Accurately Forecasting the Health of Energy System Assets

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Abstract— **in this paper we present a review into data driven prognostics and its relevance to resilience in energy systems. A data driven remaining useful life prediction for Li-ion batteries utilizing data analysis via a relevance vector machine (RVM) model is shown to be within 5% accuracy when applied to large lifecycle datasets. Results demonstrate that due to the agile nature of prognostic models and their accuracy, prognostics and health management methods will be vital to resilient and sustainable energy systems.**

Keywords—prognostics, energy systems, data analysis, machine learning

Introduction

A nation's energy infrastructure provides critical support to society e.g. heating, lighting etc., as well as being an integral system to other vital services such as transportation, telecommunications, food and water, manufacturing, the built environment and healthcare. Societies critical services and their relationship with national energy infrastructure is becoming increasingly complex and interdependent, thereby making them susceptible to catastrophic and cascading failure under stress. Furthermore, as energy infrastructure transitions to an integrated multi-vector system in order to maximize energy efficiency and security of supply, there is an increasing emphasis on understanding the near to real-time health of vital assets within this infrastructure. Whereas previously it was sufficient to commission and design infrastructure not to fail [1] increasing dynamic loads on our energy system and an objective of addressing the energy trilemma, has driven a demand for advanced predictive lifecycle management of energy infrastructure assets.

To provide a context, it's estimated that the Grid within the United States requires around $2 trillion in upgrades by 2030 [2]. In the UK, the Department of Energy and Climate Change (DECC) estimated that 2010-14 there will have been over £16 billion of investment in the electricity network. Further to that, they estimate that 2014-2020 a further £34 billion needs to be invested [3]. Unsurprisingly there is a global preference to defer investment in the existing electrical networks. Over the last fifteen years there have been serious disruptions to the Grid in Europe, Asia and America that have exemplified the risks of a non-resilient system [4, 5, 6, 7], which have had serious economic impacts. One of the most severe blackouts to have occurred in the last twenty years was the 2003 Northwest US Canada blackout [4]. Due to a lack of system visibility and a very serious IT system failure the system operators lost situational awareness of the power grid in their care. An unfortunate combination of a grid with limited monitoring, IT failure and an unforeseen power plant failure meant that the Northeast power system collapsed. This resulted in economic damage estimated at between $4.5bn and $10bn across manufacturing, service and government industries [5].

In July 2012, India suffered the world's most widespread electricity grid failure, which at its worst extent had isolated almost the entire Northern, Eastern and North-Eastern Electricity grid. The Ministry of Power report of August 2012 [7] identified several key factors in this failure. The first was that the Indian power operators had scheduled, in error, a series of major outages and had severely weakened key interregional power interconnections. This lead to severe overloading and tripped the line. However, neither on the 30th or 31st of July was a fault actually observed in the system, indicating a clear lack of system visibility. The lack of available telemetry data crippled the observability and state estimation of the Indian grid and prevented the load dispatch centres from shedding load effectively.

Within this paper we propose the application of prognostics to predictive lifecycle management of energy storage devices, namely Li-On batteries. Section I presents an overview of data driven prognostics. Section II provides a description of the experimental set-up, with sub-section A presenting analysis of the results. Finally, conclusions are presented in Section III.

I. Prognostics and Health Management

Prognostic models predict the remaining useful life (RUL) by assessing the degradation or deviation of a system from a benchmarked healthy system state [8]. The successful application of prognostic methods is dependent on tailoring the prognostic model to the given application. PHM methods can be categorized as data driven, simulated e.g. Physics of Failure models, and Fusion an integration of data driven and simulated. In this work, the focus is on data driven methods in alignment with the increasing volumes of data within our energy system. The following section provides an overview of data driven prognostics.

A. Data-Driven Approach

The data driven approach is an application of machine learning and statistical pattern recognition on data collected at system, subsystem, or component level. Determining unhealthy data in a vast database of healthy data can be a significant

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challenge. Furthermore, when faced with raw data values additional data cleaning and data normalisation must be performed to reduce noise associated with sensor error or the environment. Any algorithm employed for PHM must achieve three fundamental requirements: diagnose faults and predict failure, ensure collected data is reliable and reject or filter noise [9]. Prognostic algorithms are often based on neural networks (NN) and fuzzy logic or statistical approaches, including gamma processes, Markov model and regression based models such as Gaussian Process (GP), Relevance Vector Machine (RVM) or least square regression [10]. NN and GP tend to be widely used in the field of prognostics, however it is worth mentioning that there is no single algorithm that fits every system therefore, it is important to select it based upon application factors such as data type, uncertainty, expected noise and size. To illustrate some of the weakness as well as limitations of data driven methods three very different algorithms are examined, NN, GP and the state of the art RVM. NN originate from the artificial intelligence domain, in which a network model learns to produce a desired output in a similar way the human brain does. When applied to PHM, the NN can learn to estimate the level of degradation or lifespan corresponding to given inputs such as data features, time, usage conditions and operating environment state. As soon as the learning phase is completed, provided the neural network received quality and sufficient training data the diagnosis and prognostics phase can commence. Machine learning NN became synonym to artificial intelligence with the recent breakthrough in deep learning methods attracting attention in both academia and industry through platforms like Deep-Mind and IBM Watson. Despite the relatively wide spread use of deep learning techniques, it is only in recent years that such methods have been applied to the field of PHM. However, noisy sensory data typical to PHM applications poses a significant hurdle in the implementation of such techniques. There are many types of deep learning algorithms, such as deep belief networks, Boltzman machine or auto encoders. The use of deep learning techniques has been illustrated by Deutsch and He in the analysis of bearing RUL using vibration sensor data [11]. The approach included a Restricted Bolzman Machine (RBM), a generative stochastic artificial NN that learns a probability distribution over the set of inputs, in this case vibration amplitudes. The RBM method learns the weights and biases in the unsupervised stage, afterwards using them as input in the supervised learning algorithm. The RUL method has been validated through vibration data collected from hybrid ceramic bearing run to failure, proving that deep learning can be accurately used for PHM purposes. Another application of deep learning methodology has been captured by Yan and Yu in their study of anomaly detection for gas turbine combustors [12]. In this paper the supervised denoising autoencoder (SDAE) deep learning method has been used to hierarchically learn features from the sensor measurements of exhaust gas temperatures. The identified features were then used as inputs to a neural network classifier, extreme learning machine (ELM), for anomaly detection. There are however three major limitations in neural networks based prognostics: (1) finding adequate number of nodes and layers, (2) obtaining relevant weights and (3) dealing with uncertainty introduced by training data [10]. Determining the exact number of nodes and layers is problematic and highly dependent on variables affecting the output as well as user experience in building neural networks. Finding optimum weight parameters is still challenging, the performance of NN algorithm deteriorates with non-optimum weight values. Finally, the quality of the data is crucial, most measured data includes noise and bias. Bias can be the error caused by sensor calibration or malfunction, while the noise error is simply the mismatch between the training data and the output. A possible solution is to implement NN that are robust to input noise such as the one used by Yan and Yu for anomaly detection, namely the SDAE classification network. Statistical approaches to data driven methods, including GP and RVM function operate by fitting a probabilistic model to the available data. [5]. GP is a common regression-based method and it has the advantage of mapping the simulated outputs identically to the measured data, however it does have its drawbacks. GP performance is highly influenced by its model, sharing a similar issue to NN. In this case the model is based on the covariance function, which in turn is difficult to attain despite the various types available, squared exponential, rational quadratic constant or linear. Extensive research has been conducted to determine the most suitable function, however much uncertainty on the exact function still remains. Another issue related to the GP model is the cumbersome acquisition of scale parameters that determine the smoothness of regression model as well as the data sample sizes [9].While a large set of training data improves the model learning/training phase, it also demands increased computational times. Statistical approaches utilising extracted data features have proven to be well suited for prognostics purposes as illustrated in the literature and later exemplified through the case studies in the present material. One such method is the state of the art Relevance Vector machine (RVM). RVM is essentially a supervised learning technique, derived from the eminent Support Vector Machine (SVM) employing a Bayesian probabilistic approach. For convergence purposes an arbitrary kernel function is normally employed. Due to the mathematical nature of the model there are significant advantages over other methods including a strong generalisation and interference capability at low computational costs. A detailed explanation of RVM is beyond the scope of the present material, however a more in depth analysis introduced by Tipping (2000) [13] is widely available. Largely, the data-driven approach can be regarded as a clever data analysis solution, a black box that does not consider the system geometry, subsystems interactions or material properties. It is merely a probabilistic approach to pattern recognition of sensory data. In addition, it can be difficult for data driven methods to estimate the RUL in the absence of complete historical knowledge of the product parameters. The experimental set-up, detailed in section II, provides a full lifecycle analysis of Li-On batteries, in which the performance of RVM will be evaluated.

II. EXPERIMENTAL SET-UP

Lithium Ion (Li-ion) battery technology is increasingly important in the both the decarbonisation of transport and energy. Hybrid architectures are increasingly common, being used to efficiently balance power demands with traditional combustion engine systems [16]. Within national energy infrastructure storage technologies are being used for

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applications such as providing demand response in the network, aiming to aid the grid to supply peak power with reduced generating capacity [17]. Common issues associated with Li-ion battery technology such as cell ageing hinders implementation in mission critical systems.

The battery data used to conduct the prognostic experiment were obtained from the open-source, life cycle test data repository of the National Aeronautics and Space Administration (NASA) Ames Prognostics Center of Excellence (PCoE) [18]. In this dataset, 34 lithium-ion battery packs (4 batteries in one pack) were used to run the life cycle test in different experimental conditions. Each battery pack was run repeatedly through charge and discharge operations. A typical charge and discharge process is regarded as a valuable cycle, which is the key measurement of the RUL of the batteries in this study. Specifically, in the charging process, batteries are charged at a constant current of 1.5A until the battery voltage reached 4.2V, then batteries were continued to be charged at a constant voltage until the charge current dropped to 20mA. Discharging was carried out at constant current at 2A until the battery voltage dropped from 4.2V to a cut-off voltage. The experiments were conducted in two different room temperatures (25°C and 4°C) and four different cut-off discharge voltage (2.7V, 2.5V, 2.2V and 2.5V) for different packs. Furthermore, the experiments were terminated when batteries reach their End-of-Life (EOL) criteria of 30% fade in initial rated capacity (70% remaining capacity). Beyond this point, the batteries are no longer considered as reliable power generating assets [17].

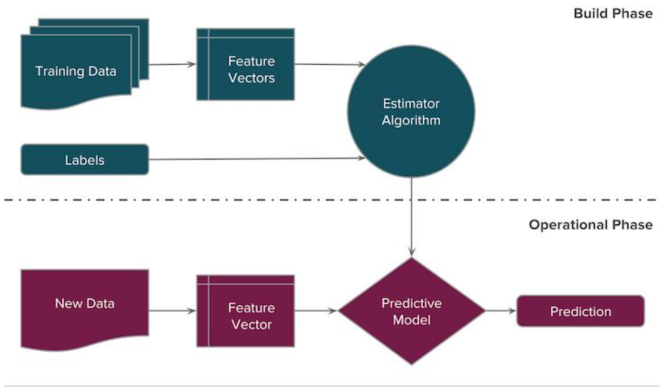

Figure 1 Supervised learning architecture

RVM is a type of Support Vector Machine (SVM) which uses Bayesian inference to obtain probabilistic results and allows the use of arbitrary kernel functions. This mitigates the limitations intrinsic to SVM's as reported by Tipping, 2001 [12]. The following section presents the results of the actual lifecycle testing and predicted remaining useful estimates from RVM.

A. *Experimental Results and Analysis*

To evaluate the proposed battery RUL prediction algorithm, we adopt the battery NASA battery dataset we introduced in section II. To measure the error of the predicted RUL of the battery, we define the absolute error, AE, and relative error, RE, as;

$$AE = \|R - R°\| \text{ and } RE = \|R-R°\| / R,$$

where R is the actual RUL value and R° is the predicted RUL value.

First, we implement the RUL estimation with battery No. 5 in this dataset, in which different starting points are selected. These starting points are selected, namely the 40th, 60th, and the 80th cycles. The RUL prediction results are shown as Table 1. The algorithm was applied to a random selection of batteries from the NASA dataset and it was shown by initialising the algorithm at different stages within battery lifetime Ci, a maximum Relative Error (RE) of 8% was observed meaning all batteries had their RUL predicted to within 10 cycles of the actual lifetime. The plots in Figures 2-4 show a strong visible correlation throughout the asset lifetime.

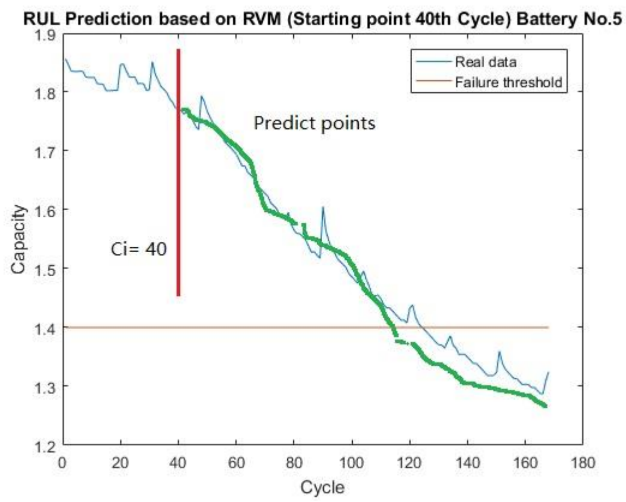

Figure 2 Remaining Useful Life predictions of Battery No.5 starting at the 40th Cycle.

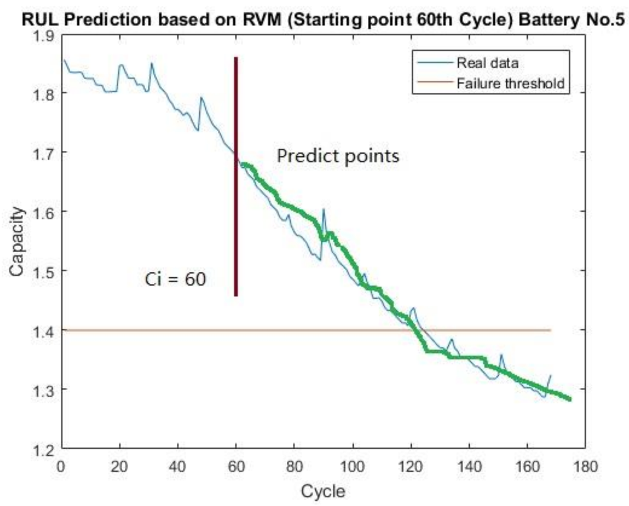

Figure 3 Remaining Useful Life (RUL) prediction of battery No. 5 after the 60th cycle

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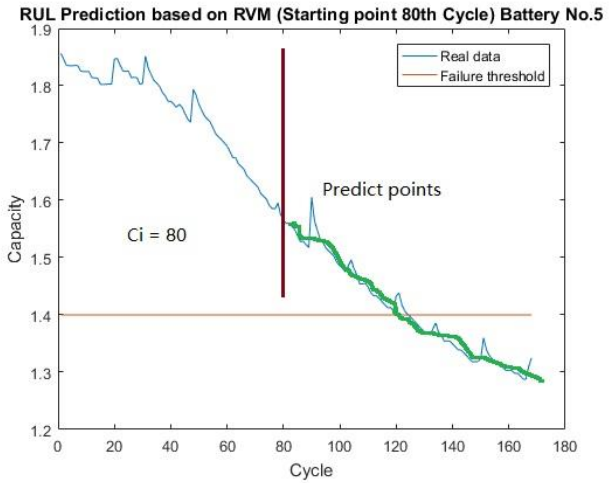

Figure 4 Remaining useful life prediction of battery No. 5 after the 80th cycle

Elementary experiment result for RUL prediction for Battery No.5, No.6, and No.7					
Battery No.		RUL Comparison			
		True RUL	Predicted RUL	Error (cycle)	Estimation error (%)
Battery #5	At cycle 40	124	117	7	5.6
	At cycle 60	124	120	4	3.2
	At cycle 80	124	121	4	3.2
Battery #6	At cycle 40	112	103	9	8
	At cycle 60	112	102.5	9.5	8.4
	At cycle 80	112	107	5	4.4
Battery #7	At cycle 40	166	158	8	4.8
	At cycle 60	166	159	7	4.2
	At cycle 80	166	159	7	4.2

Table 1 Remaining Useful Life predictions for Battery No.5, 6 and 7.

Our result shows that the RVM estimation has a good performance in the long term prediction on forecasting the battery RUL. In particular, the latter the starting cycle is (cycle 80), the more accurate the resulting RUL prediction will be. To verify and evaluate the adaptability of the proposed method, we also implemented the RUL prediction experiment using other batteries. The experimental results with battery No. 5, No. 6 and No. 7 are shown as Table 1. Similar to that of battery No. 5, the prediction precision measurements AE and RE are satisfactory. The prediction precision proves that the proposed method has a good performance for the application we consider.

III. Conclusions

In this work, challenges in maintaining a resilient energy system and the role of prognostics in predicting asset health (lifetime) has been outlined. The experimental results from the NASA battery data have been used to test the predictive capacity of the proposed Relevance Vector Machine (RVM) algorithm. The results for 3 different battery packs shows that regardless of the starting point, whether 40th, 60th or the 80th cycle, the proposed algorithm and prediction procedure can generate a remaining useful life (RUL) prediction that lie within 10 cycles of the true battery RUL. Our prediction tracks closely the real test cycle data, and performance measurement RE lies within 8% for all batteries analysed.

When considering widespread implementation of prognostics into a complex infrastructure, such as an energy system, a challenge relates to analyzing large volumes of data. The authors believe that data compression methods are required to reduce data volumes of which there are several strategies: selective data acquisition and front & back end data processing or combinations of the aforementioned. The common goal of these strategies is the optimisation of the Shannon Entropy of recorded data, that is a minimisation of the quantity of recorded redundant data. Selective data acquisition reduces data volume by monitoring the live data and applying decision making to the data recording process. Use of recording triggers, such as identifying interesting changes in the monitored data and using this to trigger writing the data to storage is one example of a selective data acquisition routine. This type of method is best suited to applications where data storage is minimal or costly. This can also allow dynamic data rates to be used. Front end processing allows localised decision making to take place and decisions to be made about which data is to be kept. This differs from selective acquisition in the sense that it records and stores the data initially and makes decisions about deleting and discarding or compressing data after it has been recorded, whereas selective data acquisition makes decisions about which data to physically record based on a real-time observed value i.e. selective data acquisition has no long term history to refer to. Front end processing can be used in applications where: access to offline data transfer is limited or not possible, reasonable local data storage is available, low latency is required. Back end processing is the remote processing of data which involves transmitting data offsite for processing using large data-centres and/or powerful computer servers. This method allows a simpler PHM system to be installed at the front-end on equipment for monitoring. This can be applied where: data transfer is a possibility/required, powerful computation is required, high latency can be tolerated, data integration for platform based PHM is in use. Due to the challenges mentioned, the area of prognostics for energy systems remains a highly topical and challenging area of research with significant scope for Fusion prognostic models.

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