

Thermal management of a Li-ion battery pack in cold weather including aging

J. Jaguemont^{1,2}, L. Boulon^{1,2}, Y. Dubé^{1,2}

¹*Université du Québec à Trois-Rivières, Québec, Canada*

²*Institut de Recherche sur l'Hydrogène, Québec, Canada*

Summary

The poor performance of Lithium-ion batteries in cold climates is a major concern because they suffer a huge loss in capacity and degradation. Thus, this makes battery-powered vehicles challenging to park in cold environment. To prevent that from occurring, battery packs are heated following a thermal strategy with a battery thermal management system (BTMS). Thermal solutions exist but must be optimized. Therefore, this paper proposes to describe a methodology for establishing a thermal management algorithm for an electrified vehicle unplugged from the grid.

Keywords: Lithium-ion, hybrid-electric vehicles, cold temperature, aging, thermal management.

1 Introduction

Cold weather is an important matter for electric and hybrid vehicles (EVs/HEVs) because the chemical process that produces electricity is slowed at low temperatures, hence a loss of energy. In places like Canada, Russia, or Scandinavian countries where the temperature during winter drops below -20°C that lasts at least four to six months, driving an EV turns out to be a problem. To prevent that from happening, battery packs are heated via a battery thermal management system (BTMS). In general, HEVs/EVs are connected to the electrical network, and the BTMS starts heating regardless of energy consumption. But in some cases, EVs are not plugged to the grid so the BTMS uses energy from the battery pack, creating an impact on total autonomy, which makes for example parking outside unplugged a problem. Strategies exist and must be optimized because generally, at sub-zero temperature, batteries have poor energetic performances and degrade faster. Some examples can be found in literature. For instance, according to the Nissan Leaf Manual [1], the electrical battery heaters turn on at -17°C, heat up the pack to -10°C and then turn themselves off until the battery temperature decreases to -17°C again. Even though it is not a generalized thermal management, at these temperature limits, degradation and hazardous mechanisms occur [2] that can limit the energy and power capabilities of the battery pack. Thus, current strategies are working but improvements can be realized. Therefore, this paper proposes to describe a methodology for establishing a thermal management algorithm for a HEV unplugged from the grid.

Experimental results show an important interaction between the electrical, thermal aging phenomena at low temperatures. Thus, the primary objective in this work is to propose a thorough battery model that will estimate the voltage, temperature and degradation of Li-ion battery.

In addition, in this paper, the objective is set to be the development thermal management for an unplugged battery-based vehicle in cold weather. The necessity for such a management encourages the use of optimization algorithms. Optimization methods have been applied to numerous tasks in the domain of automotive technology such as battery thermal performance optimization in electric vehicles [3], [4], hybrid

electric vehicle power management (i.e., the power split between combustion engine/fuel cell and electric motor) [5], [6] and other systems [7]–[9].

The scenario used in this study is presented in Section III. It represents a working day of a HEV in cold weather. The optimization is performed with two objectives: (i) maximizing the available energy in the Li-ion pack when the vehicle is restarted and (ii) minimizing the degradations resulting from cold temperatures. Additionally, the optimization process is based on a calendar aging electro-thermal model.

Moreover, the optimal solution is focused on economic performance; therefore, this paper proposes a short sensitivity study that considers the combined effects of total capacity fade cost, fuel-provided electricity pricing and remaining energy.

The rest of this paper is organized as follows: Section II presents the electro-thermal and aging model of a battery pack. Section III presents the case study of an electric vehicle in cold weather and describes the optimization tool for algorithm resolution. Results of the simulation are discussed in Section IV. Finally, conclusions are given in Section V.

2 Model development

2.1 General model

In this study, a calendar aging electro-thermal model is used. The aim of the model is to reproduce the cell's electrical and thermal performance in cold weather because, as explained in the literature, low temperatures reduce the amount of energy delivered from a Li-ion cell. In addition, previous experimental tests were performed on a prismatic LiFeMnPO₄ cell to emphasize those effects; their results are listed in [10]. The tested cells had a rated capacity of 100 Ah and a nominal voltage of 3.2V with a working voltage range from 2.5 V to 3.8 V. The tests consisted of constant discharging currents at low temperatures. The calendar aging model is also based on experimental data that was presented in a previous work [11], [12]. Calendar aging tests covered two temperatures tests: 25°C and -20°C.

In addition, the model is composed of three sub-models, namely an electrical, thermal and aging model that are presented in Fig. 1; more details about the parameters extraction can be found in [12], [13]. A short description of the modelling is shown here, only their validation is presented in the next subsection. For more information about experimental protocols and model parameters please refer to our last articles [13], [12].

The electrical part of the model is based on the electrical equivalent circuit (EEC) [14], [15] approach and uses a MATLAB/Simulink® interface. The aim of the part is to reproduce the cell's electrical performances in cold weather because, as explained in the literature, low temperatures reduce the amount of energy delivered of a Li-ion cell. Additionally, a thermal model is coupled with the electrical part to estimate the cell temperature and there is a strong connection between the electrical and thermal aspect [16]. The thermal part simply solves a heat diffusion problem of a four-cell battery pack connected in series. Each one is divided in two parts: core and crust and they are linked together with a thermal contact resistance. Various discharging tests on an actual battery pack were carried out, and then cell's parameters and thermal characteristics were obtained. The tested pack was made of 4 prismatic LiFeMnPO₄ (LFMP) cells. The cell had a nominal capacity of 100 Ah and a nominal voltage of 3.2 V, with a working voltage range of 2.5V and 3.8V. The entire battery model was built on this LFMP battery pack.

As mentioned earlier, accelerated aging tests were used to determine the effect of the ambient temperature on the performance of three 100Ah LFMP lithium-ion cells. Two of them were aged through a normalized driving cycle at two temperature tests (-20°C and 25°C). The calendar test was carried out on one single battery at -20°C and mid-range of state-of-charge (SOC) (50%). Their capacities were continuously measured every two or three days. From the experimental results, two degradation rates were extracted, which are the principal observation of the battery lifespan: 0.048%loss/h at -20°C and 0.000758%loss/h at 25°C. A graphic of the results is plotted in Fig. 2.

A mathematical equation with empirical parameters is used to reproduce the capacity fade (degradation rate) over temperatures. A regression with a 4th polynomial order is chosen and fitted with Matlab, as depicted in Fig. 2. It is defined as:

$$\%_{loss}(T)/h = (a.T + b.T^2 + c.T^3 + d.T^4 + e) \quad (1)$$

with $a = -0.0009224$, $b = -3.71e^{-5}$, $c = -6.6e^{-7}$, et $d = 6.23e^{-9}$ et $e = 0.0086$.

In the simplified EEC, the irreversible capacity loss is then calculated with the temperature and the storage time.

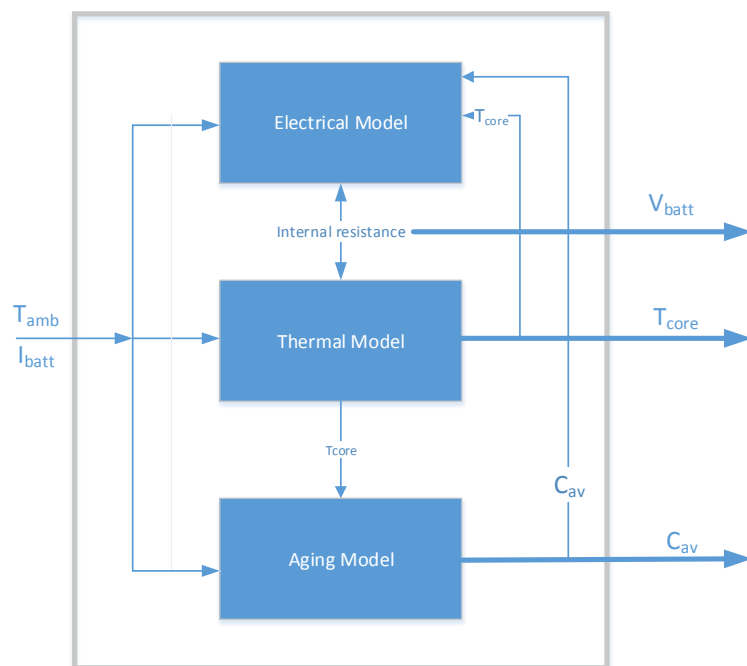


Fig. 1. Structure of the complete battery model used in this research.

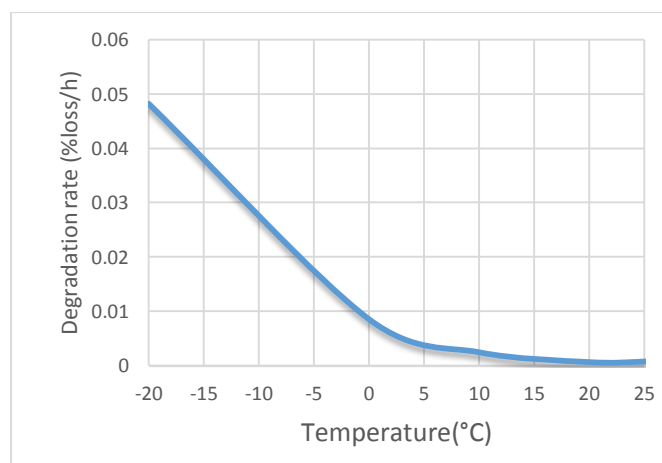


Fig. 2. Lithium loss degradation rate vs temperature with a polynomial fitting.

2.2 Validation

To validate the three parts of the model, comparisons of the cell output data and the simulations were performed under the same solicitations. For the experimental part, the tested cell was a prismatic LiFeMnPO₄ cell. The cell has a nominal capacity of 100 Ah and a nominal voltage of 3.2 V, with a working voltage range of 2.5V and 3.8V. In addition, extensive experimental validations of the three parts (at a cell level and at a pack level).

For the thermal part, the test consisted of applying a constant current of 100A and four initial temperatures (-20, -10, 0 and 25°C). For the electrical model, the validation test consisted of a random current taken from a driven vehicle as input. The good thermal and electrical models agreements with experimental results underline the validation of the model developed in this work.

Finally, Fig. 3 presents the results of the capacity fade measurement and simulation (in dashed lines) for the calendar aging test at -20°C. The estimated voltage profiles in Fig. 3 match the actual voltage with the one obtained from the experimental test, showing the validation of the aging part of the model.

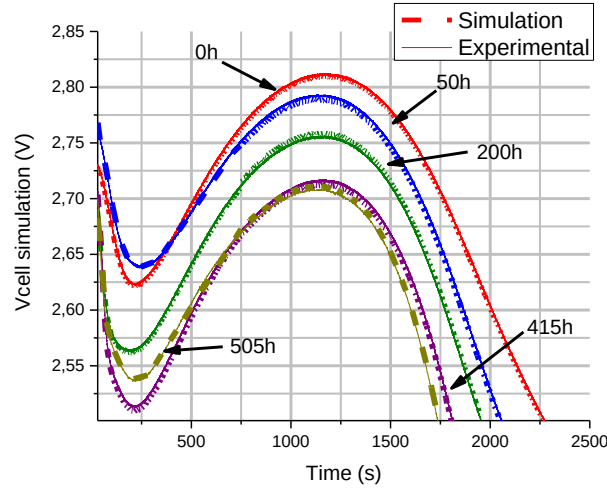


Fig. 3. Validation of the battery pack aging model at -20°C for calendar validation

2.3 Heating-pad model

There are several methods that can be used for heating a battery pack: external heating, such as electrically heated thermal jackets, warm air heating, and liquid heating [17], [18]. In the paper, an insulated enclosure with an internal heating element is chosen as a thermal strategy, as shown in Fig. 4. The heating pad is placed on each side of the cell, and the casing is insulated. Each large face of the pad delivers identical heat flow to the cells. For this case, the battery insulation is a 10 mm-thick wool glass material with a thermal conductivity of 0.038 W/(m.K).

The global thermal dynamic system includes the heating source and the insulated film to represent the thermal solution. The equations are:

$$\left\{ \begin{array}{l} \frac{dU_{hp}}{dt} = Q_{gen_{hp}}(t) + Q_{gain_{hp}}(t) - Q_{loss_{hp}}(t) \\ \frac{dU_{ins}}{dt} = Q_{gain_{ins}}(t) - Q_{loss_{ins}}(t) \\ \frac{dU_{crust}}{dt} = Q_{gain_{crust}}(t) - Q_{loss_{crust}}(t) \\ \frac{dU_{core}}{dt} = Q_{gain_{core}}(t) - Q_{loss_{core}}(t) \\ Q_{loss_{hp}}(t) = Q_{gain_{ins}}(t) + Q_{gain_{crust}}(t) \end{array} \right\} \quad (2)$$

where U_{hp} is the internal energy of the heating pad and U_{ins} is the insulation film. In the model, if the heating pad is on, obviously, $Q_{gain_{hp}}$ is equal to zero. $Q_{gen_{hp}}$ is programmed as an additional heating source and is simply represented by supplementary joule heating:

$$Q_{gen_{hp}} = R_{hp} \cdot (I_{hp})^2 \quad (3)$$

with $Q_{gen_{hp}}$ as the external heat generation provided by the heating pads as opposed to $Q_{gen_{core}}$, which corresponds to the internal heat generation (joule losses) occurring inside the core. R_{hp} (Ω) is the resistive element characterizing the heating pad. This work considers the heating while the vehicle is plugged on the grid. Consequently, I_{hp} is the current of the heating pad delivered by an external power source and thus, there is no output current originating from the pack.

Again, the heating pad heat losses are transferred to the insulated film Q_{gain_ins} , and the crust, Q_{gain_crust} , by conduction. The heat losses, $Q_{loss_{ins}}$, can be calculated by using natural convection with the ambient air.

$$\begin{cases} Q_{loss_{hp}} = Q_{cond} \\ Q_{loss_{ins}} = Q_{conv} \end{cases} \quad (4)$$

Moreover, the additional heating source changes the direction of the heat flow occurring at the crust. The crust receives by conduction the heat provided by the heating pads instead of the core. Additionally, because the thermal body of the crust is higher than the core, the crust transfers to the core the heat received by the heating pad in terms of conduction losses.

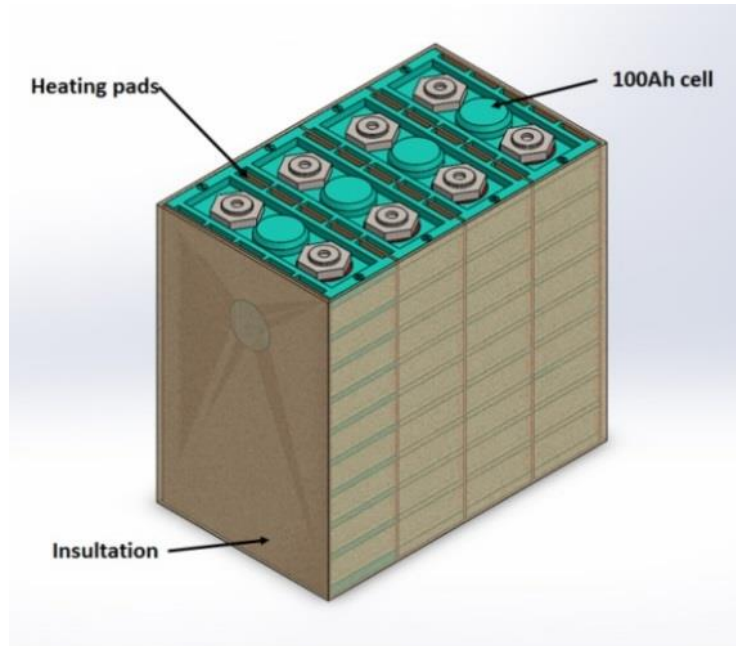


Fig. 4. Improved battery pack thermal model.

Table 1. HEATING ELEMENT FEATURES

<i>Heating pad [manufacturer]</i>	
Main characteristics	Value
<i>Watt densities (W/cm²)</i>	0.78
<i>Wire-wound element thickness (mm)</i>	1.4
<i>Dimensions (Length x Width) (mm)</i>	212 x 125
<i>Insulation [manufacturer]</i>	
Main characteristics	Value
<i>Type</i>	Wool glass
<i>Specific heat (J/kg.K)</i>	920
<i>Thermal conductivity (W/m.K)</i>	0.038
<i>Density (kg/m³)</i>	27

<i>Heating pad [manufacturer]</i>	
Main characteristics	Value
Thickness (mm)	10

3 Battery thermal management study

3.1 Problem description

This part describes a study case for the optimization process. The scenario is displayed in Fig. 5, and the application is a HEV, *i.e.*, an internal combustion engine (ICE) and Li-ion batteries are used to power the vehicle. In our thermal management, the battery pack is the same with which the model was established; it is made of four prismatic LiFeMnPO₄ cells that are rated at 100 Ah and 1.28 kWh (320 Wh each cell). Furthermore, it should be noted that the study is focused only on the battery behavior in a cold environment and is not focused on the ICE.

Although this hybrid system is efficient, frequently, the HEBT is parked overnight in a construction site and is left unplugged from the grid. Therefore, in cold weather, battery performance rapidly decreases because of an absence of thermal strategy. The study case assumes this scenario.

After a work day (17h00), the HEBT is left unplugged for the night (15 h) in a parking lot in Canada where the external temperature does not exceed -20°C. The problem is defined as follows: the optimal strategy has to manage the temperature of the cells in a temperature range where the maximum cell energy is found and the minimum degradation because of the cold weather happens after 15 h. Each dashed line in Fig. 5 represents a possible thermal management with a specific temperature trajectory. In this study, several hypotheses are introduced:

1. The Li-ion battery pack is made of four LiFeMnPO₄ cells rated at 100 Ah.
2. The initial temperature of the pack is set at 20°C and the batteries are charged to 90% after the work day.
3. The overnight parking time is defined as 15 h.
4. The battery pack thermal technique is a heating pad powered solely by the batteries' energy.

Moreover, the optimal strategy is compared with other thermal strategies: first, a strategy where the heating system is not used, called zero strategy, second, a constant temperature strategy where the pack's temperature is maintained at 25°C regarding the energy spent. In addition to the optimal strategy, to verify the optimal strategy efficiency, basic variables will be changed in the simulations:

1. Three ambient temperatures will be simulated: 25°C, 0°C and -20°C.
2. The length of the stopping time will be tested with three simulation times: 2 h, 15 h and 23 h.
3. The prices for the batteries that are currently set to \$153/cell will be modified to a lower cost to observe the variation of the optimal solution.

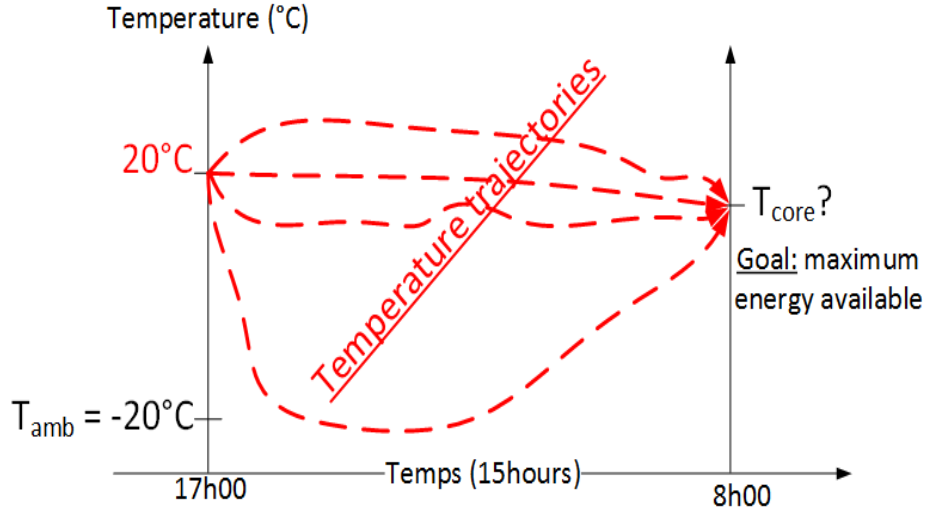


Fig. 5. Improved battery pack thermal model.

3.2 Battery pack thermal management

In this paper, the optimization technique searches for (i) management that operates the battery preferably within a temperature range in which it is stressed least (degradations) and (ii) reaching the maximum energy available at the end (final step). Thus, in economic terms, the algorithm minimizes the cost of electricity that is provided by fuel (directly from the ICE, which will recharge the batteries the next morning) and the cost degradation of the battery pack during the 15 h so that, at the final step, noted N , a maximum energy is available in dollars. This leads to the function:

$$J = \min(c(N) + \sum_{k=1}^N d(u, k)) \quad (5)$$

with k defined as a discrete time interval with a duration of 360 s and u defined as the control variable that minimizes/maximizes the function J , also known as the battery current I_{batt} . d is the cost function of the amount of Li-ion battery degradation. The degradation cost is set to the price of one cell (30.6 USD/%Li loss due to aging). Four cells make up the battery pack; therefore, four degradation rates will be added together to yield the cost function d . In (12), $c(N)$ is a cost function.

It reflects the cost, in dollars; of the energy lost resulting from the electricity spent during the 15 h. The algorithm will, therefore, find the maximum battery energy by minimizing this cost. It is calculated, first, with the available energy (12):

$$E_{disp}(N) = E_{av}(N) \cdot SOC(N) \quad (6)$$

with SOC , the mean state-of-charge of the pack and E_{av} the available energy (Wh). Then, to obtain the lowest possible cost function, a new variable is integrated, E_{loss} . E_{loss} is the loss of energy, and it defines the difference between the initial energy at $t = 0$ and the remaining energy at $t = N$:

$$E_{loss}(N) = (E_{init} - E_{disp}(N)) \quad (7)$$

with E_{init} , defined as the initial energy of the battery pack in Wh, herein 1150 Wh at 20°C and 90% of SOC [13]. Specifically, the algorithm seeks the minimum electricity consumption cost to reach the initial energy at the end of the night. Finally, the electricity prices for a Wh produced by the ICE for the cost function c are set to 4×10^{-4} USD/Wh, which are representative of the 2015 national averages in Canada; thus $c(N)$ is defined as:

$$c = E_{loss}(N) \cdot 4e^{-4} \quad (8)$$

Moreover, to reach an optimal solution, the algorithm uses a single control variable, the current delivered to power the thermal pad:

$$u(k) = I_{batt} \quad (9)$$

where u is the control value that is applied to the battery model.

The optimization problem in (12) is a constrained nonlinear optimal control problem with three states. In general, the state constraints are defined as:

$$x_T(k) = [x_{T_{core,min}}, x_{T_{core,max}}] \quad (10)$$

$$x_d(k) = [x_{CCF_{min}}, x_{CCF_{max}}] \quad (11)$$

$$x_{Qe}(k) = [x_{Qe,min}, x_{Qe,max}] \quad (12)$$

where x_T is the mean temperature of the pack, x_d is the CCF and x_{Qe} is the battery charge Q_e (Ah), each at timestamp k . Additionally, $x_{i,min}$ and $x_{i,max}$ are minimum and maximum admissible values over the cycle for each individual state, i , respectively.

The optimal control problem that was previously formulated is solved using a numerical technique called dynamic programming (DP). Although its computational burden increases dramatically with the number of states, DP generally approaches the global optimum and was therefore chosen for solving the study case. The next sub-section is dedicated to the optimal control problem formulation for DP.

3.3 Dynamic programming

Dynamic programming (DP) is a method for solving a complex problem by breaking it down into a collection of sub-problems where decisions are made with the objective to minimize (maximize) a certain mathematical expression of cost function. Generally, the cost function is written as [19], [20]:

$$J = g_n(x_n) + \sum_{k=0}^{n-1} g_k(x_k, u_k) \quad (13)$$

For solving a given problem, the DP uses controls $u_0, u_1, \dots, u_{n-1}$ to minimize/maximize the cost function J that is open to constraints. The DP technique is based on Bellman's Principle of Optimality [20], stating that the optimal dogma can be reached if different parts of the problem (sub-problems) are solved first before combining the solutions of the sub-problems to reach an overall solution.

The dynamic programming approach seeks to solve each of the single-stage sub-problems involving only the last stage first and then the sub-problem involving the past two stages, past three stages, etc. Once the solution to a given sub-problem has been computed, it is stored or "memorized"; the next time the same solution is needed, it is simply recalled. Further details and explanations on DP procedures can be found in [20] along with a schematic of forward dynamic programming.

4 Results and discussion

In this paper, the objective is to propose an improving battery thermal solution for an unplugged EV in winter. The thermal management is a compromise between the energy cost contained in the battery pack to heat the battery and the aging rate of the cells.

The presented results (Fig. 6) are obtained considering three thermal strategies: optimal thermal strategy (red line); constant temperature strategy (blue line), in which the temperature is maintained at 25°C regarding the energy spent; and zero strategy (green line), in which the heating pads are not used. Table III incorporates the main specific data (energy spent, cost, etc.) for the three strategies.

The thermal strategy found by the algorithm describes a three-phase path that combines two heating methods: the "keep-warm" method [21] to maintain the battery temperature around 21.1°C, and the "thaw and heat-up at start" method [21] which raises the pack to 25°C with high power before start. This rapid heat-up

consumes approximately 30 Wh per cell. One can notice that 25°C is where the maximum energy is depleted; therefore, it makes sense for the algorithm to reach this optimal temperature at the end. As a result, the optimal temperature leads to the maximum available energy (746 Wh) and the minimum criterion J of 0.45, indicating the best temperature path.

Regarding the constant temperature strategy, the temperature of the pack stays at 25°C for 15 h, which reduces the stress from the degradation at this temperature, but leads to constant energy consumption. Consequently, the available energy is less than with the optimal strategy of 716 Wh; the criterion J is superior than the optimal strategy (0.51). For the zero strategy, the heating pads are not used; thus, the current depletion remains 0 A during the 15h and the SOC of the pack stayed around 90%. As a result, because the pack is left to rest in a cold environment, the battery pack's energy is significantly affected by calendar aging; 694 Ah remain and the criterion J is a bit higher (11.18) than the optimal strategy.

In conclusion, considering the optimization problem, the two non-optimal thermal strategies emphasize the need for an optimal strategy. The best thermal strategy is better than the two non-optimized strategies in terms of available energy and degradation savings; the approach was found to be a compromise of both the degradation and the energy consumption. Moreover, the optimal current dynamic is representative of what could be implemented in an actual vehicle (Fig. 7).

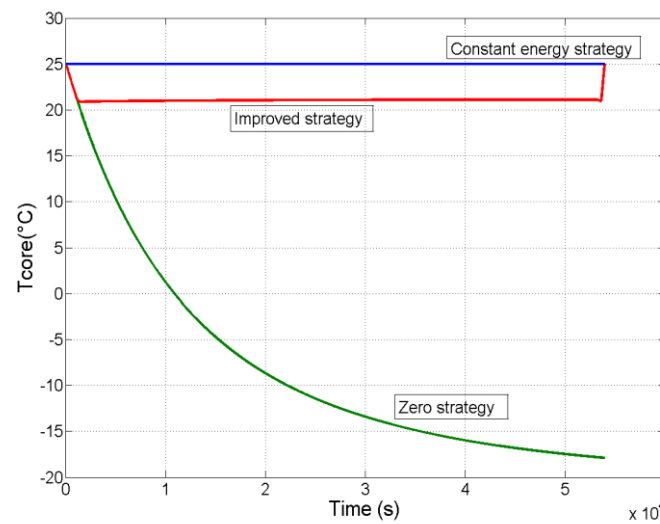


Fig. 6. Temperature evolution curves for three thermal strategies.

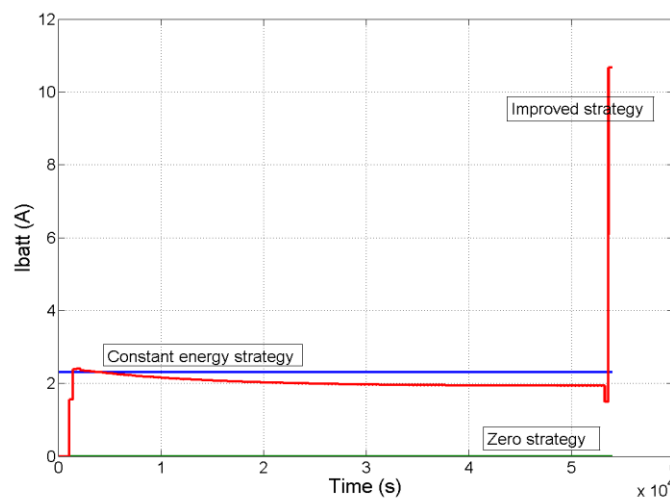


Fig. 7. Current profiles for the three strategies.

Table 2. OUTPUT DATA OF THE SIMULATION TESTS

Main characteristics	Constant temperature strategy	Zero strategy	Optimal strategy
Consumed energy (Wh)	443	0	407
%Liloss (degradation)	0.044	1.4	0.038
Final energy (Wh)	716	694	746
Cost in energy lost (USD)	0.17	0.18	0.16
Cost in degradation (USD)	0.34	11	0.29
<i>J</i>	0.51	11.18	0.45

The final energy is obtained by (7) and represents the remaining energy considering the temperature, the current delivered, the SOC and the degradation. The cost in energy is calculated with a cost rate of a kWh produced by fuel of 0.4 USD/kWh. Then, the total cost of degradation is obtained with the cost rates of each cell, 1.53 USD/Ah. Because the battery pack is made of four cells, four cost rates are added together. Finally, *J* is the sum of the degradation cost and the remaining energy is converted to dollars.

5 Conclusion

In this paper, dynamic programming (DP) was used to find the optimal strategy to dictate the battery such that it is operated in a gentle temperature range, whereas the least amount of electric energy is used for tempering and less stress because of degradation is occurring. The study case associated with the solution was based on an actual scenario where an HEV is parked outside overnight and is left unplugged in cold weather. The optimization routine was run on an aging and electro-thermal model. The thermal strategy found by the algorithm described a three-phase path that combines two heating methods: the “keep-warm” method to maintain the battery temperature at approximately 21.2°C and the “thaw and heat-up at start” method, which raises the temperature of the pack to 25°C with high power before starting. With the battery used in this paper, the degradation cost dominates the heating energy cost; thus, the ambient temperature influence is weak. However, the optimal maintained temperature is very dependent on the energy cost versus degradation cost ratio.

Finally, this study noted the management of EVs/HEVs, where aging because of cold weather is usually not considered. Parking outside at work or parking outside overnight could be an issue with the actual strategies, mainly because time and cold temperatures have critical impacts on battery lifetime.

Proper thermal management of the battery pack allows a good compromise between degradation and energy cost. In conclusion, the method presented in this work is simple to implement in a cheap controller and thus, it is effective to use in an actual vehicle.

For future works, since it has not been considered, varying nature of ambient temperature should be taken into account and simulated to be close to a real application. Also, it would be interesting to optimize a battery pack used in cold weather as opposed to a stand-alone situation.

Acknowledgments

This work is supported by the Natural Sciences and Engineering Research Council of Canada.

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Authors



Joris Jaguemont received a Master Degree in electrochemistry from University of Versailles (UVSQ, France) in 2012. He obtained his PhD in 2015 from the department of Electrical Engineering at UQTR. Dr. Jaguemont has the position of Postdoctoral Fellow at ETEC dept. and MOBI research center at VUB in the field of characterization, electrical, thermal, electrochemical and lifetime modeling of various rechargeable energy storage systems. His studies deal with characterization, modeling (electrical, thermal, ageing) of electrical batteries (Lithium, Nickel metal hydride, lead-acid) in BEVs, HEVs and PHEVs).



Loïc Boulon (M'10) received the master degree in electrical and automatic control engineering from the University of Lille (France), in 2006. Then, he obtained a PhD in electrical engineering from University of Franche-Comté (France). In 2009 and 2010, he was a postdoctoral researcher at University du Québec à Trois-Rivières (UQTR, Canada). Since 2010, he is a professor at UQTR and he works into the Hydrogen Research Institute. His work deals with modeling, control and energy management of multiphysics system. His research interests include hybrid electric vehicles, energy and power sources (especially battery in cold weather operation), and fuel cell systems. He is member of Electric Mobility Canada and he is YP chair of IEEE St-Maurice Section since 2010. Since 2014, Prof. Dr. Loïc Boulon is president of the technical and economic committee of the Electric Vehicle Innovation research consortium (Inno-VE). In 2015, Loïc Boulon was general chair of IEEE-Vehicular Power and Propulsion Conference in Montréal (QC, Canada).



Yves Dubé received the B.Sc. degree in physical engineering, the M.Sc. degree in mechanical engineering, and the Ph.D. degree in simulation and control all from the Université Laval, Quebec, QC, Canada, in 1977, 1979, and 1985 respectively. He is currently a Professor in the Department of Mechanical Engineering, Université du Québec à Trois-Rivières, Trois-Rivières, QC, Canada. He is the author or coauthor of more than 30 publications and is the holder of one patent. His current research interests include the area of renewable energy, hydrogen combustion engine development, and control of mechanical systems. Dr. Dubé has been member of the Ordre des Ingénieurs du Québec, QC, since 1977 and a Professional Engineer since 1977.