Effect of Temperature Distribution on the Predicted Cell Lifetimes for a Plug-In Hybrid Electric Vehicle Battery Pack

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Abstract

Monitoring and preserving state-of-health of high-voltage battery packs in electrified road vehicles currently represents an open and growing research topic. When predicting high-voltage battery lifetime, most current literature assumes a uniform temperature distribution among the different cells of the pack. Nevertheless, temperature has been demonstrated having a key impact on cell lifetime, and different cells of the same battery pack typically exhibit different temperature profiles over time, e.g. due to their position within the pack. Following these considerations, this paper aims at assessing the effect of temperature distribution on the predicted lifetime of cells belonging to the same battery pack. To this end, a throughput-based numerical cell ageing model is firstly selected due to its reasonable compromise between accuracy and computational efficiency. Subsequently, experimentally measured temperature and C-rate profiles over time in a driving mission are considered for three cells of the high-voltage battery pack of a commercially available plug-in hybrid electric vehicle. Obtained results suggest that due to temperature distribution in the high-voltage battery pack, the predicted lifetime for the hottest cell might be as low as 61% compared with the coldest cell of the pack. Importance and advancement of monitoring and managing the state-of-health of the single cells of an electrified vehicle battery pack might be fostered in this way thanks to the proposed study.

Introduction

Increasingly sensitive regulations regarding environmentally sustainable mobility are currently pushing car makers from traditional internal combustion engine vehicles towards alternative solutions such as electrified ones and alternative fuels, for example [1]. Hybrid electric vehicles (HEVs) have particularly proved to be an effective option for enhancing fuel economy and reducing on-road emissions. HEVs embed two energy sources (i.e. high-voltage battery and fuel) and two or more power actuators such as the internal combustion engine (ICE) and one or more electric motors, (EMs). HEVs require synergic cooperation between ICE and EMs to achieve remarkable benefits in terms of exhaust emissions and energy savings [2]. Furthermore, particular attention must be given to high-voltage batteries, which are typically lithium-ion based thanks to their high energy density [3]. The high-voltage battery is one of the most important elements of an electrified vehicle both from operational and price points of view. Moreover, it impacts on several vehicle economical aspects such as maintenance and disposal at the end-of-life. Within the HEV lifetime, inadequate battery management leads to increased degradation phenomena and consequently to an accelerated reduction of battery lifetime. Battery ageing and wear phenomena are regulated by complex chemical phenomena that lead to a progressive decrease in battery capacity, an increase in internal resistance or, alternatively, thickening of the solid electrolytic interface (SEI) [4]-[6]. The rate of the mentioned ageing phenomena increases as a function of the severity of battery operating conditions in terms of depth of discharge, number of charge and discharge cycles and temperature, to mention the most effective factors.

The importance of safeguarding the high-voltage battery lifetime has inspired several research works concerning battery state-of-health (SOH) sensitive energy management approaches for HEVs. In general, battery state-of-health deterioration is considered as an additional HEV control objective that can be studied by means of appropriate battery ageing numerical models. For example, this problem can be easily addressed by implementing local minimization algorithms such as the equivalent consumption minimization strategy (ECMS). A multi-objective cost function can be defined in ECMS including the fuel consumption rate and the battery energy consumption plus a penalty term that quantifies battery ageing. This multi-objective formulation of ECMS has been proved to have negative effects on fuel economy as the importance given to the battery ageing cost term increases [7]. Finding the optimal trade-off between fuel economy enhancement and battery lifetime safeguarding is not trivial [8]. More sophisticated HEV controllers can be implemented to this end. For example, a two-layer internet-distributed energy management system is presented in [9]. Further examples of battery SOH sensitive HEV energy management strategies include dynamic programming [10], convex optimization [11] and fuzzy logic [12].

Nevertheless, the above reviewed research works regarding battery SOH sensitive HEV energy management approaches generally lay on two important assumptions. First, the temperature of the high-voltage battery pack is often assumed to be constant over time, i.e. the battery conditioning system is supposed operating in ideal conditions. However, few recent studies have removed this hypothesis and have shown that the temperature evolution over time can have a remarkable impact on Li-Ion based battery performance [13][14]. The second assumption considers a temperature distribution that is changing in the time but is uniform between the cells of the battery pack. Nevertheless, remarkably different operating temperatures can be achieved by the single cells of a high-voltage battery pack in an HEV [15][16]. This results from the position of the single cells within the battery pack. As example, the temperature of the pack inner cells cannot be easily controlled by the battery cooling system due to the lower cooling surface available compared with the pack outer cells. Quantifying the difference among the operating temperatures of the single cells of a battery pack currently represents an open research question. There still has been no detailed investigation on how different the cell ageing rates are in a high-voltage battery pack due to their different operating temperature. To overcome the highlighted research gap, this work evaluates the impact of temperature distribution on the expected useful life of different cells of a high-voltage battery pack. A numerical model that can predict battery ageing as a function of temperature and C-rate over time is implemented to this end. Experimental data are collected for different cells of a plug-in HEV battery pack operating in charge-sustaining mode in a real-world driving mission. Results obtained by processing the collected experimental data using the implemented cell ageing model show that the temperature distribution in the battery pack for the hottest cell can lead to more than 30% reduction in terms of useful life compared to the coldest one. The importance of appropriately balancing the operation of the different cells in high-voltage battery packs of electrified vehicles can be pointed out in this way. The remainder of this paper is organized as follows: numerical approaches for modelling battery ageing available in the literature are reviewed first. A suitable model is selected for the investigated application, and a detailed description is provided. The HEV powertrain model and the experimental results are discussed. The subsequent section illustrates the numerical results obtained for the estimated cell lifetimes within the considered battery pack. Conclusions are finally drawn.

Cell lifetime prediction methodology

In this section, methodologies available in literature for modeling cell ageing will be reviewed first. Among these, a specific approach will be selected by providing appropriate motivation. The retained method will then be described in detail in the remaining portion of the section.

Review of battery ageing modeling approaches

Different categories of battery ageing modeling approaches are currently available in literature including physico-chemical models, event-oriented models, and weighted ampere-hour (Ah) models [17]. Table 1 summarizes advantages and disadvantages of the three listed categories of battery ageing modeling approaches, while the description of each category is reported as follows.

Table 1. Advantages and disadvantages of the different categories of battery ageing modeling approaches available in literature.

Methodology	Advantages	Disadvantages	References
Physico-chemical models	• Detailed information on local conditions (e.g. temperature, current, SOC) • Detailed understanding of ageing processes	• Complexity • Difficult to parametrize • Computational cost	[19][20][21][22][23]
Event-oriented models	• Standard approach for planning and designing • Computational efficiency	• Remarkable technical expertise required • Time consuming heuristic tuning • Lack of flexibility	[26]
Weighted ampere-hour (Ah) models	• Computational efficiency • Flexibility • Ease of understanding • Optimization of operating conditions	• Lack of physical or chemical basis • Requires experimental characterization of cell	[27][28][29][30]

Physico-chemical approaches can provide detailed information on the local conditions of the battery by modelling specific phenomena occurring at the anode and cathode levels (e.g. SEI increase, fracture occurrence in active material particles, evolution of the electrolyte decomposition) [18]. Differential equations are generally considered to this end [19]-[23]. Nevertheless, physico-chemical models might not manage to exhaustively model all battery ageing mechanisms triggered by phenomena occurring at a nanoscopic scale. As consequence, they cannot be used for directly assessing the effect of all stress sources on the performance of the battery. Moreover, their complexity and computational cost compromise their capability to be implemented in real-time control strategies on-board vehicles. For these reasons, physico-chemical battery ageing modelling approaches are predominantly used for basic cell research and development [24]. Alternatively, they might lay the foundations for extrapolating reduced-order computationally efficient models to be subsequently used in on-board control systems [25].

A different category involves event-oriented models, which have been derived from standard approaches applied in engineering design disciplines. Event-oriented models quantify battery ageing as a function of predefined events and neglect their order of occurrence over time [17]. In other words, these approaches depend on the assumption that the fading of cell capacity caused by an event does not depend on the previous event or on the age of the battery. While these approaches are computationally efficient methods, they require remarkable time-consuming heuristic tuning processes and lack of flexibility since the battery ageing process is related to a small set of predefined events only [26].

A third category of ageing models relates to weighted ampere-hour (Ah) models (also called performance-based models). These assume that a battery can achieve an overall lifetime Ah throughput, which is typically weighted based on current magnitude, temperature, and other factors. These models are computationally efficient and easily adaptable to different battery technologies [27]. Moreover, they allow optimizing the battery operating conditions, which is a fundamental requirement for real-time on-board implementation [29][30]. As a minor drawback, they do not relate to the physical or chemical properties of the cell, instead they are extrapolated from ageing tests performed under several battery operating conditions.

The above performed discussion suggests Ah models as the best trade-off approach between rapidness and accuracy in estimating battery ageing. Ah models thus prove enhanced potential for implementation in on-board vehicle control units. The battery ageing Ah model selected in this paper will be described in the next section.

Ah battery ageing model

An Ah model has been retained from [7] and implemented in this work to estimate battery ageing.

The battery SOH can range from 1 to 0, respectively indicating beginning and end of life. At a generic time instant t_i, the battery SOH can be evaluated using equation (1):

$$SOH(t_i) = SOH_0 - \int_0^{t_i} S\dot{O}H(c,T)\,dt$$
$$\text{with } S\dot{O}H(c,T) = 0.2\,\frac{c}{3600 \cdot N(c,T)} \tag{1}$$

where SOH_0 is the initial SOH, $S\dot{O}H$ stands for the instantaneous reduction rate in SOH, c is the instantaneous battery C-rate. c is evaluated here as the ratio between the battery power in kilowatts and the rated battery capacity in kilowatt-hours. N stands for the number of evaluated roundtrip cycles that can be achieved during the entire battery lifetime. The factor of 0.2 is correlated with the factor N being evaluated for a 20% reduction in residual capacity corresponding with a value of 0 for battery SOH. The factor of 3600 allows converting the units of c from 1/hour to 1/second. N is not a constant value, but rather it depends on the battery operating conditions (i.e. temperature T and C-rate). Evaluating N requires determining the percentage of battery capacity loss $\Delta Ah_{batt\%}$. This can be performed by implementing the methodology introduced by Bloom et al. in 2001 [31] that takes inspiration from the Arrhenius equation describing the evolution of the chemical reaction of ideal gases. The traditional Arrhenius equation has been adapted as in equation (2) aiming at modeling battery ageing [32].

$$\Delta Ah_{batt\%} = B(c) \cdot e^{-\frac{A_f(c)}{T}} \cdot {Ah_{tp}}^{z} \tag{2}$$

The change in cell capacity $\Delta Ah_{batt\%}$ is a function of an empirical pre-exponential factor B, an ageing factor A_f, the lumped cell temperature T, a power-law factor z and the total lifetime ampere-hour throughput Ah_{tp}. Factors B and A_f are determined based on the instantaneous battery c-rate c. The numerical values for the ageing parameters of an A123 26650 $LiFePO_4$ chemistry cell were previously determined by performing a one-year long experimental campaign. In particular, three ANR26650M1-B cells were installed in a thermal chamber and connected to a battery cycler. Three current profiles were determined by performing numerical simulations of an HEV controlled by dynamic programming in the worldwide harmonized light vehicle test procedure (WLTP). Obtained current profiles were then repeatedly fed to the battery testing cells using a 75A and 0-5 V rated channel of an MCT 75-0/5-8ME Digatron Power Electronics battery cycler. The cells were characterized in terms of residual capacity, open-circuit voltage, internal resistance, charge power capability and discharge power capability as they aged. Finally, the collected experimental data were used to calibrate the battery ageing model. The interested reader can consult [14] to get more details concerning the experimental campaign performed and the tuning process for the numerical ageing model. Retained values for the parameters of the described Ah battery ageing model are reported in Table 2. In particular, values for the factor B reported in the third row of Table 2 correlate with the respective values of the C-rate listed in the fourth row of Table 4.

Table 2. Parameters of the battery ageing model for A123 26650 cells.

Parameter	Value	Units of measure
Ageing factor, A_f	3,814.7 – 44.6·c	K
Power law factor, z	0.55	-
Empirical pre-exponential factor *B(c)*	[21,681 ; 17,307 ; 12,934 ; 13,512 ; 15,512 ; 12,099 ; 11,380; 13,656 ; 16,342 ; 14,599]	-
Current C-rate, c	[2 ; 4 ; 6 ; 8 ; 10 ; 12 ; 14 ; 16 ; 18 ; 20]	1/h

As mentioned earlier, the battery is assumed here to reach the end of life (i.e. SOH=0) when 20% of its initial capacity is lost. Therefore, the overall value of $\Delta Ah_{batt\%}$ can be set to 20% and Ah_{tp} can be determined as a function of c and T using equation (2). Subsequently, the total number of lifetime roundtrip cycles N can be calculated using equation (3):

$$N(c,T) = \frac{Ah_{tp}(c,T)}{2 \cdot Ah_{batt}} \tag{3}$$

where Ah_{batt} stand for the rated battery capacity in ampere-hours. The factor 2 in the denominator is to account for Ah_{tp} including both the charge and discharge Ah. Figure 1 shows the number of allowed battery roundtrip cycles for different temperatures on a logarithmic scale as given by the implemented ageing model.

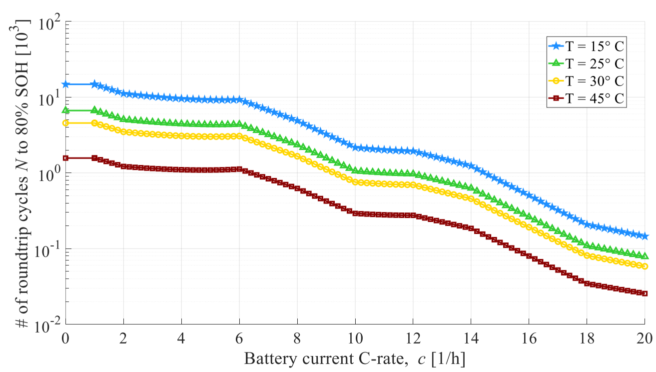

Figure 1. Number of allowed battery roundtrip cycles as function of the C-rate and temperature as predicted by the implemented ageing model.

The described Ah numerical model is implemented in Matlab® software and it allows predicting the battery capacity fading as function of battery C-rate and temperature. For the modeling in this paper, it is assumed that ageing is independent of SOC, as supported by the ageing test results presented in [33]. This also is likely what happens for the retained case study because the HEV powertrain is studied while operating in charge sustaining mode, where the battery SOC stays within a narrow band.

Results

This section presents numerical results obtained by implementing the selected Ah battery ageing model. A real-world driving mission performed by a plug-in HEV is considered to this end. The test vehicle features a P0-P4 plug-in hybrid electric powertrain which is illustrated in Figure 2. A smaller electric machine (MGP0) is connected to the internal combustion engine (ICE) by means of a belt. Both MGP0 and ICE propel the front axle through a six-speed stepped-gear transmission (TR) and a final drive (FD). On the other hand, a larger electric machine (MGP4) is directly connected to the rear axle in P4 position. This electrified powertrain architecture can propel the vehicle through both axles and coherently can also defined as a "parallel-through-the-road" HEV. The high-voltage battery pack is electrically connected to both MGP0 and MGP4 through bidirectional AC/DC converters.

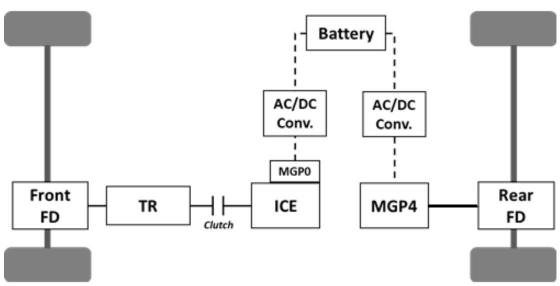

Figure 2. Schematic representation of the hybrid electric powertrain of the test vehicle.

As far as the HEV energy management is concerned, the test vehicle can operate in three different modes [34]:

1. Electric mode, in which the ICE is disconnected from the road and the vehicle is propelled only by the MGP4;
2. Hybrid mode, in which MGP0, MGP4 and ICE simultaneously supply tractive power to the HEV. The torques of MGP0 and MGP4 are typically controlled to have the ICE working as close as possible to its optimal operating region;
3. E-save mode, in which the ICE is used to both propel the vehicle and charge the battery. This can be performed by employing MGP0 and MGP4 as electrical generators.

The main characteristics of the power and energy sources included in the test vehicle are reported in Table 3.

Table 3. Main characteristics of the powertrain components.

Component	Parameter	Value
ICE	Max power (kW @ rpm) Max torque (Nm @ rpm)	96.7 @ 5500 270 @ 1850
MGP0	Max power (kW) Max torque (Nm	14.9 48
MGP4	Max power (kW) Max torque (Nm)	44 250
High-voltage Battery	Nominal capacity (kWh) Voltage (V)	11.4 400

Time series of the signals experimentally collected on-board the test vehicle are illustrated in Figure 3, Figure 4, and Figure 5 in terms of C-rate, SOC and temperature, respectively. Both C-rate and SOC are measured at the battery pack level and are assumed having the same values for all the cells of the battery pack. Both C-rate and SOC respectively illustrated in in Figure 3 and in Figure 4 have been normalized according to reference values for confidentiality reasons. The time series of the vehicle speed trace indirectly represents the power demanded to the HEV powertrain. As it can be noted, the normalized values of C-rate are principally located around or below 0.5, whereas a peak point is achieved during the last part of the driving mission in which a strong acceleration phase is encountered. Then, the normalized trend of the cell SOC throughout the mission is reported in Figure 4. A charge sustaining behavior is clearly highlighted as the final cell SOC value is almost equal to the initial one.

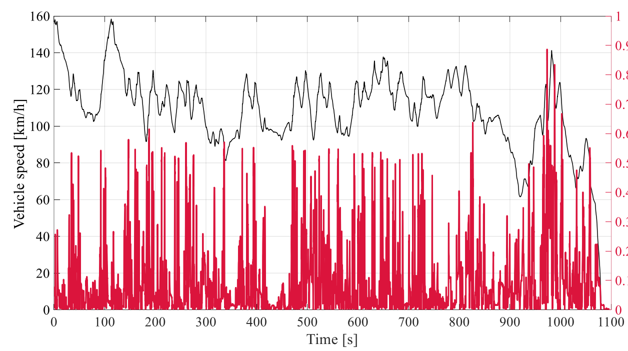

Figure 3. Time series of the normalized battery C-rate values measured throughout the real-world driving mission.

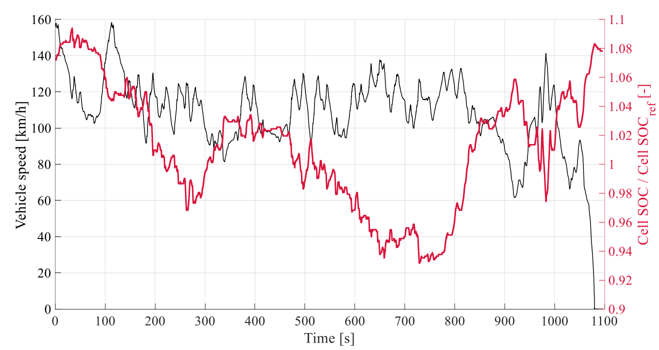

Figure 4. Time series of the normalized battery SOC measured throughout the real-world driving mission.

Finally, temperatures for three different cells of the battery pack have been measured during the real-world driving mission and have been reported in Figure 5. The coldest cell temperature ranges around 34 °C, the average around 37 °C and the hottest around and above 40 °C. For the sake of clarity, since the Ah battery ageing model does not require the information about the cell SOC, only the C-rate and cell temperature traces have been considered as inputs of the model and employed to produce an estimation of the cell SOH variation. It should be noted that the battery pack of the commercially available plug-in HEV features nickel manganese cobalt (NMC) cells. Nevertheless, a numerical ageing model for these cells was not available. To overcome this drawback, the battery pack was assumed being constituted by A123 26650 cells due to the availability of data for modeling the ageing behavior [33].

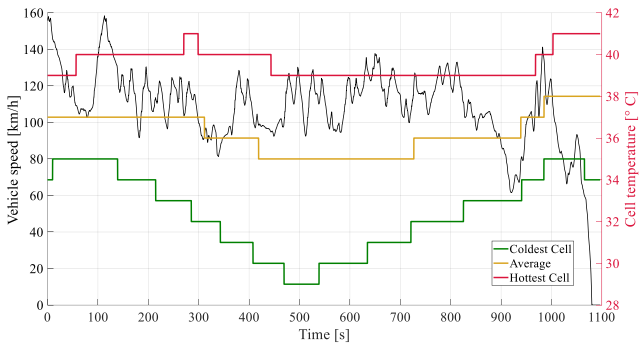

Figure 5. Time series of three different cell temperatures measured throughout the real-world driving mission.

According to the equations of the Ah battery model presented in this paper, three different cell lifetimes have been predicted based on the measured cell temperatures shown in Figure 5. The cell SOH decays are reported in Figure 6 along with the driving mission velocity profile. The initial cell SOH has been assumed to be similar for each testing scenario and equal to 1 (i.e. new cells). From the beginning onwards, the variation of the cell SOH appears to be dependent upon the cell temperature as hotter scenarios produce a larger reduction of the SOH with respect to colder conditions. The cell lifetimes could hence be estimated assuming the driving mission to be repeated iteratively until the cell reaches its end-of-life. Obtained results are reported in Table 4. Consistently with the estimation of the cell SOH at the end of the first run along the real-world driving mission, even a very small absolute variation in the cell SOH can lead to a relevant long-term reduction of the cell lifetime. Indeed, the numerical ageing model predicts the average cell and the hottest cell to exhibit around 23% and 39% shorter lifetime compared with the coldest cell of the battery pack. Obtained results demonstrate that remarkable differences can be achieved in terms of predicted lifetime among the cells of the same battery pack due to the temperature distribution.

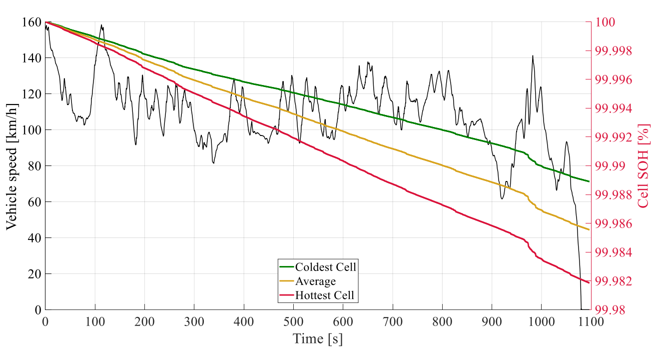

Figure 6. Variation of the battery SOH throughout the experimental driving mission estimated for three different cell temperatures.

Table 4. Cell lifetimes estimated for three different cell temperatures.

	Coldest cell	Average cell	Hottest cell
Final SOH (%)	99.9889	99.9856	99.9819
Cell lifetime (km·1000)	294	226 (-23.1%)	180 (-38.8%)

Conclusions

With this research work the effect of temperature distribution on the expected lifetime for three different cell working conditions (namely operative temperature) of a plug-in HEV battery pack has been evaluated. Analyses were carried out considering a throughput-based cell ageing model. Temperature and C-rate profiles for three cells of the test plug-in HEV battery pack were experimentally measured in a real-world driving mission and considered as an input for the analysis. The obtained results show how the performance in terms of battery useful life worsens relevantly (-38.8%) when considering either the coldest cell or the hottest one. Thus, it is highlighted that a temperature non-homogeneity between the cells of a battery pack is not a negligible factor. Conversely, proper balance between cells and appropriate battery pack thermal management should be considered. Future studies will focus on the development of HEV controllers sensitive to battery pack inhomogeneities by implementing dedicated control strategies and ageing models.

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References

1. Doucette, Reed T., and Malcolm D. McCulloch, "Modeling the Prospects of Plug-in Hybrid Electric Vehicles to Reduce CO2 Emissions", *Applied Energy* 88 (7): 2315–23, 2011.

2. Guzzella, L., and Sciarretta A., "Vehicle Propulsion Systems: Introduction to Modeling and Optimization", Berlin ; New York: Springer, 2015.

3. Anselma, P. and Belingardi, G., "Next Generation HEV Powertrain Design Tools: Roadmap and Challenges," *SAE Technical Paper* 2019-01-2602, 2019.

4. Vetter, J., P. Novák, M.R. Wagner, C. Veit, K.-C. Möller, J.O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing Mechanisms in Lithium-Ion Batteries", *Journal of Power Sources*, 147 (1–2): 269–81, 2005.

5. Onori, S., Spagnol, P., Marano, V., Guezennec, Y., and Rizzoni, G., "A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications", *International Journal of Power Electronics*, *4*(3), 302-319, 2012.

6. Casals, L. C., González, A. M. S., García, B. A., and Llorca, J., "PHEV Battery Aging Study Using Voltage Recovery and Internal Resistance From Onboard Data", *IEEE Transactions on Vehicular Technology* 65 (6): 4209–16, 2016.

7. Ebbesen, S., Elbert, P., and Guzzella, L., "Battery state-of-health perceptive energy management for hybrid electric vehicles," *IEEE Transactions on Vehicular technology*, *61*(7), 2893-2900, 2012.

8. Silva, Samuel Filgueira da, Jony Javorski Eckert, Fabrício Leonardo Silva, Ludmila C.A. Silva, and Franco Giuseppe Dedini, "Multi-Objective Optimization Design and Control of Plug-in Hybrid Electric Vehicle Powertrain for Minimization of Energy Consumption, Exhaust Emissions and Battery Degradation", *Energy Conversion and Management* 234: 113909, 2021.

9. Zhang, Yi, Heping Liu, Zhigang Zhang, Yong Luo, Qiang Guo, and Shuiping Liao, “Cloud computing-based real-time global optimization of battery aging and energy consumption for plug-in hybrid electric vehicles”, *Journal of Power Sources*, 479: 229069, 2020.

10. C. Patil, P. Naghshtabrizi, R. Verma, Zhijun Tang, K. Smith and Ying Shi, "Optimal battery utilization over lifetime for parallel hybrid electric vehicle to maximize fuel economy," *2016 American Control Conference (ACC)*, Boston, MA, 2016, pp. 1524-1529, 2016.

11. S. Xie, X. Hu, Q. Zhang, X. Lin, B. Mu, H. Ji, “Aging-aware co-optimization of battery size, depth of discharge, and energy management for plug-in hybrid electric vehicles”, *Journal of Power Sources*, Vol. 450, 2020.

12. R. Du, X. Hu, S. Xie, L. Hu, Z. Zhang, X. Lin, “Battery aging- and temperature-aware predictive energy management for hybrid electric vehicles”, *Journal of Power Sources*; 473: 228568, 2020.

13. Del Prete, M., Anselma, P., and Belingardi, G., "Identifying Critical Use Cases for a Plug-in Hybrid Electric Vehicle Battery Pack from Thermal and Ageing Perspectives," *SAE Technical Paper 2021-01-1251*, 2021.

14. Anselma, P. G., Kollmeyer, P., Lempert, J., Zhao, Z., Belingardi, G., and Emadi, A., “Battery state-of-health sensitive energy management of hybrid electric vehicles: Lifetime prediction and ageing experimental validation”, *Applied Energy*, *285*, 116440, 2021.

15. Fathabadi, H., “A novel design including cooling media for Lithium-ion batteries pack used in hybrid and electric vehicles”, *Journal of Power Sources*, *245*, 495-500, 2014.

16. Smith, K., & Wang, C. Y., “Power and thermal characterization of a lithium-ion battery pack for hybrid-electric vehicles”, *Journal of power sources*, *160*(1), 662-673, 2006.

17. Sauer, D. U., and Wenzl, H., “Comparison of different approaches for lifetime prediction of electrochemical systems—Using lead-acid batteries as example,” *Journal of Power sources*, *176*(2): 534-546, 2008.

18. Barré, A., Deguilhem, B., Grolleau, S., Gérard, M. et al., “A review on lithium-ion battery ageing mechanisms and estimations for automotive applications,” *Journal of Power Sources*, 241:680-689, 2013.

19. Laresgoiti, I., Käbitz, S., Ecker, M., and Sauer, D. U., “Modeling mechanical degradation in lithium ion batteries during cycling: Solid electrolyte interphase fracture,” *Journal of Power Sources*, *300*, 112-122, 2015.

20. Heinrich, M., Wolff, N., Harting, N., Laue, V., Röder, F., Seitz, S., and Krewer, U., “Physico-chemical Modeling of a lithium-ion battery: an ageing study with electrochemical impedance spectroscopy”, *Batteries & Supercaps*, *2*(6), 530-540, 2019.

21. Paul, N., Keil, J., Kindermann, F. M., Schebesta, S., Dolotko, O., Mühlbauer, M. J. et al., “Aging in 18650-type Li-ion cells examined with neutron diffraction, electrochemical analysis and physico-chemical modeling,” *Journal of Energy Storage*, *17*, 383-394, 2018.

22. Schmalstieg, J., Rahe, C., Ecker, M., and Sauer, D. U., “Full cell parameterization of a high-power lithium-ion battery for a physico-chemical model: Part I. Physical and electrochemical parameters,” *Journal of The Electrochemical Society*, *165*(16), A3799, 2018.

23. Fuller, T. F., Doyle, M., and Newman, J., “Simulation and optimization of the dual lithium ion insertion cell,” *Journal of the Electrochemical Society*, *141*(1), 1, 1994.

24. Meis, C., Mueller, S., Rohr, S., Kerler, M. et al., "Guide for the Focused Utilization of Aging Models for Lithium-Ion Batteries - An Automotive Perspective*," SAE Int. J. Passeng. Cars – Electron. Electr. Syst.*, 8(1), 2015.

25. Liang, Y. and Makam, S., “PHEV Hybrid Vehicle System Efficiency and Battery Aging Optimization Using A-ECMS Based Algorithms,” SAE Technical Paper 2020-01-1178, 2020.

26. S. Han, S. Han, H. Aki, “A practical battery wear model for electric vehicle charging applications”, Applied Energy 2014; 113: 1100-1108.

27. Maheshwari, A., Paterakis, N. G., Santarelli, M., & Gibescu, M., “Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model,” *Applied Energy*, *261*, 114360, 2020.

28. You, H., Dai, H., and Li, L., “The Aging Law of Low Temperature Charging of Lithium-Ion Battery,” SAE Technical Paper 2019-01-1204, 2019.

29. Liu, Y., Liao, Y. G., and Lai, M., “Aging Simulation of Electric Vehicle Battery Cell Using Experimental Data,” SAE Technical Paper 2021-01-0763, 2021.

30. Yang, Z., Mamun, A., Makam, S., and Okma, C., “An Empirical Aging Model for Lithium-Ion Battery and Validation Using Real-Life Driving Scenarios,” SAE Technical Paper 2020-01-0449, 2020.

31. Bloom, I., Cole, B. W., Sohn, J. J., Jones, S. A., Polzin, E. G., Battaglia, V. S. et al., “An accelerated calendar and cycle life study of Li-ion cells,” *Journal of power sources*, *101*(2), 238-247, 2001.

32. Anselma, P., Kollmeyer, P., Belingardi, G., and Emadi, A., "Multitarget Evaluation of Hybrid Electric Vehicle Powertrain Architectures Considering Fuel Economy and Battery Lifetime," *SAE Technical Paper* 2020-37-0015, 2020.

33. Wang, J., Liu, P., Hicks-Garner, J., Sherman, E., Soukiazian, S., Verbrugge, M. et al., “Cycle-life model for graphite-LiFePO4 cells,” *Journal of power sources*, *196*(8), 3942-3948, 2011.

34. Anselma, P. G., Del Prete, M., and Belingardi, G., “Battery High Temperature Sensitive Optimization-Based Calibration of Energy and Thermal Management for a Parallel-through-the-Road Plug-in Hybrid Electric Vehicle”, *Applied Sciences*, *11*(18), 8593, 2021.