PHM OVERVIEW ON BATTERY MODELS APPROACHES

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The Battery Management Systems (BMS) brought a new impetus to the battery energy management which lead to an increase in battery life. But the BMS fails when the State of Charge (SoC), State of Health (SoH), State of Life (SoL) or Remaining Useful Life (RUL) prognostics systems do not provide the required accuracy. Despite the increase of complexity and accuracy of battery models, the poor performance with floating temperature and load profiles persists. With the development of innovative products on wide-ranging applications, the battery materials, technologies, reliability and safety are being pressed to their limits. Therefore, a huge amount of work is still necessary, not only on the development of new battery technologies but also on the BMS, battery models and metrics accuracy improvements. The paper gives a comprehensive overview of the applicability, accuracy, weaknesses and advantages of the most recent battery models. The paper will also discuss how the Prognostics Health Management (PHM) can support a technologic impetus on battery affairs with battery models and metrics accuracy improvements.

Keywords: Battery prognostics, model-based, data-driven, fusion.

1. Introduction

The use of battery power for portable applications becomes increasingly widespread. The Internet of Things (IoT) advent is providing new development vectors in battery technology: Wireless Sensor Nodes (WSN) with high-precision measurement capability, battery powered wearable fitness/medical devices, industrial signal chains with isolated power and wireless battery powered field instruments. These new applications require great power efficiency which means longer battery lives with less maintenance as well as simplified power supply design [1], [2]. To address these demanding challenges the BMS designer must strike a balance between the competing priorities of higher performance and lower power consumption. The BMS operation is based on the prognostics estimation of battery metrics such as State of Charge (SoC), Remaining Useful Life (RUL), etc. Many successful examples on lithium-ion batteries (LIBs) have shown the promising potential of PHM improving the battery performance and metrics prognostics. The actual PHM case studies are mainly based on the use of model-based and data-driven approaches, and validated with constant discharge profiles of current and temperature. This approach does not meet the requirements of the modern battery applications, where the performance parameters must be estimated very accurately in real time, with highly nonlinear profiles of discharge currents and environmental operating conditions [3], [4]. With this project we intend to achieve three main objectives: Investigate and develop hybrid techniques of fusion for battery RUL prognostics; Identify which critical issues on modern battery applications are not completely solved by the actual PHM approaches; Apply the design conceptual basis, techniques and tolls to a real case study of non-rechargeable batteries, for decision-making and definition of intervention policies.

This paper is divided in the next three sections: (2) Battery models. Describe and classify the fundamental PHM approaches for battery metrics estimation: model-based, data-driven and fusion. The benefits and constraints of each approach method are also discussed. (3) Final discussion. This section discusses the fundamental gaps in PHM approaches, related with the unsolved problems on the battery metrics prognostics, namely, the inconsistencies of solving highly non linear problems involving linear approximations. With a real case study of non-rechargeable batteries and exploring the research opportunities of some recent publications from references, the paper presents and discusses the guidelines to improve PHM development on battery prognostics. (4) Conclusions. This section gives an overview of the article highlights and the most significant aspects of the proposed work.

2. Battery Models

From the PHM viewpoint there are three main approach classes used for battery performance evaluation: physics-of-failure (PoF) or model-based, data-driven and fusion [4].

2.1. *Model-based or PoF approach*

The PoF models have the ability to identify the root causes and failure mechanisms that may contribute to battery failure [4]. This model approach can be divided into four categories: empirical, electrochemical engineering, multi-physics and molecular/atomistic models [5], as represented in Table 1.

Table 1. Battery model-based groups.

Electrochemical	Single particle Ohm porous Pseudo two dimensional
Multi-physics	Thermal Stress-strain & particle size/shape distributions Stack
Molecular /atomistic	Kinetic Monte Carlo Molecular dynamics Density functional theory
Empirical	Analytical Stochastic Circuit Centric

Comparing the different model-based approaches in the most accurate models are the molecular/atomistic, multi-physics and electrochemical. But the accuracy of these approaches demands complexity, resources and time computing, making this type of models only applicable on the battery design by manufacturers [6]. By contrast, the simpler empirical approaches are more adequate for modern online BMS. The circuit centric approaches are simpler and are very disseminated by different studies. But the determination of components values is time-consuming and requires complex laboratory conditions. The accuracy of the models is affected by the dynamic transient of the components and test frequency. The studies published show that these models are only suitable to represent the system under stable conditions of temperature and load currents. In turn, analytical models are too much simple to be successfully applied on the modern complex working conditions of batteries [7]. By contrast, for the modern non-linear operating conditions of batteries the stochastic models are more accurate in the estimation of the SoC and RUL. The results given in the form of probability distribution functions (PDFs) accounting for uncertainty [4].

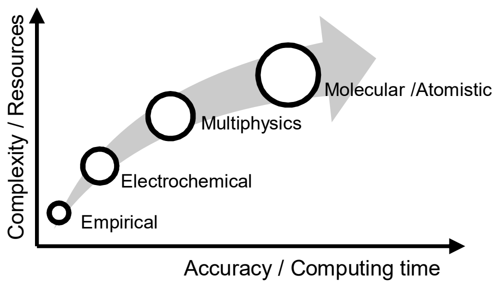

Figure 1. Battery Model-based approaches versus computational demands.

2.2. *Data-driven approach*

On the RUL prognostics estimation, the data driven approaches can be used as black-box models that can grasp the system degradation behaviour based on monitored data without requiring specific knowledge of the system. These features make the data analysis methods the most popular for RUL prognostics [8]. In different published studies Esteves & Nunes [4] and Wu et al. [8] show that from the point of view of PHM, the data-driven approaches can be subdivided into two major groups, the statistical and machine learning methods (Table 2). The statistical based models also can be separated in two subgroups namely, on directly observed state processes (online) and on indirectly observed state processes (offline) (Table 2). In turn the on-line state processes can be classified in Stochastic models and Continuous time stochastic models. The off-line processes are separated in Statistical models and Stochastic non-linear filtering models [4].

Table 2. Data-driven approach methodologies.

<table>
<tr><td rowspan="2">On-line</td><td>Stochastic</td><td>Autoregressive model (AR)</td></tr>
<tr><td>Continuous time Stochastic</td><td>Wiener process</td></tr>
<tr><td></td><td>Machine learning</td><td>Artificial Neural Network (ANN)
Support Vector Machine (SVM)
Relevance Vector Machine (RVM)
Particle Swarm Optimization (PSO)
Dempster-Shafer Theory
Bayesian Monte Carlo</td></tr>
<tr><td rowspan="2">Off-line</td><td>Stochastic non-linear filtering</td><td>Kalman Filter (KF)
Extended Kalman Filter (EKF)
Unscented Kalman Filter (UKF)
Particle Filter (PF)
Spherical Curvature Particle (SCPF)</td></tr>
<tr><td>Statistical</td><td>Hidden Semi-Markov Model (HSMM)
Gaussian Process
Bilinear Kernel Regression</td></tr>
</table>

The work published by Wu et al. [8], describes the data-driven approaches most used on battery prognostics. Most disseminated Machine Learning methods are the Artificial Neural Network (ANN), Support Vector Machine (SVM), Relevance Vector Machine (RVM), Particle Swarm Optimization (PSO), Dempster-Shafer Theory and Bayesian Monte Carlo. The proposed on-line Stochastic models are the Wiener Process and the Autoregressive (AR) approach. Prediction-based filtering techniques include the Kalman filter (KF), Extended Kalman filter (EKF), unscented Kalman filter (UKF), Particle filter, and Spherical curvature particle. Statistical approaches include the Hidden

Markov model (HMM) and the Hidden semi-Markov model (HSMM), Gaussian process, Gaussian process regression (GPR), multi-scale Gaussian process modelling method in wavelet analysis and the Bilinear Kernel regression.

The works referred above regard the batteries operation in ideal laboratory controlled conditions with linear approximations of temperature and current discharge, which is far from the real battery operation conditions with time-varying environment, random varying current, self-recharge characteristics, and different system configurations [8]. From the data-driven approaches universe, the stochastic methods have more accuracy on prognostics estimation by producing the results in PDFs by accounting for uncertainty.

2.3. *Fusion approaches*

Comparing the RUL prognostics methodologies presented above, the PHM fusion or hybrid approach can be an alternative option for battery reliability prognostics with accuracy, precision, cost efficiency and saving qualification time. The fusion approach combines the model-based or PoF with the data-driven tools, taking full and direct double advantage of the benefits from both approaches in order to estimate the RUL under operating and non-operating life-cycle conditions. The model-based is helpful on battery design stage for studying the battery dynamics and performances under specific load profiles and environmental conditions or to identify faults thresholds. The data-driven approach is suitable for on-line applications, quantifying the RUL or monitoring the degradation level of performance parameters [4].

A recent work, from Xing et al. [9] predicts the remaining useful performance (RUP) by merging an empirical exponential and a nominal regression model to track the battery degradation trend over its life cycle, based on experimental data analysis. Alternatively, Fang et al. [10] propose an adaptive iterative extended Kalman filter (IEKF) of simultaneous state and parameter estimation based for the SoC estimation and a MM-AdaSoc algorithm. However in both cases the fusion models are only validated with constant discharge currents and with constant controlled temperature.

3. Final discussion

From the literature review presented in Section 2, it was possible to identify some critical topics that have impact on the reliability, life cycle and performance of batteries, that are not completely fully treated on published studies, namely: battery technology, working environmental conditions, recovery effect, quiescent currents and load discharge current profile.

Concerning battery technology, the studies published take up predominately the LIBs models, and fail to address the non-rechargeable batteries models and BMS particularities. But the non-rechargeable batteries are still a good technological option for IoT, WSN and health devices due to its higher energy density comparatively to the rechargeable batteries [11], [12].

The discharge current profile ties the battery life expectancy and performance. A battery can be discharged by three basic different modes: constant resistance, constant current and constant power. The constant power mode has the lowest average discharge current from the three discharge modes, resulting in the longest service time. The battery discharge type can be continuous or intermittent. The intermittent discharge can improve and extend the battery service life, through the voltage battery recovery effect (VBRE). The VBRE is the battery voltage which drops during a heavy discharge, will rise after a rest period. This phenomena is being interpreted as an energy battery recover [11]. However the existence of the battery recovery effect phenomena is rejected by Narayanaswarmy et al. [13]. This fact reflects the lack of standardization on the PHM tests and results analysis techniques used by different authors and previously discussed by Esteves & Nunes [4]. It is also important to analyze the negative impact of the quiescent current on the battery life and SoC of IoT, health devices and WSN [11], [12].

The discharge temperature has a pronounced effect on battery service life, capacity, performance and voltage characteristics [14]. More complex discharge load profile and ambient conditions make the model adjustment more difficult and laborious. Except for the electrochemical and multi-physics models, all the others approaches not embody the effect of dynamic temperature and dynamic load discharge profile on the battery performance and prognostics estimations.

For these reasons future work will be centred on the design and improvement of fusion approaches for the prognostics of battery metrics on non-rechargeable batteries, similar to the diagram on Figure 2. Figure 2. The model is based on five modules: data acquisition system, historic database, model-based, data-driven (offline) and data-driven (online). The data acquisition system captures the battery signals: voltage, discharge current profile and ambient temperature. From the historic data, off-line data-driven approaches (statistical tolls and machine learning methods), can estimate the performance trends for the model-based approaches directed for the stochastic models based on the Markov theory.

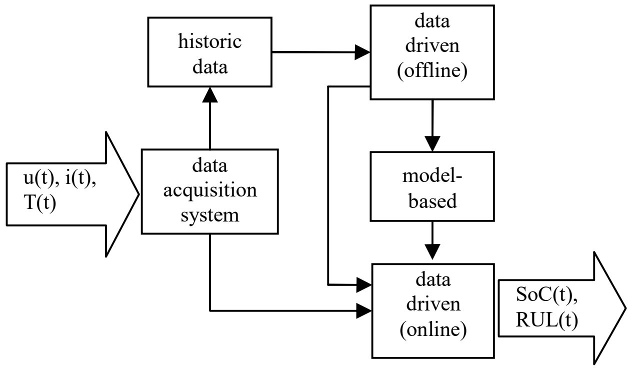

Figure 2. Simplified fusion approach functional diagram.

The data-driven (online) block is divided in two levels: The SoC measurement based on the Coulomb counting adjusted by an EKF and adjustment factors (temperature, voltage and discharge rate), extracted from stochastic model via tools like the Machine learning. The second level for RUL prognostics, is made with an EKF with two inputs. The models AR formulated from the historic data are the base for Wiener process or Brownian motion random walks with the adjustment factors extracted from the stochastic models via machine learning tools.

4. Conclusion

This paper gives an overview over the three basic PHM approaches, namely, model-based or PoF approach, data driven-approach and fusion or hybrid approach, used on RUL and other battery metrics prognostics. The model-based and data-driven approaches still show weakness in deal with highly non-linear battery load profiles and dynamic environmental conditions associated with the modern battery applications. Therefore, the effects of the temperature, non constant discharge current profile and discharge rate still remain critical issues to solve on the battery performance and metrics prognostics. The modern IoT and WNS applications and the non-rechargeable batteries with its own particularities are opportunities to explore new battery models.

The future work may be focused in the development of fusion approaches based on stochastic and machine learning models for online RUL prognostics in order to incorporate solutions for the critical issues mentioned above.

References

[1] A. Walsh. Powering a Precision SAR ADC Using a High Efficiency, Ultralow Power Switcher in Power Sensitive Applications. *App. Eng.* 2016.

[2] Internet of Things. IoT news. [Online]. Available: http://www.iottechnews.com/. [Accessed 29 01 2017].

[3] G. Bai, P. Wang, C. Hu and M. Pecht. A generic model-free approach for lithium-ion battery health management. *Applied Energy,* 15 Dec. 2014.

[4] M. A. M. Esteves and E. M. P. Nunes. PHM: Perspectives in Engineering Systems Reliability Prognostics. *ESREL*. Zurich. 2015.

[5] V. Ramadesigan, P. Northrop, R. Braatz and V. R. Subramanian. Modeling and Simulation of Lithium-Ion Batteries from a Systems Engineereing Perspective. *Jou. of The Electrochemical Society,* pp. 31-45, Dec. 2012.

[6] B. Bole, C. S. Kulkarni and M. Daigle. Adaptation of an Electrochemistry-based Li-Ion Battery Model to Account for Deterioration Observed Unde Randomized Use. *Annual Conference of The PHM Society*, 2014.

[7] G. Aurilio, D. Gallo, C. Landi, M. Luiso, A. Rosano, M. Landi and V. Paciello. A Battery Equivalent-Circuit Model and an Advanced Technique for Parameter Estimation. *Instrumentation and Measurement Society.* 2015.

[8] L. Wu, X. Fu and Y. Guan. Review of the Remaining Useful Life Prognostics of Vehicle Lithium-Ion Batteries Using Data-Driven Methodologies. *Inter. Jour. of Molecular Sciences,* vol. 6, pp. 1-11, 2016.

[9] Y. Xing, E. W. M. Ma, K.-L. Tsui and M. Pecht. An ensemble model for predicting the remaining useful performance of lithium-ion batteries. *Microelectronics Reliability,* vol. 53, no. 6, pp. 811-820, 2013.

[10] H. Fang, X. Zhao, Y. Wang, Z. Sahinoglu, T. Wada, S. Hara and R. A. d. Callafon. State-of-Charge Estimation for Batteries: A Multi-model Approach. *American Control Conf. (ACC)*, Portland, Oregon, USA, 2014.

[11] Y. Zhang and J. N. Harb. Characterization of Battery Behavior for Battery-Aware Design of Wireless Sensing Networks. *Journal of the Electrochemical Society,* vol. 162, no. 6, pp. A820-A826, 2016.

[12] M. He. Why Low Quiescient Current Matters for Longer Battery Life. *Meet. the Design Challenges of Wearable and IoT Devices*, S. Jose, 2017.

[13] S. Narayanaswarmy, S. Schlueter, S. Steinhorst, S. Chakraborty and H. E. Hoster. On Battery Recovery Effect in Wireless Sensor Nodes. *ACM Transactions on Design Automation of Electronic Systems,* vol. 00, 2016.

[14] S. Chanagala and M. M. Khan. Effect of Battery Dynamics and the Associated Technologies on the Life Time of Wiereless Sensor Networks. *IOSR Jour. of Elect. and Comm. Engineereing,* vol. 9, pp. 32-37, Jan. 2014.