quad (34)$$

The input and state are bounded by

$$u_{min} \leq u_{i[k]} \leq u_{max} \quad (35)$$

$$x_{lower} \leq x_{i[k]} \leq x_{upper} \quad (36)$$

where $x_{i[k]}$ represents $T_c$ and $u_{i[k]}$ represents $P_{active}$. $Q$ and $R$ are positive symmetric weighting matrices. $P$ is obtained by solving the corresponding algebraic Riccati equation. Penalties are imposed when violating the upper or lower constraint. If $x_{i[k]}$ is within the zone, the penalty is zero.
The trade-off between the benefit of BER $P_{rec}$ and the cost of additional cooling $\Delta P_{cool}$ is found by minimizing

$$J = -P_{rec} + \frac{1}{\eta_{tot}} \Delta P_{cool}$$  \hspace{1cm} (37)$$

where $\eta_{tot} = \eta_{ac} \cdot \eta_{electric}$ with $\eta_{ac}$ the efficiency of the AC system and $\eta_{rec}$ the lumped efficiency of the electric path, including efficiencies of the electric machine, power electronics and battery. Assume 70% of the braking energy can be recuperated at most, which is served as an input. Note that the optimal braking power that can be recovered is decided by the controller. Equation (37) is expanded as

$$J = -0.7 \cdot I_{rec} \cdot V_{batt} \cdot \gamma_{rec} + \frac{1}{\eta_{tot}} \cdot K_{mpc} \cdot (I_{rec} \cdot \gamma_{rec})^2 \cdot R_{batt}$$  \hspace{1cm} (38)$$

where $\gamma_{rec} \in [0,1]$ is the recovery ratio and $K_{mpc}$ is the MPC gain. Necessary condition gives

$$\gamma_{rec}^* = 0.35 \cdot \frac{\eta_{ac} \cdot V_{batt} \cdot C_c}{K_{mpc} \cdot I_{rec} \cdot R_{batt}}$$  \hspace{1cm} (39)$$

4. SIMULATION RESULTS

In order to assess the performance of the proposed controller, two current profiles are used, as shown in Fig. 4. The current profiles are derived from their corresponding driving cycles, which are modified from the New European Driving Cycle and the Federal Test Procedure.

Fig. 4. Current profile. (Top to bottom) $I_1$, $I_2$.

4.1 Brake energy recovery

To identify factors that influence BER, four tests are conducted using current profiles $I_1$ and $I_2$, illustrated in Fig. 5. The controller aims to find the trade-off between the recovered benefit and the associated cost due to extra cooling. In this figure, $I_{ava}$ represents the available braking power and $I_{rec}^*$ represents the recovered braking power. It can be observed that with the same current profile but different AC efficiencies, the recovery ratios are different. The higher the AC efficiency, the higher the recovery ratio. Moreover, with the same AC efficiency but different current profiles, the recovery ratios are different. The more intensity the current profile, the higher the recovery ratio.

By plugging $\gamma_{rec} = 1$ and $I_{ava,max}$ (the maximum current in each current profile) into Equation (38), the threshold efficiencies are quantified to be 8% for $I_1$ and 6% for $I_2$. This implies that, for example, if the AC efficiency is higher than 8% for current profile $I_1$, the braking power can be fully recuperated. Furthermore, a hard constraint, i.e., the BER controller is closed when the cell temperature exceeds the upper limit, is considered. In this case, even though the efficiency of the AC system is higher than the threshold, some part of the braking energy still cannot be recovered. This condition implicitly relates to the density of the available braking power. Therefore, there are three factors that affect BER: the efficiency of the AC system, the intensity and density of the braking energy. The former two factors are consistent with the analytical solution Equation (39).

Fig. 5. Recovery ratio with current profiles $I_1$ and $I_2$ (Top to bottom) $I_1$, $\eta_{ac} = 15%$; $I_2$, $\eta_{ac} = 5%$. $I_1$, $\eta_{ac} = 5%$; $I_2$, $\eta_{ac} = 5%$.

4.2 Temperature range control for EVs

Electrified powertrains generally comprise electric vehicles (EVs) and hybrid electric vehicles (HEVs). These two types of vehicles have different ways of driving, which would result in a difference in thermal behavior. Hence, EVs and HEVs are studied individually. In this subsection, assume the vehicle under consideration is an electric vehicle. Current profile $I_1$ is used to evaluate temperature control performance, and the result is demonstrated in Fig. 6. In EVs, the battery as the only energy source generates a significant amount of heat, which forces its temperature to stay around the upper bound. As a result, temperature range control degrades to reference tracking and active cooling is activated all the time to maintain the battery...
temperature at its upper limit. It can be observed that on-off control has big oscillations, which is not able to keep the battery at its optimal operating temperature. The developed zMPC consumes significantly less cooling power than the common on-off control.

4.3 Temperature range control for HEVs

It is assumed that the vehicle under consideration is a (plug-in) HEV. To mimic power split and for the sake of simplicity, a current profile $I_3$, modified from $I_1$, is created, where the current equals to zero for a period of time. It means no electric power from the battery is required and the engine propels the vehicle during this period. The controller should keep the battery temperature within the predefined temperature window. The cell temperature is shown in Fig. 7. From this figure, it is clear that passive heating dominates until its temperature reaches the upper constraint. Then, cooling mode engages. When the battery current equals to zero and no heat is generated, the battery temperature gradually decreases because of convection to the ambient air. Once the battery temperature is smaller than the lower constraint, the heating mode engages. A 39.3% energy consumption reduction can be achieved comparing to traditional on-off controllers. More importantly, the result computed from zMPC does not depend on vehicle topologies and driving profiles, which would output optimal solution in any scenario.

5. CONCLUSION

A zMPC approach for battery thermal management in electrified powertrains is presented. The SOH model is implemented to update SOC estimation and heat generation. Taking into account of the benefit of recovering braking power and the cost of extra cooling power, the recovery ratio is identified to be dependent on the efficiency of the AC system and the intensity and density of the available braking power in a driving cycle. The developed zMPC is able to maintain the battery temperature inside its optimal operating temperature range with minimum energy consumption. Compared with the conventional on-off approach, significant energy consumption reduction can be achieved. Furthermore, the optimal performance obtained from zMPC is independent of driving cycles and vehicle configurations.

REFERENCES

Arenas, A., Onori, S., Guezennecc, Y., and Rizzoni, G. (2015). Capacity and power fade cycle-life model for plug-in hybrid electric vehicle lithium-ion battery cells containing blended spinel and layered-oxide positive electrodes. Journal of Power Sources, 278, 473–483.

Mathworks (2016). Vehicle electrical and climate control systems, https://mathworks.com/help/simulink/examples/vehicle-electrical-and-climate-control-systems.html.

Mathworks (2018). Vehicle hvac system, https://mathworks.com/help/physmod/simscape/examples/vehicle-hvac-system.html.

Park, S. (2011). A comprehensive thermal management system model for hybrid electric vehicles. Ph.D. thesis, University of Michigan.

Pham, T., Kessels, J., Bosch, P., Huisman, R., and Nevels, R. (2013). On-line energy and battery thermal management for hybrid electric heavy-duty truck. Proceedings of the 2013 American Control Conference, 710–715.

Serrao, L., Onori, S., Sciarretta, A., Guezennecc, Y., and Rizzoni, G. (2011). Optimal energy management of hybrid electric vehicles including battery aging. Proceedings of the 2011 American Control Conference, 2125–2130.

Sundstrom, O., Guzzella, L., and Soltic, P. (2011). Torque-assist hybrid electric powertrain sizing: From optimal control towards a sizing law. IEEE Transactions on Control Systems Technology, 18, 837–849.

Tao, X. and Wagner, J. (2016). A thermal management system for the battery pack of a hybrid electric vehicle: modeling and control. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 230, 190–201.

Xu, Z. and Zhao, J. (2004). Zone model predictive control algorithm using soft constraint method. Fifth World Congress on Intelligent Control and Automation, 1, 650–653.