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RESEARCH ARTICLE

Statistical Models for Condition Monitoring and State of Health Estimation of Lithium-Ion Batteries for Ships

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***Abstract**:* Battery systems are increasingly being used for powering ocean going ships, and the number of fully electric or hybrid ships relying on battery power for propulsion is growing. To ensure the safety of such ships, it is important to monitor the available energy that can be stored in the batteries, and classification societies typically require the state of health (SOH) to be verified by independent tests. This paper addresses statistical modeling of SOH for maritime lithium-ion batteries based on operational sensor data. Various methods for sensor-based, data-driven degradation monitoring will be presented, and advantages and challenges with the different approaches will be discussed. The different approaches include cumulative degradation models and snapshot models, models that need to be trained and models that need no prior training, and pure data-driven models and physics-informed models. Some of the methods only rely on measured data, such as current, voltage, and temperature, whereas others rely on derived quantities such as state of charge. Models include simple statistical models and more complicated machine learning techniques. Insight from this exploration will be important in establishing a framework for data-driven diagnostics and prognostics of maritime battery systems within the scope of classification societies.

***Keywords**:* battery; condition monitoring; data-driven analytics; diagnostics; state of health

I. INTRODUCTION AND BACKGROUND

The safety of electric ships is ensured by classification societies. Fire is one major concern, but a totally different safety aspect is to ensure that the available energy and power stored in the battery are sufficient to cover the required propulsion system demand [1]. Loss of propulsion function at sea can lead to critical scenarios and serious accidents such as collision or grounding. Hence, trustworthy monitoring of the available energy in the lithium-ion battery is essential for the safety of electric ships. In this work, state of health (SOH) is defined as the current capacity relative to initial (also referred to as nominal or rated) capacity. Other definitions exist (e.g., related to internal resistance), and there is no general consensus on how to define this. However, in this paper, SOH should be construed in terms of charge capacity.

The energy storage capacity of lithium-ion deteriorates as they are aging [2]. Lithium-ion batteries are typically designed with a shorter expected lifetime than ships. Thus, batteries are expected to approach their end of life (EOL, typically SOH = 70–80%) the ships they are installed in. In this situation, accurate and reliable prediction of battery capacity becomes progressively more important as the battery systems advance toward its EOL.

Currently, maritime battery systems must include an SOH algorithm, which needs to be verified annually through a physical capacity test. This test is time consuming and normally means that the ship is taken out of service for a day. However, ship-to-shore connectivity has improved recently, and it is natural to consider whether a data-driven monitoring system can replace the need for an annual test, and hence minimize downtime for the operator without compromising on safety.

This paper discusses different alternatives to data-driven capacity estimation for maritime battery systems. The main objective is to utilize sensor data from the batteries to understand the state of degradation without requiring specific tests. This paper is an extension of a conference paper presented at PHM 2023 [3], including some additional methods and new results, see also [4]. In particular, the semi-supervised learning approach and the two last methods in this paper; the open circuit voltage method and the method utilizing equivalent circuit models (ECMs), are new and were not presented in [3].

A review of various approaches for data-driven diagnostics of lithium-ion batteries for ships was presented in [5]. In the current paper, case studies with different approaches and models will be presented, including both cumulative and snapshot methods.

II. BATTERY DATA DESCRIPTION

Various datasets have been analyzed in this study. These include laboratory cycling data, data from ships in service, and some public datasets.

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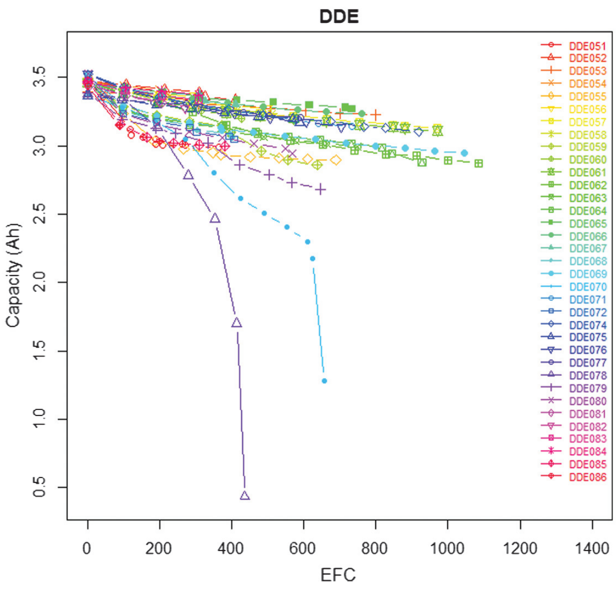

Fig. 1. Capacity against EFC for DDE cells.

A. LABORATORY TEST DATA

Degradation data from three types of lithium-ion battery cells have been obtained by cycling laboratory tests carried out by Fraunhofer. Two types of cylindrical nickel–manganese–cobalt (NMC) 18650 cells, i.e., DDE (energy cells; nominal capacity 3.5 Ah) and DDP (power cells; nominal capacity 2.5 Ah), and one type of NMC pouch cells, DDF (nominal capacity 64 Ah) have been cycled according to predetermined load matrices. Continuous cycling is interrupted regularly to undergo capacity measurements and check-ups. Hence, measured capacities are available at regular intervals for all cells. Results are illustrated in Fig. 1, which show estimated capacity as a function of number of equivalent full cycles (EFC) for the DDE cells. Similar plots for the DDP and DDF cells can be found in [3,4].

Values of current, voltage, and temperature are sampled continuously, resulting in time series of these variables throughout the experiment. Such data are available for 81 individual cells, i.e., 35 DDE cells, 30 DDP cells, and 16 DDF cells. The cells have been cycled with CCCV (constant-current-constant-voltage) scheme, i.e., they are discharged/charged with constant current until a cutoff voltage, after which the cells continue to discharge/charge at constant voltage with a gradually vanishing current.

A comparable dataset from laboratory tests with the DDE and DDP cell types at Corvus' lab is also available. However, these tests employ a somewhat different cycling scheme with CCCV charging and constant power discharging, with small rest periods in between.

Additional data have been available from DNV's battery lab, for lithium-ion cells similar to the ones used in some of the operational data.

B. FIELD DATA FROM SHIPS IN OPERATION

Operational data from electric ships with pouch cell batteries of type DDF are used in this study. These batteries consist of cell pairs connected in series within modules, which are connected in series to form packs and finally packs connected in parallel within an array. Data from these installations include pack voltage and current as well as cell voltage, temperature, and state of charge (SOC), which is a derived quantity that is calculated from the other sensor signals. An example of time series from this system is shown in Fig. 2, with from top to bottom, pack current, cell SOC, cell temperature, and cell voltage.

Field data from 6 ships with similar battery systems have been used in this study, including hybrid and fully electric vessels with varying configurations. None of these systems are very old new, and they have not experienced much degradation. Results from annual capacity tests are available, and all installations have been subject to at least two such tests.

Additional data from a somewhat older battery system, with different types of cells, have also been analyzed in this study. These have the benefit of longer time series, but with inferior data quality and more data gaps. More details of the ship data can be found in [3,6].

C. PUBLICLY AVAILABLE DATASETS

Various public datasets from different battery types exist [7], including degradation data from cycling tests that has been used in this study.

Battery data made publicly available by the NASA Ames Prognostics Center of Excellence (PCoE) have been used in this study. Specifically, randomized battery usage data [8] consisting of aging data of 18650 lithium-ion batteries under randomly generated usage profiles have been analyzed. Reference is made to [8], see also [9], for further details on these data.

III. DATA-DRIVEN STATE OF HEALTH ESTIMATION

The various data-driven approaches explored in this study include cumulative damage models, snapshot methods, and other approaches. The results from these analyses are presented in the following.

A. CUMULATIVE DEGRADATION METHODS

Cumulative methods aim at estimating the contribution to degradation from each cycle and add these up to get accumulated degradation and SOH. Hence, they model ΔSOH as a function of various stress factors and get, after n cycles, $SOC(c_n) = 100 - \sum_{i=1}^{n} \Delta SOH(c_i)$. Three such cumulative damage models have been explored in this study.

1) BATTERY AI. Battery AI uses a combination of machine learning and semi-empirical methods to model battery behavior under various real-world conditions [10]. It can analyze complex duty cycles and determine the essential abuse factors. The impact of these factors can then be modeled to predict overall degradation and capacity depletion. In short, the semi-empirical function

$$y = 100 - A \times TO^p + C \tag{1}$$

is fitted to degradation data, where TO denotes turnover and C is a calibration constant. The exponent p is estimated from empirical degradation curves, and A models the combined effect of various stress factors by a neural network trained on cycling test data, see [10] for details; see also an

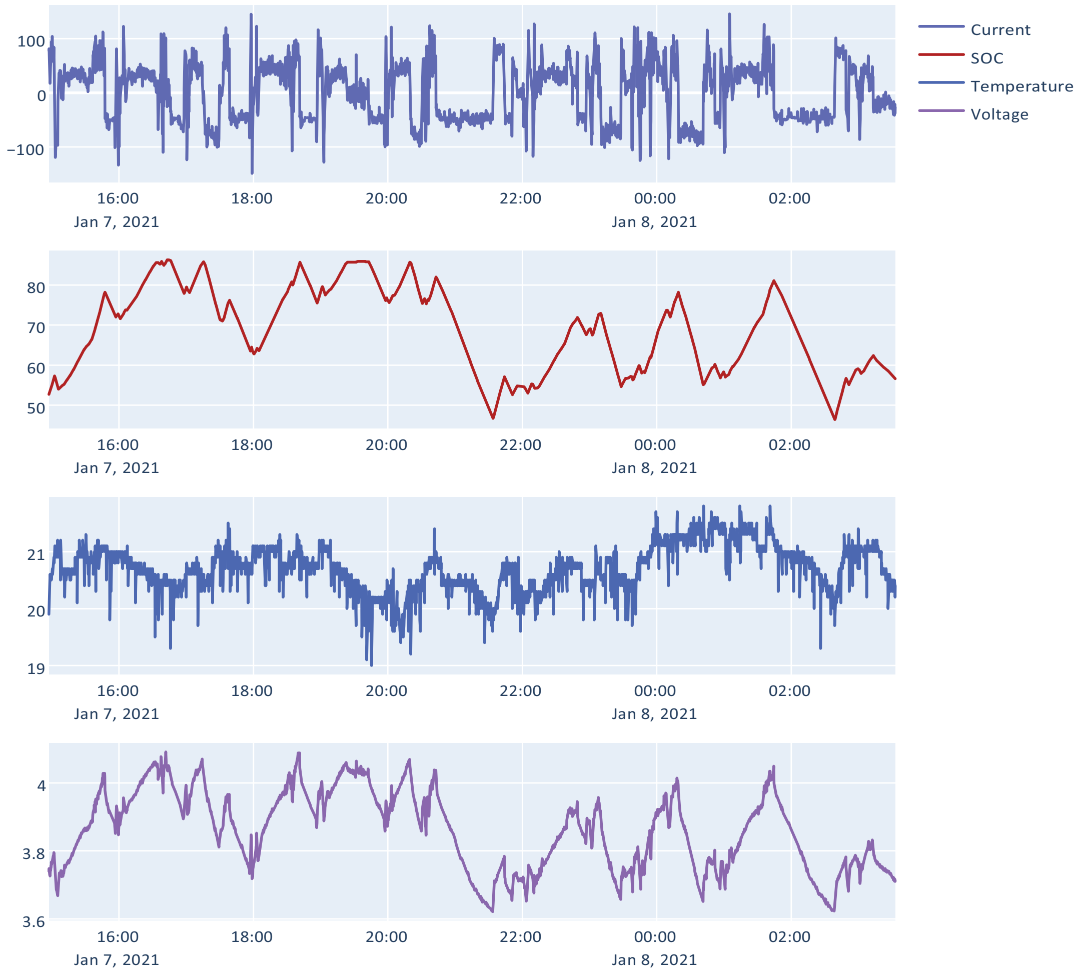

Fig. 2. Example of time series from an onboard battery system.

extended description of this case study in [6]. Overall, results are reasonably good, with deviations from the annual capacity test results in the order of 3% after one and a half year. However, it is emphasized that verification is difficult without longer time series and more extensive degradation.

One crucial aspect of the analyses using battery AI is the data preprocessing to obtain the required input format. This includes cycle decomposition to identify cycles and associated these with the stress factor. The accumulated degradation from the individual cycles is then added together. As elaborated in [6], this data processing is time consuming and computationally expensive. For very large battery systems onboard ships, containing several thousand cells and operated over several years, the mere cost of data handling prohibits large-scale implementation of this tool. Furthermore, it does not handle gaps in the data very well, something that cannot easily be avoided for data from ships at sea.

2) PROBABILISTIC CUMULATIVE MODELS. Other, more flexible cumulative models that do not rely on the semi-empirical function were investigated. Probabilistic machine learning models, including Gaussian processes regression and Bayesian neural networks, were fitted to training data from lab experiments and applied to estimate the capacity on operational data from ships in service. Results from these investigations indicate that such flexible models were not able to predict capacity very accurately, and this is mainly due to lack of representative training date, see [4] for further details.

3) MODELS BASED ON NONSEQUENTIAL AND SEQUENTIAL FEATURES. Different nonsequential and sequential models were applied to the NASA randomized usage dataset, including simple statistical models and more complicated machine learning models. These are utilizing summaries of the cumulative load profiles as features, extracted in terms of histograms or buckets of experienced conditions. For further details of these analyses, reference is made to [11], see also [6].

The main difference between nonsequential and sequential methods is that the sequential methods explicitly account for temporal information in the data. The nonsequential methods that are considered include linear regression (ordinary least squares (OLS)), penalized linear regression (ridge regression and lasso), gradient boosted trees, and support vector regression. The sequential methods include recurrent neural networks (RNN), long short-term memory (LSTM) models, transformers, and temporal convolutional neural networks (TCN). The models are trained on data for all cells except for the cell that is to be predicted.

Nonsequential features are extracted from the random walk steps in terms of histograms of times spent with different current profiles and within different bins of temperature and voltage. Additional covariates are introduced from data from the last n steps as well as the temperature and rest time immediately prior to a reference cycle. The sequential models use time-series data as input. Two alternative sequence formats are utilized: short sequences include summary statistics from each random walk step, and long sequences correspond to downsampled time series. Additional static covariates include estimated capacity from the previous cycle and temperature during the reference discharge. Several alternative models using different subsets of the features are compared in terms of their root mean square error (RMSE).

Results suggest that the nonsequential penalized linear regression models—ridge regression—perform best. Other models such as lasso, transformers, and support vector regression perform almost comparably well on average for the four cells. According to these results, relatively simple statistical models may perform better than more complicated deep learning approaches, with adequate feature engineering.

This study demonstrated that it is possible to estimate battery capacity using simple statistical models based on histograms of operating histories. It is a cumulative type of model, but the data volume is drastically reduced since only summaries of the data are needed. However, it is questionable how well such methods scale to large battery systems and how well data gaps are handled; the histograms might be biased if there are extended periods of missing sensor data. These are serious limitations of such types of approaches.

B. SNAPSHOT METHODS

As opposed to cumulative methods, snapshot methods aim to estimate SOH directly from snapshots of the data by extracting relevant features. Different snapshot models have been explored in this study.

1) REGRESSION ON CHARGE AND DISCHARGE CURVE FEATURES. Figure 3 shows examples of extracted charge and discharge curves for an arbitrary DDP cell. The different colors represent different time periods, and it is clearly seen that the curves are changing as the battery is used. Hence, it should be possible to extract relevant features from such curves and relate them to degradation and capacity loss.

In total, 44 features are extracted from the constant-current phases of selected cycles, and the overall dataset of extracted features contains 281 samples for the DDE cells and 269 samples for the DDP cells. However, it is noted that not all cells have information for all covariates.

Different basic statistical regression models are employed to predict the capacity of the cells based on snapshot features, i.e., linear regression, linear regression with missing covariates, ridge regression, least absolute shrinkage and selection operator regression (Lasso), multivariable fractional polynomial regression, generalized additive models, regression tree, random forest, and support vector regression [12].

Results presented in [12,13] suggest that this snapshot approach obtains quite good results for some of the cells, but not for others. Performance evaluations of the individual predictive models are presented in [12,13] and did not identify a particular model as being consistently best.

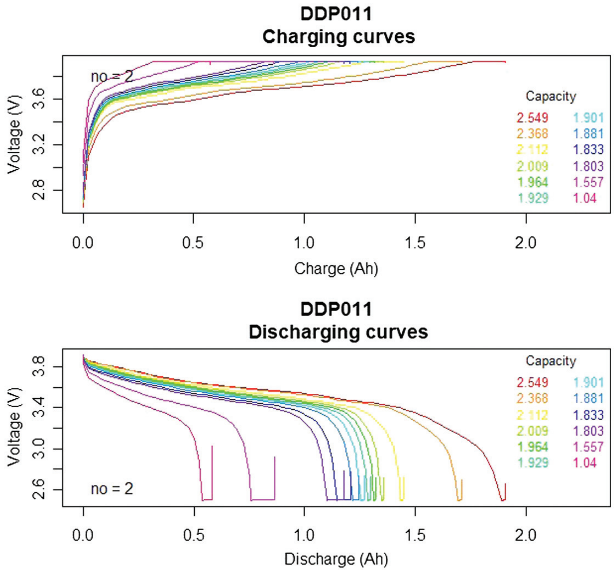

Fig. 3. Extracted charge and discharge curves from the raw time series for an arbitrary DDP cell.

The fact that the models give reasonable results for some cells is encouraging, but results need to be significantly improved for these approaches to be recommend from a ship classification perspective. More relevant training data would presumably be required to improve prediction accuracy, as discussed in [12,13].

2) A VOLTAGE-DEVIATION METHOD. The voltage deviation method (VDM), promoted in [14], exploits the correlation between an increase in internal resistance and a decrease in capacity to estimate SOH. It is applied to the NMC-type of maritime batteries in this study, and further details can be found in [3,4].

The VDM is based on features related to the voltage deviation within certain SOC ranges as well as the standard deviation of charge and discharge power and mean temperature. The regression model is on the following linear form:

$$\begin{aligned} \mathrm{SOH} &= \alpha 1X1 + \alpha 2, \\ \alpha i &= \beta i,1X2 + \beta i,2X3 + \beta i,3,\ i = 1,2, \end{aligned} \tag{2}$$

where X_1 denotes the voltage deviation feature, X_2 denotes the power deviation feature, and X_3 denotes the average temperature. The deviation features are calculated by first subdividing the data into small subsections of SOC and then calculate the standard deviation of the voltage and power, respectively, within each subsection. The voltage and power deviations are the average standard deviations over all SOC sections.

Lab data from the DDF cells are used as training data, and the fitted model is applied to operational data from ships. Note, however, that limited training data from only 6 DDF cells cycled in the lab are available.

For one vessel, preliminary results yield a sudden increase in capacity after approximately one year of operation. This is unreasonable, and upon further investigation, it turns out that this appears at the same time as fast charging is applied to these batteries. The models are unable to adequately adjust for this sudden change since such conditions were not part of the training data. This illustrates the importance of representative training data. One solution is to obtain more training data from lab experiments, but carrying out such experiments is both time consuming and expensive. Hence, relying on data-driven models that need to be trained has fundamental practical challenges.

C. SEMI-SUPERVISED LEARNING

The above case studies highlight the challenges of relying on extensive lab test data to train data-driven models. Hence, it was investigated whether operational data can be used to train such models. One challenge then is that whereas operational data contains continuous sensor measurements, actual capacity measurements are far between. Typically, one value from an annual capacity test will be available about once per year, and the data will be mostly unlabeled.

With a semi-supervised approach, the idea is to label such unlabeled data by considering a time window around the annual test where the capacity can be assumed constant. Then, time-series data within this time window can be labeled and used to train data-driven models. One such approach was reported in [15]. In the following, another approach based on general boosting machines, a type of tree-based machine learning models, will be outlined.

The tree-based model in this study has been tested on continuous data from data from 16 different vessels. The explanatory variables are various current, voltage, and temperature summaries, including maximum, minimum, average, and median values as well as integrated current and start and end voltages of the cycles. For each vessel, the algorithm has been trained on data from the 15 other vessels and used to estimate SOH and compare with results from annual capacity tests.

Overall, estimated SOH was within an error of 5% of the field tests in most cases, with only a few cells experiencing a larger deviation. This is illustrated in Fig. 4, where the estimated SOH is compared to the results from the annual capacity tests for all 16 vessels. It is observed that most estimates are within ± 5% from the test results, but with some notable exceptions. In particular, in one case, the actual SOH is seriously under-estimated by the machine learning model, and this is the cell with lowest actual SOH.

One explanation for the few large deviations between the machine learning model and the annual test results is that the training data are not sufficient. When training data are extracted from operational data from a fleet of ships with similar battery installations, one would need that all the systems in the training data have experienced at least the same level of degradation as the system one wants to predict. Hence, for the vessel associated with the most degraded batteries, it is questionable how accurate the machine learning models will be in estimating SOH. This is challenging, particularly since it will be for these vessels accurate SOH estimation is most critical. Another issue is that with operational data, one would typically have less control of the operational conditions, and it will be difficult to ensure that all relevant conditions are well represented in the training data. For further details, reference is made to [4].

D. PHYSICS-INFORMED DATA-DRIVEN MODELS

Whether relying on laboratory or operational data, training data remain a challenge for data-driven modeling of SOH. Hence, models that do not need prior training would be desired. In the following, some approaches that can relax the need for comprehensive training data by exploiting physical knowledge are explored.

1) LINEAR REGRESSION BASED ON COULOMB COUNTING. Coulomb counting exploits the fundamental relationship between integrated current and change in SOC and is often used to determine total capacity of a battery from deep charge and discharge cycles. In principle, his relationship should be preserved during partial cycling and can be utilized together with a simple linear model to estimate battery capacity and state of health.

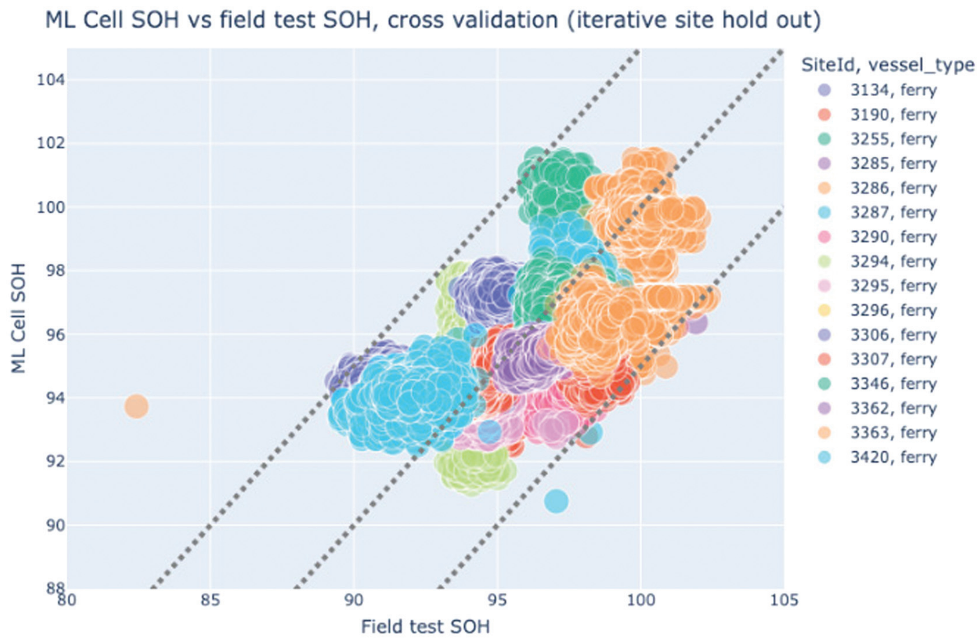

Fig. 4. Results from leave one out cross-validation for the semi-supervised approach.

The following equation describes the relationship between the total capacity Q, integrated current, and change in SOC of a battery between times t_1 and t_2:

$$\int_{t_1}^{t_2} \eta I(\tau) d\tau = Q(SOC(t_2) - SOC(t_1)). \quad (3)$$

$I(\tau)$ is the current at time τ and η is the Coulomb efficiency factor, which may be assumed to be equal to. This can be presented as a linear regression problem as suggested by [16],

$$Y = QX + \varepsilon. \quad (4)$$

The total capacity, represented by the regression coefficient Q, can be estimated by different methods, such as ordinary least squares (OLS), total least squares (TLS), or Bayesian linear regression, by collecting concurrent values for Y and X [4].

In this study, a simple OLS implementation of this model is applied to the Fraunhofer lab data for the three different types of cells. Data are collected from the first 25 cycles after each capacity measurement, and the integrated current and the change in SOC are calculated from the full charge and discharge cycles, as well as from random segments of the cycles. Figure 5 shows the extracted data and estimated regression lines for an arbitrary cell. Estimated SOH based on partial cycles are shown in Fig. 6. In summary, the results are quite good and indicate that this approach can give satisfactory results for most of the cells cycled in the lab.

The same method was subsequently tested on field data from ships in operation. Various ways of filtering the data to get comparable capacity estimates at different times were investigated and compared to results from the annual capacity tests. Although a general decreasing trend is found, the individual estimates exhibit much variability. Further filtering based on current, temperature, and depth of discharge (DOD) is explored, and reference is made to [17] for details. Extended analyses with a TLS method to account for the attenuation bias in OLS [18] are presented in [19]. However, results are variable, presumably due to the varying conditions during operation on ships in service.

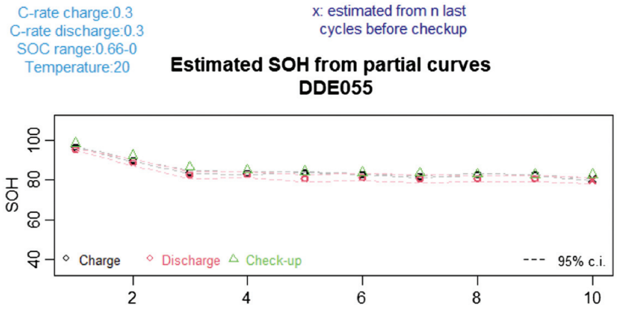

Fig. 6. SOH estimated from partial cycles with the simple linear model; check-ups indicated by the X-axis.

An ensemble of the simple linear models in Equation (5) is applied to different subsets of the data to account for the varying, nonstationary conditions during actual use. Different linear models are applied to segments of the charge and discharge curves between specified voltage ranges. This yields various estimates of SOH that may be averaged to obtain a single estimate with confidence bounds. Two types of averaging are applied, i.e., normal averaging and weighted averaging where the weights are based on the reciprocal of the standard deviation from the individual estimates.

An example of results from such ensemble models is presented in Fig. 7, where the capacity estimates are plotted over time, indicating a clear decreasing trend. In addition to the individual estimates from the different linear models, the mean and the weighted mean from all time periods are included. Also, the results from the annual capacity tests (three tests in this example) are indicated in the plot, showing general agreement with the results from the linear model. The numbers on the upper right corner in the figure denote the average voltage in the associated voltage ranges.

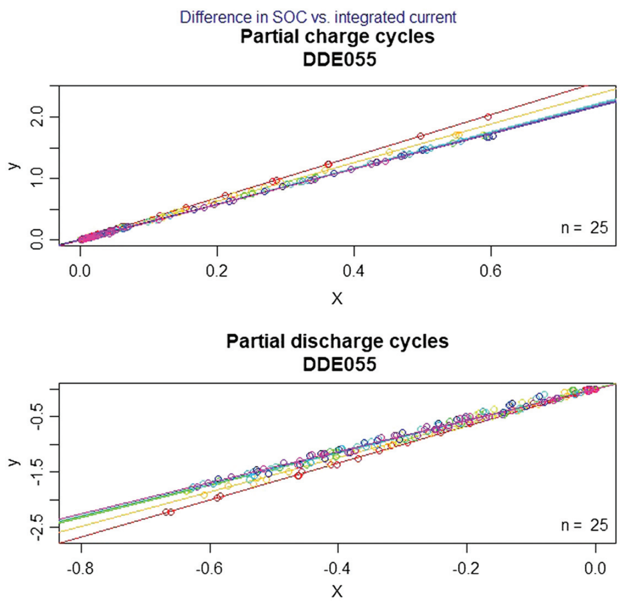

Fig. 5. Calculated $X = \Delta SOC$ and $Y =$ integrated current for partial cycles and associated regression lines.

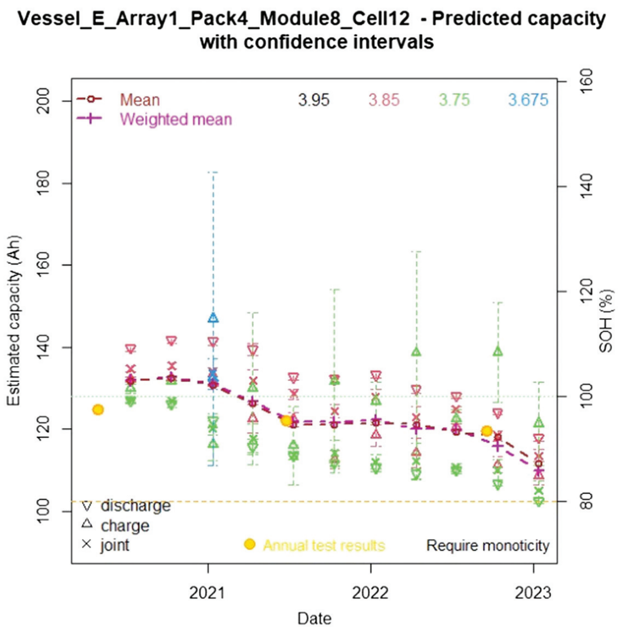

Fig. 7. Example of capacity predictions from the ensemble of simple linear models for an arbitrary cell over time.

In summary, the simple regression model based on Coulomb counting represents a promising and intuitive approach for condition monitoring lithium-ion batteries onboard ships. Its main advantages are that it does not need training data and that it is a snapshot method that does not need the full, uninterrupted time histories of the data.

One major challenge with this approach is that it relies heavily on SOC, which is not directly measured. Ideally, SOC should reflect actual temperature, current variations, and rest periods, but determining this from real data is difficult, and there are large uncertainties in calculated SOC values. Hence, it would be desirable to find a method that does not rely directly on SOC.

Another challenge is that battery capacity is not a fixed quantity, but rather a function of several parameters such as temperature, current, depth of discharge, voltage, and rest times; it will vary according to how it is operated. In reality, $Q = Q(\theta)$, where θ represents several variables influencing the capacity [20]. It is not obvious how to account for these effects in the linear regression model. Extra explanatory variables can be added, or additional carefully selected filters can be applied to the data prior to analysis.

2) OPEN-CIRCUIT VOLTAGE BASED METHOD. If the relationship between SOC and open-circuit voltage (OCV) is known, a Coulomb counting-based method utilizing the relationship between integrated current and voltage can be established. The OCV refers to the terminal voltage when there is no electric load, and the relationship between OCV and SOC can be described by an OCV-SOC curve, which may be established based on laboratory characterization. Once this is known, capacity may be estimated based on OCV rather than SOC.

To obtain the OCV when the battery is in use, there is a need to determine the overpotential and to subtract this from the measured terminal voltage. In this study, a simple ECM with a serial resistance and three RC elements with time constants 10, 100, and 1000 seconds is used. The resistance values R_s, R_1, R_2, and R_3 are estimated by least squares to minimize the difference between the average voltage and the voltage difference between the measured terminal voltage and the ECM voltage. With the fitted resistance values, the overpotential from the ECM can be subtracted from the measured voltage to obtain an estimate of the OCV. This OCV can then be fitted to the OCV-SOC curve and used to estimate total capacity.

The measured voltage and the voltage after subtracting the overpotential from the ECM are illustrated in Fig. 8. Figure 9 shows a matching of the quasi OCV to the OCV-SOC curve. Then, total capacity can be estimated by Coulomb counting [4].

This improved method was applied to operational data from several vessels to obtain daily estimates of SOH. Although results demonstrate a slight improvement compared to the SOC-based simple linear method and running averages over time are reasonable, the daily estimates vary significantly. Hence, results are still not accurate enough to relax the requirement for an annual capacity test.

3) UTILIZING EQUIVALENT CIRCUIT MODELS AND EXTENSIVE CHARACTERIZATION TESTS. Further improvement of the ECM-based Coulomb counting method has been validated to give reliable and accurate SOH estimation, under certain conditions. The ECM model in Fig. 10 is used, which includes a serial resistance, 2 RC elements, a thermal element (T), and an element representing hysteresis effects (h).

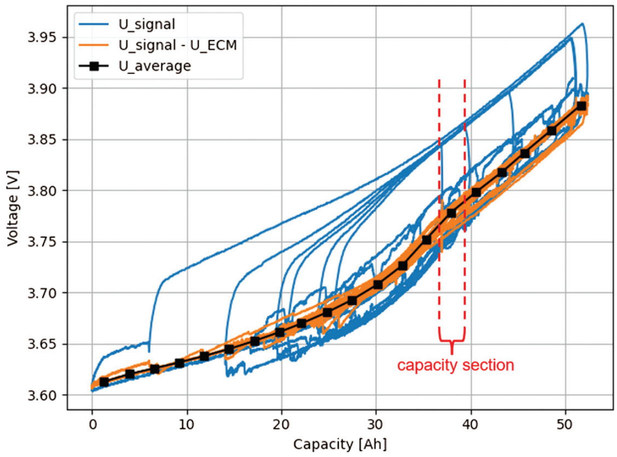

Fig. 8. Measured voltage (blue line) against the capacity. The orange line represents the monitored voltage after subtracting the overpotential calculated by the ECM. The black points correspond to the average voltage in each of the capacity sections.

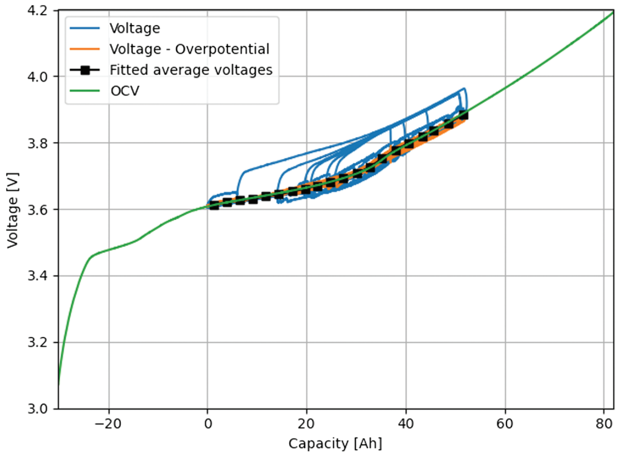

Fig. 9. The known OCV (green) is matched to the obtained quasi OCV points (black).

The cell ECM defines a set of five states,

$$\boldsymbol{x} = \begin{bmatrix} SOC \\ U_1 \\ U_2 \\ h \\ T \end{bmatrix}, \tag{5}$$

where SOC is the cell SOC, U_1 and U_2 are the voltage drops over RC_1 and RC_2, and h and T are the cell hysteresis level and temperature. Each circuit element depends on the cell states and conditions. For example, the OCV and internal resistance typically depend on SOC, SOH, T, and h, and this is modeled with extensive lookup established from comprehensive characterization tests. The cell voltage and the overpotential (OP) are given by Equations (6) and (7).

$$V = OCV(\boldsymbol{x}) + OP \tag{6}$$

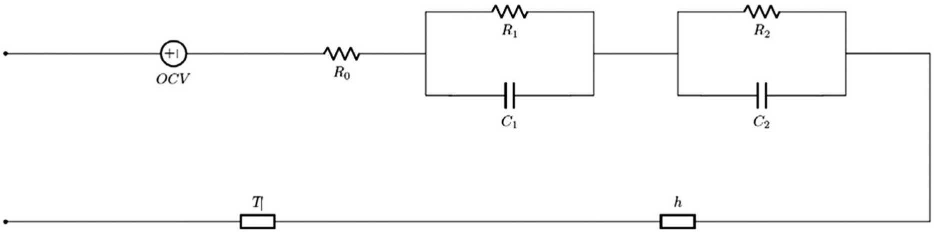

Fig. 10. The equivalent circuit model.

$$OP = IR_0(\boldsymbol{x}) + U_1 + U_2 \tag{7}$$

The states change according to a set of differential equations, Equation (8), where I is the cell current, η is the Coulombic efficiency of the cell, C_{nom} is the nominal capacity of the cell, α and β are parameters of the thermal model, T_a is the ambient temperature surrounding the cell, and f_h is a function defining the cell hysteresis model. R_1, R_2, τ_1, and τ_2 are the resistances and time constants of the RC elements, and R_0 is the electrical resistance of the cell.

$$\frac{\partial \boldsymbol{x}}{\partial \boldsymbol{t}} = \begin{bmatrix} \eta \frac{I}{SOH \times C_{nom}} \\ \frac{IR_1(\boldsymbol{x}) - U_1}{\tau_1(\boldsymbol{x})} \\ \frac{IR_2(\boldsymbol{x}) - U_2}{\tau_2(\boldsymbol{x})} \\ f_h(\boldsymbol{x}, I) \\ \alpha R_0(\boldsymbol{x}) I^2 - \beta(T - T_a) \end{bmatrix}, \tag{8}$$

Note that integrating Equation (8) between two SOC values gives Equation (3), where $Q = SOH \times C_{nom}$. Hence, the ECM method estimates the overpotential and the hysteresis effects that allow the lookup of SOC to consequently calculate the actual capacity and SOH.

This method has been verified against field data in different ways, including comparison to annual test results and comparison with laboratory checkups of field returns, and has been found satisfactory for estimating SOH for lithium-ion cells based on operational data provided that sufficiently deep cycles are experienced. Estimation from a DOD of 60% results in errors below 1%, while DOD of 40% gives errors up to 3%.[1] If an error in the order of 5% is deemed acceptable, then preliminary results indicate that for some cell chemistries, reliable estimates can be obtained DOD $\geq$ 25%. However, this may vary for different types of cells, and further validation is needed to establish more precise restrictions of DOD for the ECM-based method.

IV. DISCUSSION

The different data-driven approaches to SOH estimation that have been investigated in this paper each have some advantages and challenges. The snapshot methods, although being attractive from a practical point of view, have some limitations when it comes to reliability and accuracy. This is believed to be mostly related to the need for comprehensive datasets for model training. In principle, such training data can be obtained from extensive laboratory testing, but in practice, it will remain difficult to ensure that any realistic operational condition is well represented in the training data.

On the other hand, cumulative methods may provide more reliable results, but face the practical problem of ensuring that the complete operational history is available to the algorithm. Extended disruptions in the online data collection and possible data gaps would render such methods inaccurate. Moreover, cumulative methods in general might not scale very well, due to the enormous amount of data needed from large battery systems. In this study, cumulative models were tested for selected cells and were found to be very computationally demanding. Moreover, the cumulative models tested in this study all need to be trained, and access to sufficient representative training data remains a big challenge.

In principle, training data can be obtained by lab cycling tests. However, in practice, this is expensive and time consuming: cycling battery cells into EOL requires several months or years of cycling. Hence, semi-supervised learning was explored to exploit the large amount of available unlabeled operational data. However, such a method would still have some challenges, i.e., that one would typically only have training data for early life, and the fact that one will not have control over the operational conditions that are covered by the training data. Hence, it is difficult to recommend such approaches in general.

Another approach that was found very attractive is the simple linear model based on Coulomb counting. This is based on fundamental relationships between current and SOC, and thus need not be trained. Moreover, it can be used on snapshots of data. However, it was found difficult to obtain sufficiently reliable and accurate SOH estimates from this method without full charge and discharge cycles. This is because this method is heavily dependent on SOC, which is associated with uncertainty. Various filters and ensemble models were tried to account for the fact that capacity would be highly dependent on operating conditions, but the dependency on SOC remains challenging.

To avoid the strong dependence of SOC, an extended method that rather relates capacity to OCV was developed. This method utilizes a simple ECM to estimate OCV from voltage measurements during cycling. Then, an OCV-SOC curve is used to fit the estimated OCV and estimate capacity. All model parameters in such a model can be fitted based on snapshots of the data, and the only prerequisite is that the OCV-SOC curve is known. This can be found from characterization tests.

Initial results with such an ECM-based approach yielded quite variable results, although average predictions were reasonable. However, by supplementing such an approach by comprehensive look-up tables from characterization tests to account for temperature and current effects, and by carefully fine-tuning the ECM model, reasonable SOH estimates can be obtained. This approach provides reasonable estimates from operational data provided that deep enough cycles are experienced. Hence, this approach

[1]The errors refer to the difference between estimated SOH and SOH obtained from annual tests or lab tests.

can be used to improve the annual capacity test, which may be performed based on normal operational data without requiring a specific test protocol or disruption of operations. Some requirements regarding DOD might be needed, but this can presumably be achieved during normal operation. In summary, this is believed to be the most promising method explored in this research, and it can be proposed for data-driven verification of SOH for ship classification.

The methods explored in this paper have exploited both laboratory data and actual data from ships in service. Results have revealed that it is easier to obtain good results on lab data collected under controlled conditions and that some methods fail to perform reliably on field data even though results on lab data were satisfactory. However, since the methods should be applied to actual sensor data from ships during operation, it is emphasized that it is the performance on these data that are important when selecting a method for recommendation to classification societies.

One common challenge that remains for all models is that proper verification and validation is difficult without more validation data, i.e., longer time series and more annual test results. Most available field data are from relatively early life, and it is difficult to use this to fully validate how the methods will work toward EOL. Hence, it is recommended that further validation is performed when the battery systems are approaching EOL. This could be complemented with more exact characterization of field returns when modules are replaced.

It should be noted that battery degradation mechanisms depend on battery chemistry and cell type. Hence, it is difficult to validate a particular data-driven method in general. New cells and chemistries would require updated training data and possibly also completely different models. Hence, the observations made in this study cannot be assumed to generalize to any type of battery.

It is acknowledged that particular conditions and abuse of the batteries can significantly accelerate battery degradation. Hence, it is believed that in addition to monitoring SOH, it will be important to also monitor relevant usage parameters such as temperature, current, and voltage, to ensure that these stay within the specifications. Special attention should be put on cells that have experienced usage outside recommended levels of these usage parameters.

Some general observations have been made in this study, as summarized in the following:

- Snapshot methods are in general preferable to cumulative methods
- Training data are challenging, and models that do not require extensive training data are preferable
- Pure data-driven models might not be enough and should be combined with physics-based models such as ECMs
- Cell-to cell variation indicates that SOH should preferably be performed on cell level
- A certain DOD might be needed to obtain reasonable results. Hence, for ships that are only doing very shallow cycles, an annual test might still be required

V. SUMMARY AND CONCLUSIONS

This paper outlines several approaches to data-driven SOH estimation for maritime batteries and presents results from applying them to different battery datasets.

Some purely data-driven methods, including cumulative and snapshot models, semi-supervised learning, and simple models depending on SOC, are used. However, none of the purely data-driven methods achieved the necessary reliability and accuracy for them to be recommended as an alternative to annual capacity tests for verifying SOH calculated from the battery management system.

However, by combining physical models and data in a clever way, an approach for estimating battery capacity based on data from normal operations is proposed as an alternative to the annual capacity test. This method employs an ECM, and Coulomb counting together with look-up tables established from extensive characterization testing to enable probabilistic prediction of capacity based on sensor data collected during normal operation. In particular, it allows for the effect of varying temperature, current, and voltage to be taken into account and can therefore relax the requirements of the test protocol for the annual test, i.e., requirements on slow constant charge and discharge and rest times. The only requirement is that some relatively deep cycles need to be experienced during operation. This is believed to be a significant improvement compared to current capacity tests, which implies a disruption of normal operations.

The proposed method has been tested and verified to work reasonably well on several use cases. However, further validation is recommended to build even stronger confidence in the method, particularly for battery systems approaching their EOL. Moreover, further testing and validation is recommended on different types of batteries and chemistries. Notwithstanding, it is suggested that this method could be presented as an improved way of performing the required verification of SOH that offers notable benefits for operators of electric ships.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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