Personal Introduction
Assessing Machine Learning Models for Li-ion battery Prognostics

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As electric power becomes increasingly important in the energy transition, so does the need for accurate battery prognostics methods to ensure its safe and effective implementation. In the field of prognostics, models and data-driven methods are applied to predict the time-dependent performance of a system. However, it is often difficult to develop accurate models of complex components or systems without resorting to equally complex physical models, and thus the majority of current research focuses on the application of stand-alone data-driven and machine-learning methods. In this research, we intend to integrate and thus build upon these methods by forming a hybrid model, and applying it to Li-ion battery state of charge (SOC) prediction. By comparing the performance of this hybrid model against the performance of existing, commonly used data-driven models, we can evaluate the application of such a hybridized method in prognostics as a more viable alternative to conventional models.

The performance and health of a battery is typically characterised by either its state of health (SOH), or state of charge (SOC) [1], and thus it is desirable to develop a model describing these parameters. In current research, most data-driven battery prognostics methods can be categorised as either statistical or machine learning methods [2]. A commonly applied machine learning method is the artificial neural network (ANN), which can be a simple feed-forward network, or more complex convolutional and deep neural networks (CNNs and DNNs). However, since these cannot model temporal data, more often recurrent neural networks (RNNs) such as the long-term memory model (LSTM) are applied [3]. Another supervised machine learning method is support vector regression (SVR), however it presents a lower accuracy when compared to other machine-learning methods like ANNs [4] unless the model is optimised. This is the case for cross-validated particle swarm optimisation (PSO-SVM) models, which decrease the error to a level comparable to ANNs [5].

Commonly used statistical methods include Gaussian process regression (GPR), and decision trees. Such methods have the advantage of providing the prediction uncertainty analytically [6]. Additionally, in current applications of GPR to prognostics, the basic statistical method has been enhanced through periodic covariance functions and dynamic modelling [1], [6]. Random forests and gradient boosted trees are both based on decision trees. As an ensemble learning method, random forests may reduce the risk of over-fitting when compared to single decision trees, but are at the same time computationally expensive [7].

In the case of large data-sets computational efforts can be reduced by sampling the set and distributing it across multiple computing elements [8].

Although the methods primarily applied are machine-learning or statistics based, there is also a portion of research focusing on physical and filter models. The complexity of a physical model should be chosen based on the accuracy required. Since more refined models require more computational effort, these are less generally applicable [9]. Smit et al. apply conservation of energy to derive a a relatively simple physics based model, which as a result can be applied generally to multiple battery types [10]. Physical models can be combined with machine learning methods. For instance, Wen et al. apply a physics-informed neural network (PINN) to battery prognostics [11]. An alternative is a filter-based model, such as the extended Kalman filter, which as opposed to the linear Kalman filter, is able to provide accurate results when applied to prognostics [12]. Another commonly used filtering method is particle filtering, but its main challenge is a lack of particle diversity in small data-sets [13].

The SOC is defined as the ratio of current battery charge, to total possible charge [14]. As previously mentioned, this research focuses on the application of hybrid models to predicting Li-ion battery SOC, and comparison against the stand-alone methods developed thus-far. It follows that the overall aim is to evaluate the effectiveness of hybridized data-driven models in battery prognostics, by addressing what models can be effectively combined, and which facets of existing models would in combination enhance their stand-alone performance. The proposed methodology, in which distinct stand-alone models are developed before hybridization, first addresses these sub-questions, such that a conclusion to the main research question follows naturally. As such the method can be applied step-wise, and thus efficiently, to the sub-problems constituting the central research aim.

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