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Towards a probabilistic error correction approach for improved drone battery health assessment

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Health monitoring of remote critical infrastructure, such as offshore wind turbines, is complex and expensive. For the offshore energy sector, the accessibility for on-site asset inspection is hampered due to their harsh and remote location. In this context, inspection drones are crucial assets. They can perform multiple tasks, which are benefitial for the industry and society, including the improved reliability of critical and remote infrastructure. However, the reliability and safety assurance of inspection drones is complex, as they are autonomous systems and they require incorporating run-time operation and degradation knowledge. Focusing on the health assessment of inspection drones, their battery is a key component, which is a single point of failure and determines the probability of a successful operation. In this context, this paper presents a novel concept for inspection drone battery health assessment through a probabilistic hybrid approach which combines physics-based battery discharge models with data-driven error forecasting strategies. Results are validated with real data obtained through different offshore wind inspection flights of drones.

Keywords: Prognostics & health management, battery, discharge, hybrid prognostics, uncertainty.

1. Introduction

The revolution in robotics and autonomous systems (RAS) is unstoppable. The advance of autonomous system applications, such as autonomous transport and autonomous inspections, generate multiple benefits for the industry and society, including the improved driving security in autonomous transport, and improved reliability of critical and remote infrastructure through specialized robots and drones Feng et al. (2021).

However, the reliability assurance of RAS is complex, as it requires incorporating advanced intelligence that should evolve according to run-time operation Floreano and Wood (2015); Elghazel et al. (2015). Focusing on inspection drones for offshore wind turbine inspections, the challenging yet exciting operation context hampers the reliability assurance of drones Wang et al. (2022).

Different technological solutions have emerged to improve the design and reliability of drones. Most of the technological configurations include a combination of electrical and mechanical components, along with onboard software intelligence to adopt decisions without direct human intervention. In this context, using the ever-increasing prognostics and health management (PHM) solutions, it is possible to develop an accurate drone health monitoring approach through machine learning and uncertainty modelling methods Zio (2022).

Batteries are key components for the safe and reliable operation of drones, and accordingly, this paper presents a novel health-state estimation approach focused on batteries. There are different data-driven and physics-based health-state estimation methods Vanem et al. (2021). Focusing on unmanned aerial vehicles (UAVs), there have been proposed different battery health-state estimation methods, mainly centred on Lithium-Polymer (Li-PO) batteries . Eleftheroglou et al. (2019) presented a fully data-driven solution for UAV battery prognostics. A fully data-driven solution requires learning the battery operation dynamics from data and this seems a challenging activity. An interesting alternative is to combine physics-based and data-driven solutions in hybrid state-of-charge (SOC) estimation and prognostics models Nascimento et al. (2021). In this direction, Paez et al. (2018) adapted the physics-based Li-Ion model for Li-PO applications for UAVs and Sierra et al. (2019) presented a ubiquitous Li-Po battery discharge model for UAVs.

However, to the best of authors' knowledge, error-correction configurations have not been used for dynamic SOC estimation. Accordingly, inspired from Aizpurua et al. (2023), the contribution of this research is the proposal of a novel hybrid SOC solution, which combines physics-based battery discharge models and probabilistic data-driven error prediction models in an error-correction configuration. Namely, physics-based battery discharge models are dynamically corrected through data-driven probabilistic forecasting strategies.

The proposed approach enables the adaptive tuning of physics-based battery discharge methods via data-driven methods and error-correction configuration strategies. Through a calibration and adaptation stage, the proposed approach can learn battery discharge dynamics from a physics-based Li-Ion battery discharge model and then transfer the discharge dynamics into Li-PO battery discharge models. Results are validated with real data obtained through different offshore wind inspection flights of drones.

The remainder of this article is organized as follows. Section 2 presents the proposed approach. Section 3 presents the analysed case study. Section 4 presents results tested on a number of flights of real inspection drones. Section 5 presents discussions, and finally, Section 6 concludes.

2. Proposed Approach

The proposed approach is shown in Fig. 1. Namely, the `physics-based` modelling approach defines the physics-of-discharge of the battery. This model uses the input loading at instant t, $i_d(t)$, which is post-processed to extract error precursor variables through a `feature processing` step, which will assist in the `error prediction` stage. Finally, the last stage focuses on the dynamic error correction to estimate the discharge voltage $v_d(t)$.

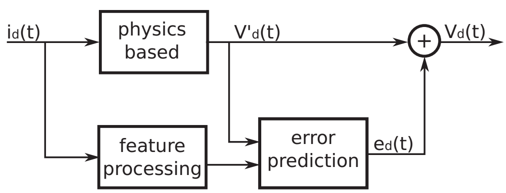

Fig. 1.: Hybrid battery discharge approach.

2.1. *Physics-based discharge modelling*

The work by Daigle and Kulkarni (2013) developed an electrochemistry-based battery discharge model. The battery voltages are defined through the amount of charge in electrodes (positive and negative). Each electrode is divided into a surface layer (s) and a bulk layer (b). The differential equations define the charge dynamics through these volumes.

The voltages are described by the following set of equations Daigle and Kulkarni (2013):

$$V_{U,i} = U_0 + \frac{RT}{nF} ln\left(\frac{1 - x_{s,i}}{x_{s,i}}\right) + V_{INT,i} \quad (1)$$

$$V_{INT,i} = \frac{1}{nF}\left(\sum_{k=0}^{N_i} A_{i,k}\left((2x_i - 1)^{k+1} - \frac{2x_i k(1-x_i)}{(2x_i-1)^{1-k}}\right)\right) \tag{2}$$

$$V_o = i_{app} R_o \tag{3}$$

$$V_{n,i} = \frac{RT}{F\alpha} arcsinh\left(\frac{J_i}{2J_{i0}}\right) \tag{4}$$

$$J_i = \frac{i}{S_i} \tag{5}$$

$$J_{i0} = k_i(1 - x_{s,i})^{\alpha}(x_{s,i})^{1-\alpha} \tag{6}$$

$$V = V_{U,p} - V_{U,n} - V_o' - V_{n,p}' - V_{n,n}' \tag{7}$$

$$\dot{V}_o' = (V_o - V_o')/\tau_o \tag{8}$$

$$\dot{V}_{n,p}' = (V_{n,p} - V_{n,p}')/\tau_{n,p} \tag{9}$$

$$\dot{V}_{n,n}' = (V_{n,n} - V_{n,n}')/\tau_{n,n} \tag{10}$$

where U_0 is a reference potential, R is the universal gas constant, T is the electrode temperature (K), n is the number of electrons transferred in the reaction (n=1, for Li-Ion), F is the Faraday's constant, J_i is the current density, J_{i0} is the exchange current density, and k_i is a lumped parameter of several constants including a rate coefficient, electrolyte concentration, and maximum ion concentration. $V_{INT,i}$ is the activity correction term (0 ideal conditions). We use the Redlich-Kister expansion with N_p=12 and N_n=0 Daigle and Kulkarni (2013). The τ parameters are empirical time constants used to model the voltage-change transition dynamics.

Eqs. (1)-(10) define the discharge dynamics for Li-Ion cells. The input parameter is the load i_{app}, the state-status variables are $q_{s,p}$, $q_{b,p}$, $q_{b,n}$, $q_{s,n}$, V_o', $V_{n,p}'$, $V_{n,n}'$ and the output of the model is the estimated cell voltage V.

It should be noted that the discharge model is fitted with battery-specific parameters to reflect its discharge dynamics. However, as the battery degrades with the applied current and other age-acceleration factors, e.g., the discharge dynamics change and the ageing rate should be integrated to model the ageing of the battery. This work presents a data-driven parameterization of the discharge model through an error correction configuration.

2.2. *Feature Processing*

The dataset consists of three variables: the load current of the drone, the estimated voltage derived from the electrochemical model, and the target variable representing the difference between the estimated voltage and the actual voltage recorded on the drone. Using this base dataset, a set of features are extracted which may help in the error prediction. These features, should be able to capture the dynamics which are not captured by the physics-based approach and use them to train the error prediction model.

Feature extraction is performed using a rolling window of length M (M=100 in this case) for the available variables. Namely, the following features are extracted: mean, maximum, minimum, kurtosis, crest factor, form factor, impulse factor, integrative and derivative of the original signal.

The set of features are then evaluated for their value for improving the error-prediction accuracy. This is done in this case through the intrinsic importance functions of the implemented machine learning models defined in Section 2.3. The resulting variables with the highest predictive information are used in the testing set for validation purposes.

2.3. *Data-driven prediction modelling*

For the error-prediction modelling of the physics-based approach, different machine-learning (ML) models have been trained and tested.

Random Forests (RF) regression is an ensemble of recursive trees Breiman (2001). Each tree is generated from a bootstrapped sample, and a random subset of descriptors is used at the branching of each node in the tree. RF creates a large number of trees by repeatedly resampling training data and averaging differences through voting. RF is a valuable option for capturing the intricate relationships between the statistical features extracted in the Section 2.2 due to its effectiveness in capturing complex relationships and handling nonlinearities.

Gradient Boosting (GB) Regression is a method that sequentially combines an ensemble of decision trees as a weighted sum that can be expressed as Friedman (2001):

$$\hat{y} = \sum_{n=1}^{N} c_n f_n(x) \tag{11}$$

where N is the number of stages, $\hat{y}$ is the prediction variable, each $f_n(x)$ is a regression tree or forest, which represent the steps to the final solution, with weight c_n, being x the set of values. Thus, it places a higher emphasis on data points that were previously misclassified, leading to improved prediction accuracy. Therefore, given its robust predictive performance, gradient boosting proves to be a well-suited choice for the proposed approach Friedman (2001).

Quantile Gradient Boosting (QGB) are based on boosting methods that sequentially combine an ensemble of weak learners as a weighted sum of base-learner models to reduce the ensemble error Friedman (2001):

$$\hat{y}_t = F_N(x_t) + \varepsilon_t = \sum_{n=1}^{N} f_n(x_t) + \varepsilon_t \tag{12}$$

where $F_N(x_t)$ is the ensemble of N regression trees, each $f_n(x_t)$ is a regression tree and ε_t is an error term. The new regression tree $f_{n+1}(x_t)$ for the pinball loss function $L(.)$ is estimated as follows:

$$\underset{f_{n+1}}{argmin} \sum_{t} L(y_t, F_N(x_t) + f_{n+1}(x_t)) \tag{13}$$

This optimization is solved through the steepest descent algorithm Friedman (2001), where each $f_n(x_t)$ is designed to be maximally correlated $F_N(x_t)$. The implementation of the pinball loss function (Eqs. 14) enables the probabilistic prediction Verbois et al. (2018).

$$L_{q,t}(y_t, \hat{y}_t^q) = \begin{cases} (1-q)(\hat{y}_t^q - y_t) & \hat{y}_t^q \geq y_t \\ q(y_t - \hat{y}_t^q) & \hat{y}_t^q < y_t \end{cases} \tag{14}$$

where q denotes the targeted quantile and $\hat{y}_t^q$ and y_t denote the estimated q-th quantile and the true label at time t, respectively.

The pinball loss function is asymmetric, penalizing underestimation and overestimation differently. The hyperparameter q in QGB determines the quantile level where lower q values emphasize higher quantiles (overestimation), while higher values emphasize lower quantiles (underestimation). By minimizing the pinball loss during training, the model learns to estimate desired quantiles, capturing the variability and uncertainty associated with different levels. This allows for a comprehensive understanding of the voltage distribution during battery discharge.

These algorithms were chosen for their ability to handle complex nonlinear relationships and provide robust predictions. The RF provides a diverse set of decision trees, while GB and QGB improve prediction accuracy through sequential model building. The main objective of this research study is the evaluation of the performance of these algorithms to estimate their effectiveness for battery discharge voltage prediction.

3. Case Study

The proposed approach is tested on offshore inspection drones as show in Fig. 2.

Fig. 2.: Inspection drone example.

These drones are used for the inspection of defects in offshore wind turbines, e.g. cracks, which are processed through on-boarding processing software. The drones are equipped with Li-Po batteries, and the focus of this research is on a 6S, 30000 mAh, Li-Po battery.

For each flight, different variables are captured from the drone including the loading, and for some specific drones, the discharge voltage. There are other external variables that also affect the discharge process, such as ambient temperature or pressure. However, the focus of this paper is on the use of the loading variable to get an accurate estimate of the SOC.

Fig. 3 shows an example of the variables that are available for each flight.

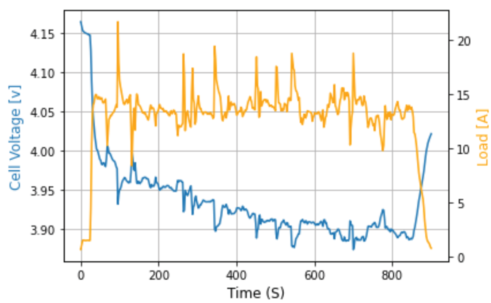

Fig. 3.: Available datasets for the flight #100.

The model validation strategy is focused on one-leave-out strategy. That is, if F flight information is available, then the error prediction model is trained on $F-1$ flight data and tested on the reserved flight information. This process is repeated to test the performance on different flights.

The overall dataset consists of 2,626 data samples obtained from six distinct flights. The length of each flight determines the proportion of samples that are used for validation. Accordingly, Table 1 displays the percentage of flight samples with respect to the overall dataset, which is used to validate the results for each flight.

4. Results

Fig. 4 shows the error prediction estimate for an individual flight using different data-driven error-correction techniques.

It can be observed that all the hybrid prediction models track the voltage discharge dynamics correctly. It can be observed that the QGB model integrates probabilistic estimates of the error and these are propagated to model the error under uncertainty.

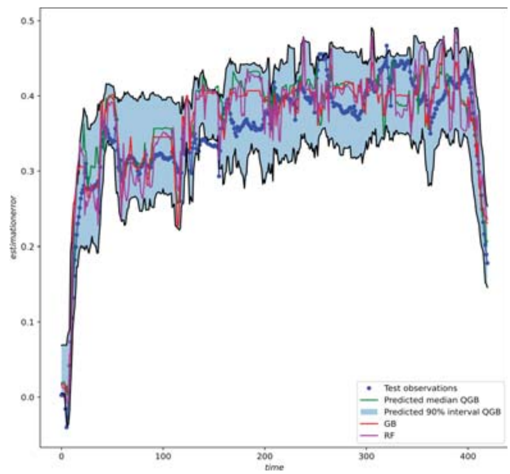

Fig. 4.: Testing set results on an inspection-drone flight #100.

In the same direction, Fig. 5 shows the corrected voltage estimate for different models, which is effectively obtained by adding the physics-based voltage estimations with the error correction estimates shown in Fig. 4.

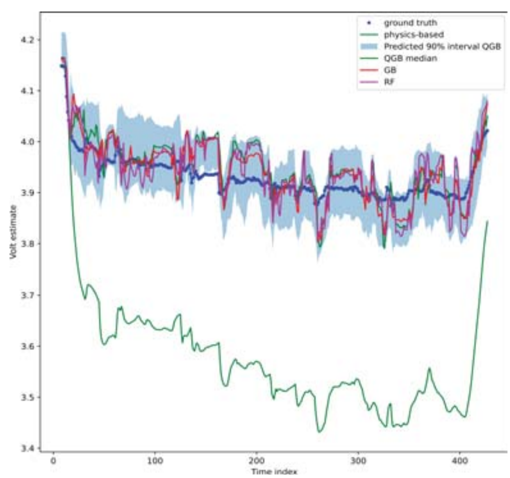

Fig. 5.: Testing set results on an inspection-drone flight #100.

Finally, Table 1 displays the mean average error (MAE) performance metrics for the different models in different configurations.

The table includes the flight number (flight), the length of the testing set (samples %), and MAE re-

Table 1.: MAE performance results on various flights.

Flight (#)	**Samples (%)**	**Physics-Based**	**RF**	**GB**	**QGB (median)**	**QGB (q=0.05)**	**QGB (q=0.95)**
100	16.3	0.35	0.035	0.03	0.034	0.061	0.064
119	15.5	0.42	0.086	0.092	0.084	0.014	0.06
87	25.1	0.43	0.061	0.062	0.064	0.08	0.059
53	41.5	0.42	0.082	0.082	0.08	0.069	0.097
51	0.9	0.025	0.015	0.019	0.022	0.01	0.088
50	0.6	0.01	0.01	0.011	0.013	0.029	0.053

sults for the physics-based model (physics-based), and for different hybrid configurations with different error-correction prediction models including RF, GB and QGB with median, 5th quantile (q=0.05) and 95th quantile (q=0.95) estimates.

From Table 1 it can be observed that the hybrid error-correction configuration effectively improves the voltage prediction error for all the different flights. Among the tested error-correction models best results have been obtained with the RF correction model.

However, it should be noted that the QGB model propagates model uncertainties, and this is a crucial factor for decision-making in uncertain environments, *i.e.* autonomous inspections.

5. Discussion

This research is part of an ongoing project. The results are promising, but there are different parts that need to be further developed and tested.

The proposed approach is adaptable to different types of batteries and drones. Namely, the main ability of the proposed approach is the correction of battery discharge estimation errors through a data-driven approach. This may be useful for different scenarios to correct diverse battery parameter errors, such as calibration errors for physics-based battery model parameters, battery degradation effects or the influence of the electrolyte type and electrode material.

The feature selection process has been done based on the importance function of the used ML methods. This is very dependent on the length of the adopted rolling window for feature extraction (N=100 in this work). This is a hypothesis which needs to be validated with an extensive sensitivity assessment.

The model proposed in this work has been tested on a limited number of flights. This will be extended and tested on additional flights, which are likely to be influenced by additional environmental factors, e.g. ambient temperature, wind speed, which affect the performance of the battery and drone.

The interest of this research is on uncertain conditions, in which the estimation of the data-driven prediction model is able to inform about the performed prediction. In this direction, this work has tested QGB method, but this is an area which requires further work, testing and calibration so as to generate informative predictions under uncertainty.

Finally, this transition will also require to use proper error quantification metrics for probabilistic error measurement and calibration, *i.e.* Continuously Ranked Probability Score.

6. Conclusions

This research has presented a drone battery health assessment approach based on physics-based models and data-driven error prediction methods. Both methods have been integrated in a hybrid error-correction configuration. Results have shown a good battery discharge prediction accuracy tested on different flights of the inspection drone.

This is a practical solution to integrate the effect of ageing on batteries. That is, as the batteries degrade, the physics-based model parameters become outdated and they require a recalibration. The proposed framework integrates this calibration naturally, through the adjustment of the physics-based model with data-driven error correction models.

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