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Data-driven state of health modelling—A review of state of the art and reflections on applications for maritime battery systems

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ABSTRACT

Battery systems are becoming an increasingly attractive alternative for powering ocean going ships, and the number of fully electric or hybrid ships relying on battery power for propulsion and manoeuvring is growing. In order to ensure the safety of such electric ships, it is of paramount importance to monitor the available energy that can be stored in the batteries, and classification societies typically require that the state of health of the batteries can be verified by independent tests — annual capacity tests. However, this paper discusses data-driven state of health modelling for maritime battery systems based on operational sensor data collected from the batteries as an alternative approach. Thus, this paper presents a comprehensive review of different data-driven approaches to state of health modelling, and aims at giving an overview of current state of the art. More than 300 papers have been reviewed, most of which are referred to in this paper. Moreover, some reflections and discussions on what types of approaches can be suitable for modelling and independent verification of state of health for maritime battery systems are presented.

1. Introduction and background

There is currently a significant push for emission reduction and a change to more environmentally friendly technologies for maritime transport, with global energy-efficiency requirements from the International Maritime Organization (IMO) as well as global and regional caps on air pollution from ships. In addition, several zero-emission zones at sea have been declared. Hence, there is a significant societal and regulatory push for emission reduction and environmentally friendly shipping. Electric or hybrid ships using batteries are an attractive alternative for many shipping segments with significant environmental benefits and large potential for fuel, cost and emission savings [1–3].

The past few years have seen a significant growth in the number of battery-powered ships. The growth is currently dominated by car ferries and offshore vessels, but the interest is growing in several other shipping segments, such as cruise and cargo vessels, and the growth is expected to continue. Currently lithium-ion (li-ion) batteries are the predominant technology, but different battery chemistries within the li-ion family, e.g. NMC (lithium nickel manganese cobalt oxide) , NCA (lithium nickel cobalt aluminium oxide), and LFP (lithium iron phosphate), may have different characteristics with respect to capacity and ageing.

The safety of battery-powered ships is extremely important. Fire and explosion are obvious risks, but another central aspect is ensuring that the available energy stored in the batteries is sufficient to cover the required propulsion or manoeuvring power demand [1]. Loss of propulsion power in a critical situation can lead to serious accidents such as collision or grounding. Therefore, a reliable estimation and prediction of the actual available energy of a battery is crucial.

Battery systems are ageing, meaning that the energy storage capacity degrades (energy fade) and the power delivery capability deteriorates (power fade) by calendar time and by charge/discharge cycles. Most maritime battery systems are designed with an expected lifetime of 10 years, and end of life (EOL) is typically defined as State of Health (SOH) = 70%–80%, where SOH stands for the ratio of remaining capacity to initial capacity (in %).[1] For ships relying on energy from onboard battery systems, it is of paramount importance to ensure that the capacity of the battery system is sufficient for the safe operation of the vessel at all times. Any failure to deliver the required amount of energy in critical manoeuvring situations may lead to serious accidents. Thus, accurate evaluation and verification of the capacity and performance of maritime battery systems is crucial to safe and sustainable operation of battery powered ships. It is noted that other

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[1] SOH may also be defined in terms of resistance, maximum power, etc. but discharge capacity is the most common way of defining SOH.

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aspects of battery degradation may be equally important. For example, degradation does not only affect the capacity and power performance, but also fire safety and thermal runaway properties are influenced by degradation [4,5].

This paper aims at describing the state of the art in data-driven methods for SOH estimation and to reflect on applications to maritime battery systems. It is based on a thorough literature survey and will outline various approaches reported in the scientific and engineering literature for utilizing sensor data to estimate the effect of degradation on the available capacity of such battery systems. However, first some background and important concepts and terminology will be briefly outlined.

The main function of a lithium-ion battery is to store and then release energy by converting chemical energy into electric energy and it typically consists of many battery cells. A lithium-ion battery cell typically consists of a few main components. These are the positive and negative electrodes, often referred to as the *cathode* and the *anode*, respectively, the *electrolyte*, a *separator* and *current collectors*. The cell's active materials reside in the electrodes, where oxidation (loss of electrons) and reduction (gain of electrons) processes take place in order to liberate or bind lithium ions (LI^+) and electrons (e^-). The liberated lithium ions are allowed to diffuse between the electrodes through the electrolyte, and the electrons can be transported by the current collectors to generate a potential between the battery terminals and hence drive a current in an outer circuit. The separator should allow for transport of the lithium-ions between the electrodes, but block electron transport to prevent internal short circuits. A rechargeable battery cell operates in two modes: charging and discharging. When fully charged, the active lithium ions reside in the negative electrode (anode) and when the battery is fully discharged, the active lithium ions reside in the positive electrode (cathode).

During discharge, when a load is connected to the battery, current is allowed to flow from the positive to the negative electrode in the outer circuit, supported by an oxidation reaction in the negative electrode. This liberates electrons (negatively charged) and lithium ions (positively charged), which are de-intercalated from the negative electrode. The electrons are transported via the current collectors to the outer circuit and the ions can move in the electrolyte through the separator to the positive electrode. At the positive electrode, the lithium ions take part in a reduction process, where they are inserted into the positive electrode. During charge a current source forces the current to move from the negative to the positive electrode. The active material in the positive electrode is now oxidized and lithium ions are de-intercalated and can move to the negative electrode in the electrolyte through the separator, where a reduction process takes place and the lithium ions are intercalated back into the negative electrode. For a rechargeable battery, this process of lithiation/delithiation at the positive and negative electrodes can be repeated many times in a sequence of charge–discharge cycles.

The available energy stored in an electric ship's battery is of uttermost importance for the safe operation of the ship. With a rechargeable battery system, the amount of energy available at all times will vary continuously as the battery is repeatedly charged and discharged, and the state of charge (SOC) is a measure of the extent to which the battery is charged relative to its capacity. That is, a fully charged battery will have SOC = 100% and a fully discharged battery will have SOC = 0%. The depth of discharge (DOD) is simply an alternative way of indicating the SOC of the battery and 100% DOD corresponds to 0% SOC and vice versa.

The terminal voltage refers to the voltage between the battery terminals with load applied. This typically varies with SOC and current. The open-circuit voltage (OCV) refers to the voltage of the battery with no load and depends on the SOC. The internal resistance of a battery is the resistance within the battery and this is generally different for charging and discharging, and may also be dependent of SOC. Impedance is another measure of the opposition to current in a circuit that also takes the effect of capacitance and inductance into account.

The capacity of a battery to store energy will typically degrade over time, and the state of health (SOH) is a measure of the battery's capacity relative to its nominal capacity, that is, the initial capacity when the battery is new. Formally, the State of Health of a battery can be defined as

$$SOH = \frac{C_{Available}}{C_{Nominal}} \times 100\%, \tag{1}$$

where $C_{Available}$ denotes the available capacity of the battery and $C_{Nominal}$ refers to the nominal capacity, typically the capacity of the battery at its beginning of life (BOL). It should be noted that there can be differences between the nominal capacity and the capacity at the BOL, and this difference can be relevant when modelling degradation. Other definitions of SOH based on capacity reflect that $SOH = 0\%$ when the available capacity is less than a certain level, typically 70%–80% of nominal capacity. Alternatively, State of Health can be defined as the increase in internal resistance or impedance in the battery relative to the resistance in a new battery. For example, an alternative definition of SOH based on internal resistance can be [6]

$$\begin{aligned} SOH_{alternative} &= \left(\frac{R_E - R}{R_E - R_I} \right) \times 100\% \\ &= \left(2 - \frac{R}{R_I} \right) \times 100\%, \end{aligned} \tag{2}$$

where R is the internal resistance of the battery, R_I is the initial internal resistance of the battery at 100% SOH and R_E is the internal resistance of the battery at EOL, that is at 0% SOH. Assuming that SOH = 0% corresponds to an internal resistance of twice the initial internal resistance (i.e., $R_E = 2R_I$), one arrives at the second alternative expression. Some definitions of SOH combine both capacity and internal resistance in order to more fully describe the battery SOH compared to considering each individually [7].

The Coulombic efficiency (CE) is an important battery parameter that is highly related to the loss of lithium inventory [8]. It is defined as the ratio between delivered capacity during discharge and stored capacity during charge, and is closely related to the battery degradation. Lithium-ion batteries are known to have an initial high Coulombic efficiency, often exceeding 99%.

Condition monitoring systems typically include diagnostics and prognostics. Within such a framework, SOH estimation would correspond to the diagnostics part where reliable estimation of SOH reflects the energy storage capacity of the battery at any given time. This would be influenced by the operating history of the battery system. Prognostics in this context would amount to predicting the remaining useful life (RUL) of the battery or the time until the battery needs to be replaced or repaired. One often distinguishes between data-driven and model based diagnostics and prognostics. Whereas a model based approach relies on a physical model for the mechanisms at play and the relationship between relevant variables, a data-driven approach is based on relevant data to learn the correlations between relevant variables. A hybrid model can draw from both approaches where first principles can be used to establish a model for the degradation of the batteries, but where parameters and important relationships can be learnt from data. In this paper, the focus is on data-driven methods for SOH estimation and RUL prediction, and the overall goal is to identify reliable models that can estimate SOH and predict RUL based on sensor measurements from a maritime battery system in operation without requiring periodic capacity tests.

Modern batteries are equipped with a battery management system (BMS), which is important for the safe operation of the battery, and also for optimizing the use of the battery [9]. A BMS should monitor the state of a battery at all times and protect the battery from operating outside its safe operating area (SOA), e.g. in terms of limits to charge/discharge currents, voltage limits and temperature limits, to prevent accidents such as explosion or thermal runaway. It collects sensor measurements of basic parameters such as voltage, current and temperature and uses these to calculate and monitor various derived parameters and quantities such as SOC and SOH. It controls the battery's environment, e.g. the temperature by regulating the flow of coolants, balances the battery and reports important data about the battery. Typically, data used for data-driven modelling of battery SOH are gathered from the BMS and include both sensor measurements and derived parameters. However, it may be difficult to get access to data directly from the BMS and data collected at string, module or system level will often be the data that are available.

The remainder of this paper is organized as follows: First, some important factors influencing the degradation of batteries are discussed, prevailing classification rules for electric ships are briefly introduced, and some particularities of maritime batteries and the motivation for this paper is given to conclude this introduction section. Then, Section 2 provides a brief meta-review of relevant previous review papers. Section 3 presents a comprehensive review of literature on SOH modelling, and groups different approaches in a few categories, useful for further evaluation. The main focus is on data-driven methods, but other approaches that may not be regarded as purely data-driven, but rely on data to make estimates of SOH, will also be covered. Section 4 presents some reflections and discussions on important aspects to consider and evaluates the appropriateness of different approaches for maritime battery systems. Finally, A summary is given in Section 5 with some final remarks and conclusions regarding SOH estimation methods for maritime battery systems.

1.1. Factors that may influence battery degradation

Some factors that influence the degradation of a battery are well known, even though the degradation mechanisms may be different for different battery types and chemistries. There are different ageing mechanisms affecting different elements of a single battery, and various independent ageing effects take place in cathodes, anodes, electrolytes, separators and any other component of a battery [10].

The cycle component of battery degradation is highly influenced by how the battery has been operated, and temperature is an important factor [11–13]. Moreover, very deep cycles typically increases the rate of degradation. That is, larger variations in SOC may result in more rapid degradation compared to more shallow cycling, although this may not always be true. Furthermore, higher levels of current will normally accelerate degradation, so charging/discharging the battery at higher C-rates are believed to accelerate degradation [14,15]. However, a recent study indicates that cyclic ageing is not directly dependent on current rate, if the temperature of the battery can be controlled and if high/low levels of SOC and voltages are avoided [16].

It has been demonstrated that battery cells may recover some capacity during prolonged rest periods after being cycled [17–19]. Hence, if battery capacity is measured immediately after a cycle or after the battery has been allowed to rest for a period, the results will be different. This is a particular important issue for accelerated ageing testing, where test data are obtained to model degradation and battery lifetimes, and may be a source of biases for such tests compared to batteries in normal operations. Experiments reported in [19] indicate that the cycle life of a battery cell may be almost doubled if a 2 day rest period is allowed every 50th cycle. However, [17] shows that rest periods shorter than around 2 h does not give notable capacity recovery. The SOC during rest periods also influences the capacity recovery, and whereas [17] suggests rest periods at 0% SOC (fully discharged) are better than 10% and 20% SOC, [19] reports significant capacity recovery at rest periods with 100% SOC (fully charged).

An overview of important battery degradation mechanisms as well as their causes and effects are given in e.g. [10,20], and Fig. 1 provides an illustration of these (reproduced from [20]). As can be seen from this illustration, there are many different causes of battery degradation and the combined effect on various stress factors on the capacity and power fade is not straightforward.

The temperatures and loads may not be evenly distributed within a battery system consisting of several modules and battery cells, and the different cells may experience different degradation trends. How the SOH of the individual cells influences the SOH of the entire battery system may not be obvious and will depend on the battery design (see e.g. [21,22]). Moreover, differences in the manufacturing process may give different degradation rates even for batteries with similar design. For used batteries, possible repairs or replacements of individual cells or battery components may influence the capacity of the battery system in ways that are hard to predict.

For maritime batteries, the duty cycle will vary according to type of operation and also the environmental conditions under which it is operated will vary. It is not obvious to what extent exposure to the marine environment will influence battery degradation, e.g. humid and saline environments, ship motions such as pitch, heave and roll or orientation of the batteries due to list or trim.

One important aspect to keep in mind when modelling battery degradation is that the degradation may not be similar in the BOL and when approaching EOL. For example, a change in the dominant degradation mode could result in sudden capacity drops. Typically, one expects to observe a so-called knee-point in the degradation curves, where a sudden change from relatively moderate degradation to a more aggressive degradation occurs towards the EOL. Hence, it might not be appropriate to train degradation models on data collected at BOL and apply them to predict degradation towards EOL. Moreover, maritime batteries should typically be replaced before a knee-point occurs in the degradation curves, to avoid swiftly deteriorating battery capacities during operation.

1.2. Classification rules for electric ships

Ocean going ships are subject to classification rules [23], and DNV has an additional class notation, **BATTERY**, for battery powered vessels [24], both all-electric and hybrid vessels that use electrical energy storage (EES) on board, built to DNV class. The **Battery(Power)** class notation is required for all ships – all-electric or hybrid – that relies on battery power for propulsion and the **Battery(Safety)** notation applies to all vessels with lithium-ion battery systems with an aggregated rated capacity of more than 20 kWh and not having the **Battery(Power)** notation. Other class societies also have rules and guidance notes on battery systems, see e.g. [25–27].

The **Battery(Safety)** class notation includes basic requirements to ensure the safety of the battery systems with regards to arrangement, ventilation, off-gas detection, cooling, fire safety, system design and operation and maintenance. In addition, the **Battery(Power)** notation should ensure that the battery system is able to deliver the necessary power needed for safe operation of the vessel at all times, also in case of a worst case failure (e.g., loss of a main power source). Hence, the focus is on ensuring sufficient capacity, and requirements cover the need for redundancy, an energy management system and operation and maintenance requirements. In particular, it is stated that the SOC and SOH of the batteries should be monitored and available to the operator and that the energy management system shall provide a reliable measure of the available energy and power at all times, taking into account the battery systems SOC and SOH. It is required that the following parameters shall be calculated, when applicable, and monitored from the navigating bridge:

- Available energy (AE)
- Available power (AP)
- Remaining time for seagoing operation
- Remaining time for seagoing operation after worst case single failure
- Remaining time for powering emergency consumers

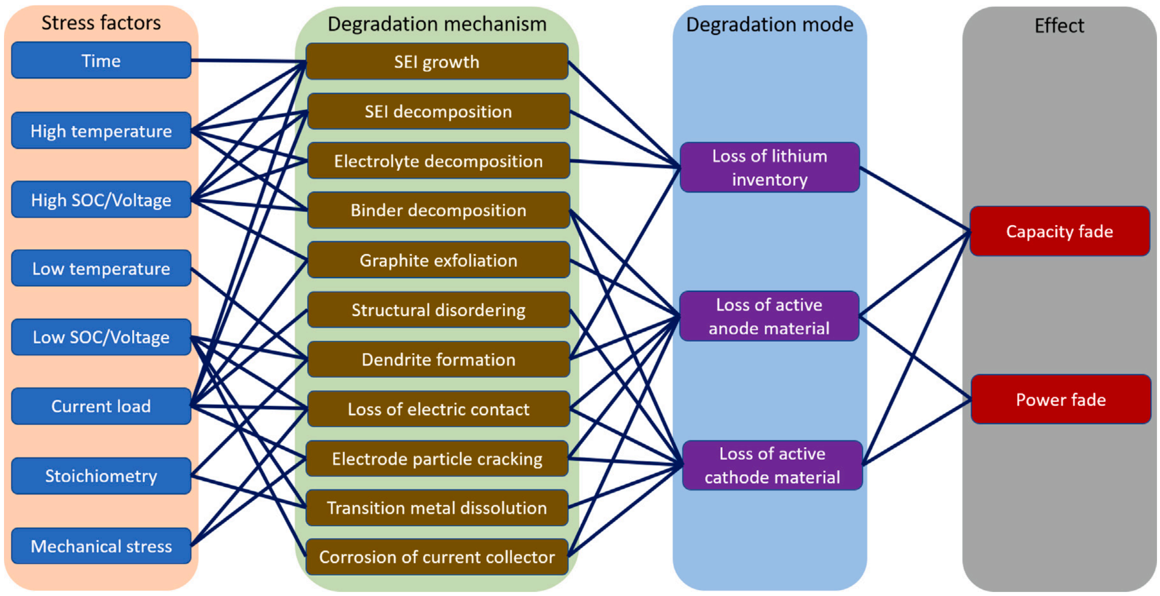

Fig. 1. Degradation mechanisms and degradation modes and their cause and effect [20].

Moreover, warnings and alarms shall be given when the EES system reaches minimum capacity as required for the intended operation or voyage, as based on the remaining time for seagoing operations after worst case single failure, or as required for powering emergency consumers.

Acknowledging the fact that the above is highly dependent on the SOH of the battery system and on accurately estimating this, a test is required to verify that the battery SOH is consistent with the SOH calculated for all the EES systems. Deviations larger than ± 5% yields an adjustment of the values in the EES system. Moreover, charging and discharging capabilities should be tested to verify maximum C-rate as specified for the intended operation of the vessel. Typically, actual capacity can be verified by Coulomb counting during a complete charge or discharge of the battery. This is normally done in an annual capacity test, which means that the vessel must be taken out of service in order to undergo controlled deep reference charge and discharge cycles with periods of rest in between. For ships with **Battery(Power)** notation, it should be verified during the annual survey that such a test has been performed within the last 12 months [28].

The main motivation for the work presented in this paper is to review state of the art and prepare to develop an alternative independent verification approach for SOH based on online measurements. This is supported by the rules that generally accepts alternatives to class requirements provided that an equivalent level of safety and reliability can be demonstrated. This review represents a first step in giving an overview of different modelling approaches and reflecting on which ones seem most suitable for maritime battery systems.

1.3. Maritime battery systems

There are particularities of maritime battery systems that makes them different from batteries in e.g. electrical vehicles, consumer electronics and grid applications. These are related to differences in battery size and designs, different operational environments and loading profiles, different safety aspects and regulatory regimes and different market mechanisms. Nevertheless, it is believed that the overall degradation mechanisms are similar and that lessons can be learned from other application areas.

This paper aims at presenting state-of-the-art in data-driven models for SOH of maritime battery systems. However, the literature specifically on maritime battery systems is scarce and not much have been reported on SOH estimation methods particularly for maritime batteries. Hence, this literature review covers SOH modelling from different battery application areas. The amount of literature on this topic is enormous and it seems an impossible task to cover all relevant papers and reports in the academic and engineering literature in detail, and even though it is believed that the selection is fair and unbiased, it cannot be guaranteed that important contributions to this field have not been unintentionally overlooked. Notwithstanding, the literature survey presented herein are believed to give a fair overview of approaches to data-driven modelling of the condition of batteries, with an emphasis on the more recent literature.

2. Meta-review of previous review papers

State of health of a battery is all about ageing and degradation mechanisms that reduce the performance and capacity of the battery over time. Some recent review papers on ageing mechanisms have been presented in e.g. [29–32]. A review of degradation mechanisms in the different components of the battery, such as the positive and negative electrodes and the separator are presented in [30]. Degradation mechanisms over the life cycle of the battery are discussed in [31], including the influence of design, production and operation. Different methods for estimating SOH are listed in [32], including methods based on internal resistance, Coulomb counting, Kalman filtering and extensions, fuzzy logic, support vector regression and a least squares (LS) approach to account for noisy measurements.

A range of methods for describing battery degradation are summarized in [29], categorized into five different approaches; electrochemical models, equivalent circuit based models (ECM), performance based models, analytical models and statistical models. The first one includes detailed models of the chemistry occurring in the battery and the second employs a simplified model where the battery is modelled by an equivalent circuit [33]. Performance based models use simple correlations between stress factors and capacity fade, which are induced from ageing tests under different conditions. Typically, calendar and cyclic ageing are modelled independently and added together. Another approach in this category is a damage-accumulation model such as the Palmgren–Miner rule model (fatigue model). The last types of approaches are referred to as analytical models with empirical data fitting and statistical methods, including techniques from time-series modelling and survival models, both requiring extensive data. According to [29], electrochemical and equivalent circuit models perform well, but may not be able to model all degradation mechanisms at play. Moreover, different models must be established for specific batteries. The same is true for performance models. Statistical models, on the other hand are more generic and can be used for different batteries, but requires a large amount of data collected over a long time to be effective. Overall, [29] concludes that only equivalent circuit models and statistical methods are appropriate candidates for online methods estimating SOH in real time and states that models that meet all performance criteria do not yet exist. A review of different empirical and semi-empirical lifetime degradation models are given in [34], relating capacity loss to various stress factors such as temperature, C-rate, charge throughput, DOD etc.

Methods for monitoring a range of different state variables of batteries, including capacity, SOH and remaining useful life, are reviewed in [35]. Methods for capacity estimation are classified into methods based on the relationship between ampere-hours charged or discharged from the battery and voltage difference before and after this charging and methods based on incremental capacity analysis (ICA) and differential voltage analysis (DVA) techniques. They also state that estimation of SOH can generally be reduced to the estimation of capacity and resistance of the battery. An overview of available techniques for on-board capacity estimation as well as a discussion of strength and weaknesses are given in [36]. They divide methods for capacity estimation into four categories: Voltage based estimation methods (mostly relying on ECMs), electrochemical model-based methods, ICA/DVA methods and ageing prediction methods. A challenge with the two first approaches is the need for underlying equivalent circuit or electrochemical models. A challenge with ICA/DVA is that results are sensitive to the conditions during charging and discharging; it typically requires the battery to be charged and discharged with a constant current and temperature over the entire voltage range. Finally, ageing prediction methods rely on data from lifetime tests, which are generally very time consuming to obtain. Notwithstanding the many approaches being reviewed, reliable capacity estimation over the battery lifetime remains a challenge and no one approach could be singled out as most suitable. A similar categorization of non-invasive diagnosis techniques is made in [37], and a total of 14 evaluation metrics are defined to compare methods. However, a common limitation with all methods is that testing requires specific conditions, corresponding to synthetic profiles, and may not perform well under more realistic operating conditions.

A review presented in [38] categorizes SOH estimation methods in a similar way, based on estimating capacity or estimating internal resistance as two overall approaches for SOH estimation. Model-based techniques such as electrochemical or equivalent circuit models are combined with so-called observes (e.g. Kalman filters with various extensions or a sliding mode observer) and inference-based approaches include fuzzy logic and neural networks with various input variables. Other approaches include measuring during specific charging and discharging operations, such as the constant current constant voltage (CCCV) approach and pulsed discharge approach. Various curve fitting approaches try to fit a curve to experimental data from repeated charging and discharging. Estimation techniques for the internal resistance include electrochemical impedance spectroscopy (EIS) and model-based observers. Notwithstanding all the available methods for estimating SOH, they are all found to have limitations. According to [38], model-based approaches are either too complex for real-time applications or too simplified for accurate estimation. Moreover, inference-based methods are not able to adapt to changing environmental conditions and require extensive training. Specific measurements such as CCCV and pulse discharge are too time consuming to perform and curve fitting techniques are too restrictive to particular battery and operation. The EIS technique is expensive and requires the battery to be at rest before being tested. In conclusion, [38] suggests that SOH should be based on more indices than just capacity and internal resistance and that a comprehensive relationship between these indices and SOH of the battery must be established, also taking account of partial charging and discharging of the battery.

A thorough review of over 200 papers on estimation of various aspects of batteries, including SOH estimation, is presented in [39]. They classify existing methodologies for both lead acid and lithium ion batteries into model based approaches and various methodologies such as genetic algorithm, fuzzy logic, neural networks, extended Kalman filters and dynamic Bayesian networks, as well as a dynamic impedance technique.

A review of SOH estimation methods, which classify methods in specific groups, i.e. experimental techniques and adaptive models, and discusses strength and weaknesses for online use as well as accuracy and precision is presented in [40]. The experimental techniques include direct measurements of voltage, current and temperature to determine the internal resistance or impedance, for example using current pulses and models based on measurements such as data fitting or data maps, probabilistic methods, Coulomb counting, regression methods such as support vector regression (SVR) using support vector machines (SVM), parity relation, failure detection, sample entropy and big data methods. Many of these methods depend on offline test data for model training. Destructive methods are also discussed, but these are obviously not relevant for SOH-verification of marine battery systems. The classification into experimental techniques and adaptive models are not entirely clear or obvious, but the authors note that experimental techniques are based on storing lifetime data and previous knowledge of the battery, whereas adaptive models calculate model parameters that are sensitive to degradation. The advantages of experimental techniques are low computational effort that allows implementation in a BMS, but they typically have low accuracy. On the other hand, adaptive models have high accuracy but high computational cost and are difficult to implement in a BMS. Moreover, experimental techniques are not suited for in-situ estimation, according to [40]. A review of degradation mechanism detection methods are also presented, e.g. using differential voltage and incremental capacity curves. It is found that such approaches can be very useful for SOH estimation and prediction, for example in combination with big data methodologies. It is concluded that, at the time of writing, there were no unique perfect solution for SOH estimation.

Another structured review of state of the art models and algorithms for SOH and RUL of batteries are presented in [41]. First, it reviews various battery models often used to model batteries and calculate various parameters, and classifies such models in four categories: (1) Electrical models (ECM), (2) electrochemical models, (3) mathematical models and (4) lifecycle models. The latter types of models are different than the others in that they require extensive offline tests for SOH prediction. Then, various SOH estimation methods are explained including Coulomb counting, open circuit voltage (OCV)-based methods, impedance spectroscopy method, Kalman filtering, machine learning/SVM, particle filtering and fuzzy logic methods. Finally, some evaluation metrics are proposed and the estimation methods are evaluated with respect to battery chemistry, computational complexity, data processing modes (online/offline methods), estimation result (SOH and/or RUL), processing time and estimation precision. They conclude that it is a large number of methods that are very heterogeneous. More complex methods are generally more accurate than simple ones, and challenges are related to estimating battery states under highly varying operating conditions.

A total of 134 papers on SOH estimation were reviewed in [42] and SOH prediction methods are classified in a similar way into model-based methods and data-driven methods. Data-driven methods include AI-based methods (e.g. ANN, SVM, RVM, etc.), filtering-based methods, statistical methods and time-series methods. In the conclusion, they suggest a hybrid method utilizing data-driven methods in combination with ICA, see e.g. [43]. The review of SOH monitoring methods in [44] classifies methods into experimental methods and model-based estimation methods. Different types of data-driven methods are reviewed, including empirical fitting methods, optimization algorithms, machine learning (ML) methods and sample entropy approaches. Finally, a multi-model fusion system is proposed as the way forward, combining various approaches, although the description of this proposed solution is not very specific. State of health estimation for lithium ion batteries in photovoltaic (PV) systems are reviewed in [45]. They state that most methods are based on voltage characterizations to extract health indicators (HIs) but also review SOH methods based on other signals, such as temperature, ultrasound and expansive forces. However, the latter may not be suited for non-stationary battery systems onboard ships.

250 scientific papers were chosen for review, from an initial set of 500 papers, of SOH and RUL estimation methods for lithium ion batteries in [46]. They distinguish between a direct assessment approach (including Coulomb counting, open circuit voltage and impedance spectroscopy), adaptive approaches (including Kalman filters and particle filters) and data-driven approaches (including fuzzy logic, neural networks and support vector machines). They continue to highlight some challenges and solutions related to accurate estimation of SOH and RUL. These include internal issues such as the influence of various battery materials, possible thermal runaway, capacity and power fade, possible over-charge and under-discharge, temperature range, hysteresis, ageing and charge–discharge rate and the need for a good battery model, and external issues related to charging method, safety and protection and others. Notwithstanding the large number of papers being reviewed, the final recommendations do not seem to be directly relevant for SOH estimation.

A more focused review on data-driven health estimation methods for lithium-ion batteries is presented in [47], which focuses on SOH defined in terms of capacity. They distinguish between methods based on differential analysis, i.e. where features are identified from differential curves of the electrical, chemical or mechanical parameters collected during battery cycling and correlated with capacity fade, and machine learning methods. Differential analysis includes ICA/DVA, differential thermal voltammetry and differential mechanical parameter analysis.

The review in [47] distinguishes between model fitted features that depend on an underlying state space model to obtain features such as internal resistance, capacitance and SOC, processed external features, for example extracted from incremental capacity/differential voltage curves and voltage gradient curves, and direct external features which are measured directly by sensors, e.g. terminal voltage, current and temperature. One challenge related to relying on model fitted features are the need for a complex model and processed external features typically require constant currents. Hence, [47] suggest that models based on the measured variables directly may be more suitable. However, crucial to all such approaches is that data are collected also for the response variable, that is, data for SOH need to be available in the training data in order to model the relationship with the features. The review presented in [47] continues with an overview of prognostic techniques for estimating RUL, all of which are dependent on the model for SOH estimation. These include analytical models (empirical and semi-empirical) and ML-based models. Finally, some advantages and disadvantages of the proposed approaches are discussed. They state that advantages of DA-methods are that they are easily implemented, are a mature technology and requires low computational effort. The disadvantages are that they require a controlled charging/discharging process, that temperature variations will affect accuracy and that noise filtering is required. On the other hand, ML methods have the advantages of good estimation accuracy, being applicable to dynamic operation conditions and that they do not require an underlying physics-based model. Their disadvantages are high computational cost and high sensitivity to the quality and amount of data available for training. Hence, it is suggested that ML-based approaches may be preferable for situations with complex operating conditions.

A review of self-adaptive battery ageing models presented in [48] points out the limitations of training data-driven models on laboratory test data that do not reproduce realistic operating profiles and focuses on self-adapting models that may be updated based on data collected during actual operation. The idea is that this will minimize the need for time-consuming and costly lab experiments and give more accurate predictions. They classify models into parametric and non-parametric models, and classify updating methods into re-training and filtering techniques. Re-training, also referred to as online training, corresponds to updating a regression-type model for the relationship between operating conditions and ageing data and is further divided into batch training – where new data are combined with the initial training data and the model is re-trained – and incremental training—which does not consider the whole available dataset to update the model. It further proposes assessment criteria in terms of model accuracy, including ability to deal with non-linearities, uncertainty management and robustness, and computational cost. However, these models assume that SOH estimates are collected from an SOH algorithm and are used to train the degradation models. For the purpose of verifying SOH estimates from such algorithms, however, independent verification cannot be achieved if the SOH estimates are used to train the models, so it is not obvious that such models are relevant for maritime battery systems. Furthermore, [48] states that self-adaptive degradation modelling is still immature and not yet ready for actual industrial applications.

3. Models for SOH estimation

In the following, a review of recent papers on the topic will be presented, focusing mostly on the past 5–6 years. An effort is made to group models in a few main categories, although some proposals may include elements from various categories. Typically, methods are grouped into experimental methods such as various forms of measurements, model-based methods relying on electrochemical or equivalent circuit models and pure data-driven methods. However, the distinction is not always crisp, and a combination of techniques will typically be employed. For example, direct measurements collect data that may need to be post-processed and analysed, hence combining measurements and data-driven methods, and model-based approaches typically use observers such as Kalman filters to estimate the state of the batteries, hence combining model-based and data-driven approaches. In for example [49] a combination of all three groups of methods are utilized; an equivalent circuit model is assumed, and electrochemical impedance spectroscopy is performed in order to estimate model parameters. Then, a recurrent neural network is trained on power cycling test data to model performance degradation due to ageing. It is noted that not all the methods reviewed in this paper is purely data-driven. However, all methods rely on data, routinely collected by sensors during all operations, or specifically collected by specific tests, in order to infer the SOH. Hence, also data-informed methods that may not be considered purely data-driven will be discussed. The categorization of the various approaches used in this review is illustrated in Fig. 2.

3.1. Direct measurement techniques

Different approaches for more or less direct measurements of SOH exist and are proposed for online SOH estimation. Some of these can be based on continuous measurements recorded by the BMS such as time series of currents, voltages and temperatures, whereas others are based on measurements collected during particular experiments or procedures. For example, the annual test currently required for maritime battery systems used for propulsion utilizes a Coulomb counting technique and a controlled charging/discharging procedure. This is one approach to SOH verification, but the need for specific charging and discharging cycles under controlled environments, with constant temperature and C-rate, means that normal operations need to be disrupted for a period of time. Nevertheless, some approaches to SOH estimation based on more or less direct measurements will be reviewed

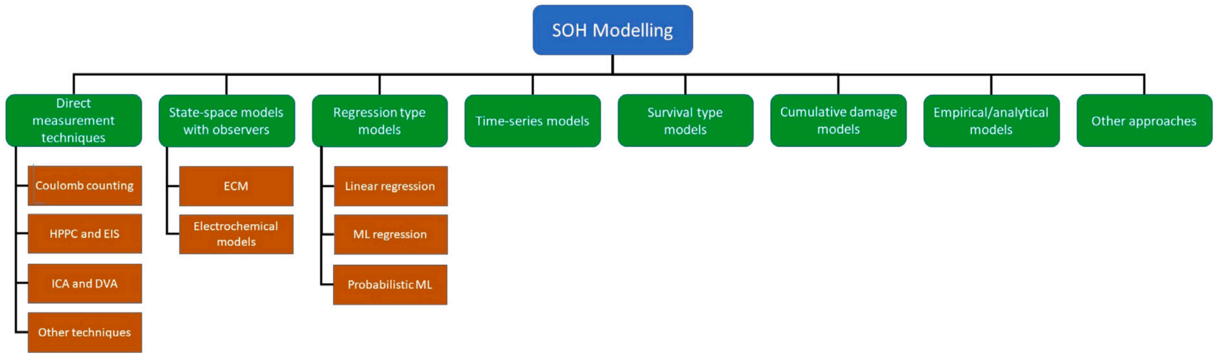

Fig. 2. Categorization of SOH modelling approaches.

in the following. According to [13] these include Coulomb counting, Hybrid pulse power characterization (HPPC) and electrochemical impedance spectroscopy (EIS), and ICA and DVA. Other measurement techniques also exist, see e.g. a more comprehensive overview in [50]. Ideally, methods that can be used based on continuous measurements of variables that are collected by the BMS under normal operations without the need for specific instrumentation or procedures would be preferable.

3.1.1. Coulomb counting

Coulomb counting, also referred to as current integration method, integrates the current to or from the battery during a full cycle to determine the capacity directly, according to the basic relation

$$Q = \int_{t_0}^{t_1} I(\tau)d\tau, \tag{3}$$

where Q is the capacity, $I(t)$ is the current at time t and t_0 and t_1 refers to the times of SOC = 0% and SOC = 100%, respectively. That is, the current is integrated over a full cycle from full to empty (or from empty to full) to count how much electric charge the battery can store. Often, the equation above can be modified by also including the Coulombic efficiency, which is tacitly assumed to be unity in Eq. (3). One practical problem with this approach is that it requires a full charge/discharge cycle to be able to estimate the maximum capacity and this is hardly ever experienced in actual normal operations. Moreover, the measurements need to be performed under controlled conditions, with constant, typically low, C-rate and a specific ambient temperature and is therefore not directly applicable as an online method. In addition, subjecting the battery to full cycles between 0% and 100% may contribute to accelerated degradation and such tests risk shortening the lifetime of the battery.

Capacity estimation can be based on Coulomb counting of deep cycles (not necessarily full), at reasonably homogeneous conditions with respect to C-rates and temperatures. The relationship between total capacity, Q, and SOC at times t_1 and t_2 is as follows, where also the Coulombic efficiency η, is included:

$$\Delta SOC = SOC(t_2) - SOC(t_1) = \frac{1}{Q}\int_{t_1}^{t_2} \eta I(\tau)d\tau \tag{4}$$

Note, however, that for this approach to be useful there is a need for accurate and reliable SOC estimates, a task which in itself is challenging.

An approach to estimate SOH based on Coulomb counting of partial cycles, i.e. over a reduced voltage interval during charging, is proposed in [51], see also [52]. This study indicated that the reduced voltage range measurements are likely to underestimate the capacity fade. Coulomb counting are also often proposed to be used together with other data-driven or model-based techniques. A Coulomb counting method for partial charging voltage profiles, where the optimal voltage ranges are identified, for single and multiple ranges, using a grid search technique and genetic algorithm, respectively, is proposed in [53].

It is possible to include a current correction term in the Coulomb counting procedure to account for the fact that capacity generally decreases as discharge current (C-rate) increases [54]. The Peukert equation describes the relationship between the discharge current (I) and the discharge time (t) by stating that $I^k t$ is a constant, where k is the Peukert coefficient [55,56]. However, this requires the battery to be discharged at a constant C-rate throughout the cycle [55], and also at constant temperature.

The Coulomb counting method is extended and used in combination with the OCV–SOC relationship for online SOH estimation in [57], using measurements of current, voltage and temperature. It addresses shortcomings with traditional Coulomb counting methods related to accumulation of errors in calculating transferred charge over time and the dependence of the method on initial SOC actual capacity estimation. A compensation factor is introduced in the current integration process to account for variations in conditions as the ratio between the capacity at the reference condition (current and temperature) and the actual operating condition. The compensation factor is assumed to be constant and is estimated at BOL of the battery. Furthermore, a temperature dependent OCV–SOC relationship is used during rest periods to obtain the SOC. The actual capacity is then estimated based on the partial capacity between two known SOC levels during normal operations of the battery. It is stated that the accuracy of this method is dependent on the depth of the cycle and on the measurement error of the partial charge estimation. A recursive least squares filter with a forgetting factor is applied to minimize the errors.

3.1.2. HPPC and EIS

Hybrid pulse power characterization and electrochemical impedance spectroscopy are methods to measure the electrochemical response of certain inputs. HHPC measures the cell voltage response to short high-current charge/discharge pulses and EIS measures the frequency response of the battery by measuring the impedance over a range of AC input at different frequencies. It yields an impedance spectrum from which it is possible to estimate various battery characteristics, such as charge transfer resistance, capacitance and ohmic resistance, as different frequencies are associated with different mechanisms in the battery, and to relate this to SOH [58,59]. However, the battery impedance is highly sensitive to temperature and EIS may be challenging to implement as an online tool since it requires stable conditions and specific hardware implementations. A passive impedance measurement technique is proposed in [60] to alleviate this, allowing the impedance spectrum to be estimated from arbitrary excitation signals by way of digital filters to be used as an online monitoring tool. See also [61] for an example of online EIS measurements. An extension of the EIS to study also higher order harmonics and nonlinear responses is proposed in [62], i.e. a nonlinear frequency response analysis (NFRA), and the method is used to study the effect of battery ageing. Some advantages of this method, as reported in [63] are that it does not require steady-state analysis and that it can be used for a specific frequency range and it is proposed that NFRA-data might be suitable for reliable SOH identification.

For EIS measurements to be used for SOH estimation, it may need to be used together with model-based or data-driven approaches, and the capacity or SOH cannot be read directly. However, equivalent circuit models for a battery can be established based on EIS measurements, as shown in e.g. [49,64], and repeated online measurements can be used to update battery model parameters to reflect the battery's internal conditions [65]. The charge transfer resistance of a battery is obtained in [66] by fitting the impedance spectroscopy with an equivalent impedance model to estimate SOH. The effects of temperature and SOC are accounted for by an analytical model. The parameters of the analytical model are based on fitting the model to data obtained by impedance measurements. EIS measurements are used as input to a Gaussian processes regression model in [67] to predict SOH and RUL, utilizing a large dataset of impedance spectra to train the model. Fractional order models have been used together with electrochemical impedance spectroscopy for battery characterization and SOH estimation, as presented in e.g. [68–70].

3.1.3. ICA and DVA

Incremental capacity analysis and differential voltage analysis measure the change in charge (Q) and voltages (V) during charging/discharging and estimates the gradient curves, dQ/dV and dV/dQ, respectively, to determine changes in electrochemical properties. Such curves will typically exhibit features like plateaus and peaks that can be associated with different mechanisms and phases in the battery and changes in these features can be ascribed to battery degradation. It is also possible to apply this method for partial charging curves, which is a huge advantage for online monitoring. However, two major challenges with this approach for online monitoring are that a constant and low current is typically needed in order to acquire accurate curves, and the differentiation of noisy, discrete data to obtain the IC (dQ/dV) and DV (dV/dQ) curves [71].

Different ways of estimating such curves are compared in [72], including a point counting method, polynomial curve fitting and neural networks. One may also assume parametric models for the voltage as a function of charge and fit the parameters from voltage measurements, as e.g. shown in [73], and [74] applies a Gaussian filter to smooth the curves and reduce the noise, before a regression model is used to relate the features of the IC curves to battery capacity. A revised Lorentzian voltage–capacity model was assumed in [75] to fit voltage–capacity curves and to extract features of interest to estimate SOH. The selected features are then used to establish a linear model between the features and SOH in order to estimate SOH. A previous study on fitting Lorentzian functions to voltage–capacity data is reported in [76]. A voltage window method was adopted in [77] due to its simplicity compared to moving average and Gaussian filters. A hybrid model combining grey relational analysis and the entropy weight method is then used to extract features from the filtered IC curves for SOH estimation. A method based on the Kalman filter is used to obtain smooth IC curves in [78], see also [79], and cubic smoothing splines are used in [80]. The level evaluation analysis (LEAN) method is proposed in [71] as a general approach to differentiating discrete-sampled data for the purpose of obtaining incremental capacity curves for battery diagnostics. It is proposed as a benchmark method that is not prone to over- or under-fitting.

SVR is used to model SOH from ICA in [81]. The area under the peaks of the IC-curve are used to estimate SOH in [82] under different operating conditions, i.e. with different DOD, temperature and C-rates. Three features from IC curves and DV curves are selected and used for capacity estimation in [43]. Three other features of IC curves are used to estimate capacity in [78], where linear models are established for each feature and the estimated capacity is the weighted average of the three estimates from each individual feature. Moreover, the coefficients of one of the linear models are modified by another linear model to account for the differences in initial charging SOC. A current interrupt technique is introduced to evaluate the cell resistance in order to account for the effect of different C-rates in ICA in [83]. Peak shift corrections are applied to the IC curves and allows ICA to be performed at higher C-rates, i.e. allowing for less time-consuming ICA.

An example of a charge–voltage curve and the corresponding IC (dQ/dV) curve is shown in Fig. 3, illustrating that flat parts of the charge–voltage curve appears as peaks in the dQ/dV curve. Even though direct measurements of currents and voltages can be used to obtain such IC curves, there is still a need for post-processing the data in order to get smooth curves, and data-driven methods must be used to extract features and relate those to SOH and degradation mechanisms. Moreover, different model-based approaches are often used to determine the open circuit voltage from the terminal voltage in order to construct OCV–SOC curves as the basis for ICA/DVA, see e.g. [84,85].

A somewhat similar method based on charge and discharge data estimates the probability density function of voltages during a discharge cycle by way of kernel density fitting of discrete voltage measurements [86]. This method is referred to as the pdf-method and is a simplified variant of ICA where the need to fit a curve to the charge/discharge data is eliminated. The probability density function will exhibit clear peaks around voltage plateaus, that is, voltages that occur more frequently during a charge or discharge cycle, and the idea is that the state of the battery can be inferred by these peaks which represent lithium intercalation/de-intercalation at the electrodes. As the battery degrades and the capacity fades, the magnitude of some of the peaks in the probability density function will decrease, and this can be used to estimate SOH, for example by integrating the probabilities over a range of voltages corresponding to relevant peaks.

A fusion of Coulomb counting and DVA is proposed in [87] as a model-free approach to obtain SOH estimation from constant current discharge data.

3.1.4. Other direct measurement techniques

Various other direct measurements techniques have been proposed in the literature. A differential thermal voltammetry approach is proposed in [88], where voltage and temperature measurements in galvanostatic operations are used to model SOH. This allows shorter measurement time than slow rate cyclic voltammetry analysis [89,90]. A differential heat analysis based on measuring gradient heat flux and temperature after discharge is proposed for SOH estimation in [91]. State of health estimation based on the Ampere-hour throughput–voltage curve and fitting a parametric curve to these is proposed in [92].

3.2. State-space models with observers

A different approach to battery modelling relies on models that approximate the battery dynamics. Typically, these may be referred to as state-space models where sensor data can be used to estimate model parameters corresponding to underlying unobservable states using so-called observers such as variants of the Kalman filter or particle filters. Two main classes of such models are equivalent circuit models and electrochemical models.

3.2.1. Equivalent circuit models

ECMs describe the voltage–current characteristics of a battery by a model of an electrical circuit with different elements such as resistors and capacitors in different series- and parallel configurations. One type of such models is the so-called nRC models where the batteries are modelled with a number n of resistor–capacitor circuits elements in series and/or parallel configurations. A simple example of such a model is shown in Fig. 4, with $n = 2$. Such models are often referred to as the Thevenin battery model [93]. Another type of simple ECMs is the Randle's circuit model [94]. More complicated models can be made by

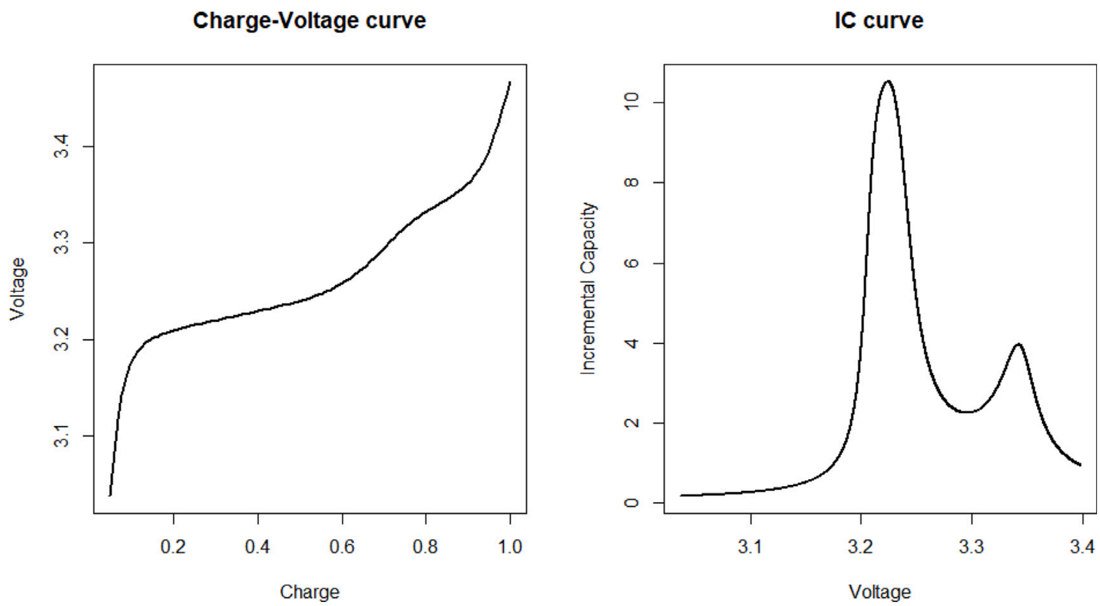

Fig. 3. A simple example of an incremental capacity curve. Plateaus in the charge–voltage curve correspond to peaks in the IC curve.

introducing additional RC circuits or other elements such as resistors, capacitors, inductors or constant phase elements. However, the chosen model will be a trade-off between accuracy, computational complexity and reliability, and often quite simple models are used.

Having established a ECM for the battery, the state of the battery is described by the battery model parameters. These are typically unobserved, but may be estimated based on measurements using various optimization techniques such as different variants of least squares methods. Various forms of constrained and regularized optimization may be employed to avoid unreasonable parameter estimates [93] and forgetting factors can be used to avoid saturation problems by giving less weight to previous data compared to more recent ones [95]. Model parameters are typically changing dynamically over time and observers such as Kalman filter and particle filters can be used to dynamically update model parameters and unobserved model states. Extensions of the Kalman filter to handle non-linear state transition and observation models include the extended Kalman filter and the unscented Kalman filter (see e.g. [96–98]). The effect of temperature may be included in such models by coupling the ECM with an energy balance or thermal model, see e.g. [13,99].

There are different ways equivalent circuit models can be extended from single cells to model battery modules and packs. One alternative is to connect one ECM per cell into a larger model, but the complexity of such a model will grow as the number of cells increase, involving a large number of parameters. This will be computationally heavier and requires much more training data. Alternatively, one may establish a single ECM for a set of connected cells that may be more manageable, but then it will not be able to capture variability between cells.

The SOH is estimated based on an ECM (the Thevenin model) with model parameters estimated by recursive least squares and assuming a linear relationship between ohmic internal resistance and capacity in [95,100]. The ohmic resistance is identified from the ECM based on internal resistance measurements (e.g. EIS) and the capacity is measured in capacity tests. Internal resistance of a battery is also estimated by an ECM in [101] which is used to determine a degradation index on the form of the ratio between actual and initial internal resistance. A similar model was assumed for electric ship applications in [2] where parameters were identified by recursive least squares and then a linear Kalman filter was used to estimate SOC and a least square approach to estimate capacity by fitting a linear relationship between capacity and a range of SOC. A 1RC model was assumed in [102], and model parameters determined by discrete time least squares are used to define a current time constant variable that are modelled to have a linear relationship to capacity which is used for online SOH estimation. 1RC models have been used in many other applications due to their simplicity and low computational cost [54,85,103].

A 2RC equivalent circuit model is assumed and battery states are estimated by a dual Kalman filter in [7]. The dual filter is a combination of a linear Kalman filter and an unscented Kalman filter and is introduced to estimate different parameters of the battery model. This reduces computational efforts since two filters of lower dimension are faster than one higher dimensional one. The first linear filter is used to estimate over-voltages and ohmic resistance and this is fed into the second filter that estimates SOC and polarization and diffusion resistances. The output from the second filter is then again used as input to the first filter for the next time-step.

A simple equivalent circuit model of lithium-ion batteries is used to represent the constant current charging profiles in [104] and to establish a mathematical expression for the voltage–time curve. The parameters of these curves can be estimated numerically and one of them is related to SOH. The same ECM was adopted in [105], and combined with an ICA based capacity model to yield a model for capacity based on the peaks of IC curves. Both the ECM and the ICA based models are generic and the approach can reportedly be applied to different types of lithium-ion batteries.

An equivalent circuit model with an additional hysteresis loop is used in [56] to account for different open circuit voltages in charge and discharge conditions. The dual adaptive extended Kalman filter is applied to determine model parameters and SOC. However, due to a flat plateau in the OCV–SOC curve at some levels of SOC, the Coulomb counting method with a current correction is used to estimate SOC in the 40%–70% range of SOC combined with the dual AEKF method for other SOC ranges. A least-squares SVM is used to predict the available capacity, based on a set of features including temperature, resistances estimated from the ECM, voltage change and voltage.

A linear parameter-varying electrical model is suggested for lithium-ion batteries in [106] where the system description is linear in different operating conditions, but where the behaviour can change according to a scheduling signal. In this way, the non-linear effects of varying temperatures and ageing can be taken into account, and an internal-resistance based SOH is determined. Parameter and state estimation is performed by a central difference Kalman filter, in order to estimate SOH and SOC from continuous on-board measurements.

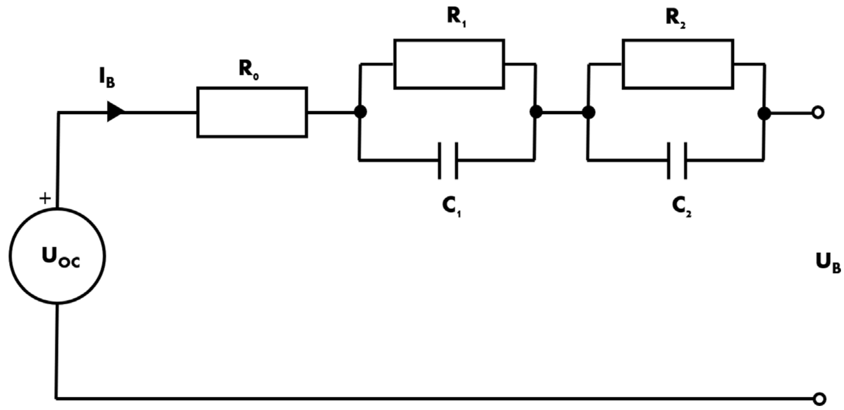

Fig. 4. A simple 2RC equivalent circuit model of a battery.

A number of more advanced observers and filter methods have been proposed to estimate model parameters and states in state-space models. An unscented particle filter is proposed in [107]. An improved particle filter, the linear optimization resampling particle filter is combined with the sliding-window grey model in [108]. Improved unscented particle filters based on Marco chain Monte Carlo (MCMC) methods [109] and combined with linear optimizing combination resampling [110] have also been proposed. Other filter based approaches include a heuristic Kalman algorithm in combination with particle filtering [111], the interacting multiple model particle filter [112], particle filters with partial stratified resampling [113] and a Gauss–Hermite particle filter [103]. A cascaded observer based on local Kalman filters and a fuzzy observer is used in [114] to determine SOC and SOH, where a state-space model based on a local model network is assumed as the battery model. A particle filter combined with support vector regression is used for SOH monitoring and RUL prediction in [115].

3.2.2. Electrochemical models

Electrochemical models typically consist of a simplified set of electrochemical equations that model the transport of charge between the positive and negative electrode in the battery cells based on the underlying physics. They describe the charge flows through the electrolyte and voltage drops at the cathode, anode and separator of the battery cells and typically include a set of differential equations, several model parameters, model states and some measurable model output. The model parameters are typically identified from battery dimensions and chemistry or are estimated based on data. Examples of such electrochemical models are given in [116–119]. Battery ageing and degradation can be modelled by changes in model parameters describing e.g. the internal resistance and charge capacity of the battery.

Again, having established an electrochemical model for the battery cell, various observers can be used to estimate and predict unobserved states based on measurements of observable model output. An unscented Kalman filter was applied in [116] to update internal states and capacity estimates for an electrochemical model, and thus track age-dependent changes in capacity.

3.3. Regression type models

Regression models range from simple linear regression models, which assume a linear relationship between a set of explanatory variables and a response variable, to complex machine-learning regression models for more complicated and non-linear relationships. One advantage of complicated models is that more accurate models may be constructed when accounting for non-linearities. However, a parsimonious model can also be preferred as it will be less likely to overfit training data and be more easily interpreted. In general, in order to use regression type models there is a need for representative training data so that the model can learn the relationship between the input variables and the response. For batteries, this means that battery test data are needed, where both the explanatory variables and the response is measured, typically based on laboratory tests. However, it is uncertain how representative the typical lab test data are for the degradation caused by more random duty cycles experienced in the field.

3.3.1. Linear regression models

A simple linear regression model is proposed in [15], where the discharge capacity is modelled as a linear function of discharge current and number of cycles, with an interaction term. The model parameters are estimated recursively by reformulating the linear model as a state-space model and using a Kalman filter. An additional model is introduced to model the capacity fade as a function of temperature, and a double-exponential model is proposed. The reason for the state-space formulation is the need for modelling a specific battery unit rather than a population of batteries as obtained from the experiments. Hence, the state-space formulation allows the models to be implemented as an online tool based on online measurements from a single battery.

Different regression models for SOH based on polynomial functions of cycle number as the only variable and polynomial and exponential functions of fully discharged voltage and internal resistance are compared in [120]. Yet another linear regression model for SOH assumes a linear relationship between SOH and the reciprocal of the unit time voltage drop, $1/V' = \Delta t/\Delta V$, for given SOC and includes a modification factor on the form of a third-order polynomial of SOC to account for different levels of SOC [121]. A kernel ridge regression model is suggested for SOH estimation in [122], which also employs semi-supervised transfer learning to transform unlabelled data into training data that can be used as model input. Six features extracted from charging, discharging and incremental capacity curves are used as model input. A naive Bayes classifier is used for regression and prediction of remaining useful life of lithium-ion batteries in [123], under different operating conditions and ambient temperatures.

The relationship between capacity, accumulated charge and ranges of SOC during cycling expressed in Eq. (4) is formulated as a regression problem in [124], where the total capacity is a regression coefficient between measured changes in SOC (predictor) and accumulated charge obtained by Coulomb counting (response). The regression problem is solved by an approximate weighted total least squares method, that accounts for both noise in predictor and response variables. Results on simulated data indicate that the method performs well, and it yields uncertainty estimates for the total capacity. This is deemed as a very attractive feature of this approach. It is noted that the approach outlined in [124] is also suggested for SOH estimation of a maritime battery system in [2]. A similar approach framing maximum capacity estimation as a total least square problem is taken in [125], where a Rayleigh quotient-based algorithm is employed to estimate capacity recursively.

A linear regression model for SOH estimation based on regional capacity is presented in [79], where the regional capacity is defined as the capacity change within a symmetric voltage region around the terminal voltage corresponding to the incremental capacity peak. This is presented as an alternative to more conventional incremental capacity analysis, where results are less sensitive to signal noise, since the regional capacity corresponds to an integral of the current measurement over time. It is demonstrated that with a sufficiently large voltage region, the relationship between the regional capacity and SOH is strongly linear so that a simple linear model performs well.

3.3.2. Machine learning regression

While the statistical approach has an emphasis on the validity of the models, which enables inference and prediction, the priority of the machine learning approach is the prediction itself: the ML models are predictive instruments which are valid insofar as they provide accurate predictions, without need of model diagnostics or specific assumptions. As a consequence, they often are complex "black box" models which provide unintelligible, though often highly accurate, results.

Various machine learning types of regression models have been used in capacity and SOH estimation of batteries. These are able to model complicated, non-linear relationships between the explanatory variables and the response, but are typically more difficult to interpret than simpler statistical regression models. Notwithstanding, as predictive power is generally more important for SOH estimation than interpretability, this is not seen as a major concern. Three data-driven methods for SOH estimation are compared in [126], i.e. a linear regression model based on ordinary least squares, a multilayer perceptron neural network and a support vector machine, all using features from incremental capacity and differential voltage curves of partial charging and discharging. The results indicate that all three models perform reasonably well and can estimate SOH within reasonable accuracy, for different features selected from IC and/or DV curves. However, it is emphasized that the linear model is more comprehensible but that the neural network provides slightly more robust results.

A support vector machine (SVM) is a supervised learning method initially used for classification problems, but that may also be used for regression. It is based on so-called support vectors and looks for hyperplanes in a higher-dimensional space that correspond to large separation distances between data points in the training data, see e.g. [127,128]. Several approaches involving support vector machines for SOH estimation of lithium-ion batteries are found in the literature.

A SVM is used to model the effect of ageing on the maximum available capacity and energy in [54], based on input features related to temperature, voltage and voltage changes and impedance factors obtained by assuming a Thévenin battery model. A similar battery model is used in [129], where a particle swarm optimization (PSO) algorithm is used together with support vector regression to estimate SOH. A SVM based model is proposed in [130] that estimates SOH based solely on variables typically available from operating batteries, such as battery current, voltage and temperature. A SVM is used in [81] to estimate capacity based on ICA for partial charging data. Incremental capacity curves found by polynomial curve fitting over relevant voltage ranges are found to be highly sensitive to the voltage range, and it is proposed to rather use support vector regression to fit the reverse charging curve, that is, the relationship between measured voltage and charged capacity. The capacity fade of the battery can then be found from the correlation with the IC peak value.

SVR is used together with partial incremental capacity curves in a different way in [131]. IC curves are obtained by various filtering and smoothing techniques, and three features of the IC curves are extracted and used as input for a support vector regression model to estimate SOH, i.e. the peak position, peak height and area under the peaks. [132] combines support vector regression with particle filters and possibilistic clustering classification for describing battery degradation and estimating remaining useful life. The geometrical area under the charging current curve during the constant voltage step of CCCV charging modes is used as feature in [133], and support vector regression is used to estimate battery capacity based on this. Another SVM, with a mixed kernel function, is presented in [134], which estimates SOH based on features extracted from a charging curve. The features are extracted from incomplete voltage charging curves, but an extreme learning machine (ELM) is trained to predict the whole voltage response from random and discontinuous charging data so that the method can work with only short-term charging data.

Other sets of features extracted from charging curves are used to estimate SOH using support vector regression in [135,136]. Two battery health indicators are proposed in [137], i.e. the time interval of an equal charging voltage difference and the time interval of an equal discharging voltage difference (see [138]), and support vector regression is used to model the SOH based on these features. Features of the terminal voltage response of a lithium-ion battery from a short-term current pulse test are used as input to train a SVM to estimate SOH in [139]. The idea is that the voltage response under the current pulse test, performed at the same battery SOC during the ageing process, will change as the battery degrades. This is used to train a SVM for SOH estimation. A support vector regression-based degradation model is proposed in [63] where features are extracted from nonlinear frequency response analysis [62] to train the model. The most relevant frequency range for battery degradation is determined based on correlation analysis, and features within this range are selected. The sample entropy of discharge voltage time series are used as features for support vector regression in [140]. The sample entropy is a measure of the regularity of a data sequence and the idea is that the discharging curve for fresh batteries are smoother than that of aged batteries so that the sample entropy will change as the battery degrades and can be used as an indicator for SOH [141]. SVR is combined with fuzzy information granulation of the data in [142], where the health indicator (time interval of equal charging current difference) and the SOH are converted to ranges rather than specific values.

The capacity of batteries is not measured directly by sensors and is therefore not available for each cycle in online battery data. If available at all, capacities will only be available for limited cycles. This raises the need for semi-supervised learning, as addressed in [143]. Here, a locally linear reconstruction method is used to determine the capacity distributions for unlabelled data based on four features extracted from the charging profiles. Then, a support vector regression method is applied to predict capacity fade and estimate the remaining useful life of the batteries.

The relevance vector machine (RVM), a technique that is similar to SVM but provides probabilistic output, is used for SOH estimation in [144]. A number of health indicators are extracted from charging voltage, charging current and temperatures and the most relevant features are determined by grey relational analysis. The dimension of the extracted features are then reduced by principal component analysis (PCA) and used to train a relevance vector machine to estimate capacity. RVM is proposed for RUL estimation of lithium-ion batteries in [145]. Relevance vector regression is also used in [146] to determine physico-chemical battery parameters from EIS that can be used to monitor ageing. Other approaches to SOH estimation utilizing relevance vector machines are reported in e.g. [140,147].

Artificial neural networks (ANN) are machine learning models known as universal approximators in that they may represent a wide range of continuous functions given a suitable number of nodes and hidden layers. They are often used in regression problems due to this flexibility and their ability to represent highly nonlinear functional relationships between explanatory variables and responses. However, neural networks typically require quite large datasets for model training, especially for deep nets with many layers. A brief introduction to neural networks is included in e.g. [127]. Various versions of neural networks are commonly used for estimating SOH based on sensor data. The trivariate joint distribution of current, voltage and temperature is used as input to train a neural network model in [148]. A K-means clustering technique is used to identify subregions and the data are represented by density values in each subregion, i.e. as a K-dimensional vector corresponding to the experienced conditions. The accumulated capacity from selected voltage ranges is used as features to train a neural network for SOH estimation in [149], and features extracted from partial incremental capacity curves are used as input to a neural network model in [150]. A feedforward neural network is used in [151] to predict SOH one step ahead, with the following input variables extracted from discharge data: temperature, starting SOC, DOD, discharge rate, charge throughput and present SOH. An artificial neural network based on incremental voltage differences is presented in [152].

A neural network based on radial basis functions is trained in [153] to model the relationship between time and terminal voltage during discharge, and to predict the end of discharge for the discharge cycle. The model parameters are estimated sequentially in a Bayesian framework using particle filters. This approach is further extended in [154] to estimate what they call state-of-life of the battery. They also include an anomaly detection module that should be able to flag an alarm when changes in the degradation process are observed, e.g. related to sudden accelerated degradation. The input data in this approach are the number of cycles, and the output is the capacity associated with that cycle. Hence, in order to apply such a model, there is a need for data containing capacity measurements at each cycle, which will typically not be available for maritime battery systems. Moreover, the model is applied to data gathered in controlled laboratory experiments, with constant temperature and current, and hence may not be well suited to model realistic duty cycles.

Extreme learning machines are single hidden layer feed forward neural networks with random initialization of the input weights and biases. Such an extreme learning machine is used in [155] to estimate capacity degradation based on ohmic internal resistance and polarized internal resistance health indicators, and thereby estimate SOH. It is noted that the health indicators are determined using an equivalent circuit model, and that the extreme learning machine reportedly outperforms a traditional backpropagation neural network. Extreme learning machines are also used for capacity estimation in [156,157] and in [158,159] for predicting battery life at short and long prediction horizons by one-step and multi-step ahead predictions of capacity.

Recurrent neural networks are a class of artificial neural networks which may also account for temporal sequences and dependencies in the data. The various nodes of the network are organized in connected successive layers to represent time, so that internal states or output from the previous time step can be used as input for the subsequent time steps. Several applications of different types of recurrent neural networks have been used for modelling of battery degradation. A dynamically driven recurrent neural network is used to simultaneously estimate a battery's SOC and SOH in [160]. Model input are battery voltage, current and ambient temperature without the need for a battery model. Battery degradation and remaining useful life are predicted using a combination of multiple linear regression and recurrent neural networks in [161]. The independently recurrent neural network (IndRNN) [162] is used for state-of-health estimation of publicly available battery data in [163]. The data consist of a sequence of randomized cycles followed by reference cycles at regular intervals where the capacity is calculated by Coulomb counting. The model then estimates SOH based on features extracted from the random cycles, including voltages, currents and temperatures, time elapsed in the random and reference cycles, time spent in various current loads and capacity calculated during the previous reference cycle. However, it appears that one of the input variables is actually the same as the response variable. Hence, these results are not realistic and further analysis where these variables are removed from the input-data are required to evaluate how such models perform.

A recurrent neural network (RNN) is trained to estimate and predict both capacity and internal resistance in [49], which may be used to estimate SOH. A series of accelerated ageing tests consisting of power cycling tests and periodic characterization protocols were performed to collect the training and test data. The RNN utilizes the current, temperature and range of SOC of a cycle as input as well as time histories of resistance and capacity, respectively, to predict resistance and capacity N steps ahead. Results show good agreement between predicted capacity/resistance and values observed in the tests. Gated recurrent unit neural networks are used to model SOH in [164].

The long short-term memory (LSTM) networks are special types of recurrent neural networks. Different types of LSTMs and other ML-techniques to estimate SOH and RUL are compared in [165] based on measurements of temperature, current, voltage, time and corresponding capacity during the discharge process of 28 batteries. They report that a variant of the LSTM – the AST LSTM – performs best overall on the different batteries that are tested. A hybrid model combining LSTM and Elman neural networks is used to predict capacity and estimate RUL in [166] based on capacity measurements. The capacity time series are decomposed into high- and low-frequency parts by empirical mode decomposition. The various high-frequency parts are modelled by the Elman NN whereas the low frequency component – the residual value – is represented by the LSTM. The empirical mode decomposition is repeated iteratively until the residual time series become a monotonic function. Another hybrid model, combining convolutional NN and LSTM is presented in [167]. This approach also employs a false nearest neighbour algorithm to determine the sliding window size for determining the training and test data sets. In these settings, the recurrent neural networks are used as time series models to model the evolution of the battery capacity rather than regression models that estimate capacity based on other measurements.

Deep learning and deep neural networks are based on artificial neural networks with many hidden layers between the input and output layers. They have performed remarkably well on a number of supervised learning applications but, due to the high number of nodes associated with the many layers, typically require massive amount of data to be trained well. Several applications of deep learning methods have been reported for capacity modelling of batteries.

A deep neural network is used to estimate SOH in [168] based on currents and voltages measured during charging and discharging. Estimation results are compared to other methods such as k-nearest neighbours, linear regression, support vector machines and shallow artificial NNs and reported to overall perform better. A hybrid gate-recurrent unit–deep convolutional NN model is presented in [169] to estimate SOH from charging curves obtained by CCCV charging of lithium-ion batteries. Estimation results from this model are compared with results obtained from support vector regression, Gaussian processes regression as well as separate gate recurrent and deep convolutional NNs (not hybridized), suggesting that the proposed hybrid model performs best on two publicly available battery data sets.

A deep convolutional neural network is used for cell-level capacity estimation based on discretized values of voltage, current and charge capacity measured during partial charge cycles in [170]. It is reported that the deep convolutional NN model performs better on the available data compared to traditional ANN and SVM methods. However, it is stressed that the effect of temperature variations are not accounted for as the data were obtained at constant temperatures. The effect of the amount of training data on the prediction error is also illustrated, showing that the accuracy improves for increasing amount of training data, but converges when the amount is sufficiently large. A deep long short-term memory network is used for online capacity estimation in [171], using voltage–time data from partial charging curves as input.

In order to address the problem of insufficient training data to achieve accurate capacity estimation, the deep convolutional NNs for capacity estimation are extended to incorporate concepts of transfer learning and ensemble learning as outlined in [172]. Transfer learning essentially allows for transferring learnings from a source task to improve the learning in a related but different target task. Ensemble learning combines predictions from several algorithms in order to reduce the risk of choosing one algorithm that performs poorly. In the study presented in [172], eight different deep convolutional NNs are pre-trained on one large battery dataset, and then transferred to be re-trained on a smaller dataset. These models are then integrated to build an ensemble model. Results were compared to different ML-methods, including random forest, Gaussian processes, as well as deep convolutional NNs trained from scratch on the target data (no source pre-training), as well as deep convolutional NNs with pre-training (only transfer learning) and an ensemble of deep convolutional NNs without any pre-training (only ensemble learning). Results indicate that the deep convolutional NN with both transfer and ensemble learning performs best overall.

Regression trees or random forests are somewhat different ML regression techniques that rather than trying to establish a functional relationship between the input variables and the responses, divide the input space into different regions and perform simple local regression within each region (see e.g. [127]). Such methods often perform well, but are known to be prone to overfitting. State of health estimation of lithium-ion batteries based on random forest are presented in [173]. Input variables are voltages and currents measured during CCCV charging. Another random forest regression model for capacity estimation is outlined in [174], based on partial charging voltage–capacity data. Other examples of applications of random forests are found in e.g. [175,176]. The XGBoost algorithm is used for SOH estimation in [177].

3.3.3. Probabilistic machine learning

Probabilistic neural networks are variants of artificial neural networks that can give probabilistic output, i.e. probability densities, rather than point estimates, which represents useful information. A probabilistic neural network for estimating SOH of batteries is presented in [178], which takes times spent in constant current charge phase, initial voltage drop at start of discharge phase and the open circuit voltage as input variables.

Gaussian processes (GP) regression is a non-parametric probabilistic machine learning technique that can be used for probabilistic predictions. Various approaches to battery SOH and capacity estimation using Gaussian processes have been reported in the literature. A Gaussian process model is used in [179] where different points on voltage–time curves with known capacities are used to train the model. This approach is said to overcome the problem with ICA and DVA that they need voltage measurements within a specific range, and voltaic measurements can be collected over very short periods – down to 10 s – of galvanostatic operation (maintaining constant current). The method relies on collecting training data offline, consisting of a set of galvanostatic charging voltage curves with known cell capacities, to be used for regression modelling based on online galvanostatic voltage measurements over a short time period during charging for cells with unknown capacity.

Another Gaussian process model is used to model capacity fade with selected features extracted from load patterns, such as time elapsed during the load pattern, charge throughput, overall time since start and possibly others related to time elapsed under certain conditions, as presented in [180]. Gaussian processes regression on different time-domain and frequency domain health indicators extracted from voltage time series to estimate SOH is proposed in [181].

Gaussian processes models aiming specifically at estimating calendar ageing during storage operations are proposed in [182,183]. Capacity is modelled with time, temperature and storage SOC in [182] and the Gaussian processes regression model is used to predict capacity one and multiple steps ahead. The model proposed in [183] is re-trained with data from operating conditions progressively observed, and illustrates how both accuracy and confidence of the model can improve after employment in such a setting. However, in order for the model to learn from operational conditions, there is a need for repeated capacity measurements, which cannot be expected to be available for maritime battery systems, especially if the annual test requirements can be relaxed. A similar Gaussian processes regression model for cycling ageing is proposed in [184], which uses throughput (Ah), temperature, DOD, average SOC, and charging and discharging C-rates as input variables to model capacity loss in each cycle. Again, it is stressed that the Gaussian process regression model is able to continuously learn from data collected during operation, something that puts less emphasis on laboratory test data and that allows training of new operating conditions. However, in order to continuously train the model, there is a need for the corresponding capacity value associated with the stress factors, meaning that periodic characterization tests are performed, or that capacity is measured by other means. This will probably not be the case for maritime battery systems.

A Gaussian processes (GP) regression model trained on a large dataset of electrochemical impedance spectra of lithium-ion batteries of varying SOH is used to predict SOH and RUL in [67]. The complete spectra are used as input, without any further feature extraction, and it is reported that the model automatically detects the spectral features important for predicting degradation. In fact, results indicate that only a few features are highly relevant for capacity prediction, and two salient frequencies in the low-frequency region carry almost all the weight in the model. It is noted that only EIS measurements from the current cycle is necessary to estimate the capacity, without any measurements from previous cycles. Moreover, upon comparison with other features extracted from discharge curves, the EIS-based features are found to give more accurate results. However, the cells used in this study have been cycled at constant charge- and discharge rates and further research is needed in order to extend the model to account for constantly changing temperatures and C-rates over time. A significantly extended dataset will then presumably be required. Gaussian processes regression is also proposed in [185], where four specific features are extracted from charging curves and used to estimate SOH. The relevance of these features for determining SOH is analysed using the grey relational analysis method. The Gaussian process model was trained and tested on battery data with variable loads provided by NASA [116,186] and found to perform reasonably well, with a maximum estimation error about 6%.

Multi-scale Gaussian process regression modelling of battery SOH is proposed in [187,188] in order to both estimate one-step ahead SOH for reliable SOC estimation and for multi-step-ahead prediction of SOH for trend analysis and prognostics. A discrete wavelet transform is performed in [187] to decompose the raw SOH time series into several signals with different scales. Gaussian processes regression models are used to separately estimate SOH based on each signal, and a final prediction is obtained by aggregating the predictions from individual models. In [188], significant features are extracted from studying the partial incremental capacity curves and used to estimate SOH. Features from ICA are also used as input to Gaussian processes regression models in [189] to estimate SOH.

Gaussian processes have also been used to forecast SOH to predict end of useful life in a prognostics setting, e.g. based on number of cycles in [190], using a mixture of Gaussian process models [191] and combined with particle filters as in [192], using combination Gaussian process functional regression [193] and with a deep Gaussian process algorithm as in [194]. The deep Gaussian process model in [194] consists of two layers, where features extracted from discharge profile data (a sequence of time, voltage and temperature extracted from a randomly selected start and end time of a discharge profile) are input to the first layer, the output from the first layer serves as input to the second layer, and the output from the second layer is the estimated capacity.

3.4. Time-series models

Time-series models represent a different approach to modelling capacity fade. Rather than estimating capacity and SOH by regressing on some explanatory variables, time-series models estimate capacity based on previously observed capacities and model the serial dependence in observed capacities. Hence, based on a history of capacity measurements, current and future capacity values can be estimated. Typically, time-series models can be used for forecasting and predicting remaining useful life of batteries.

An autoregressive integrated moving average (ARIMA) model is used to model SOH utilizing empirical model decomposition to decouple global trends from more local behaviour such as capacity regeneration from the raw SOH series in [195]. ARIMA models are commonly used for time-series analysis and is a combination of autoregressive (AR), differencing (I) and moving average (MA) series, and predictions are linear combinations of the series own history. A nonlinear degradation autoregressive (AR) model is proposed for battery RUL prediction in [196], where an accelerated degradation factor is used to supplement a linear AR model. An autoregressive model is used for prognostics of lithium-ion batteries in [197], where particle swarm optimization is utilized to determine the optimal order of the AR model based on the prediction root mean square error. Moreover, the model order is updated adaptively through metabolism as new observations are made.

A multiple-change-point linear model is proposed in [198], where an autoregressive model with covariates is used to model the slopes of the linear segments and a survival regression model is used for the lengths of the piecewise linear segments. Such a combined model is then used to model a full battery degradation path based on historical paths. This model is also used for prognostics and estimation of RUL and can provide uncertainty estimates by applying parametric bootstrap.

The impact of capacity regeneration after longer periods of rest are also included in the modelling presented in [199], where a model based on the Wiener process is outlined. The life cycle of a lithium-ion battery is divided into three parts, i.e., the overall degradation process, the capacity regeneration during the rest period and the degradation of the regenerated capacity after the end of the rest period. These three parts are modelled as three piecewise processes by a linear Wiener process, as a power law function of rest time with Gaussian noise and as a nonlinear Wiener process, respectively. This combined model is then used for one-step and multi-step ahead estimation of SOH. A two-stage nonlinear Wiener process is proposed in [200] to model capacity degradation under variable discharge currents. The two stages reflect a slow degradation and fast degradation regime, respectively, where fast degradation occurs at a later stage of the cycle life after an inflection point.

3.5. Survival type models

Survival and event history modelling is a separate branch of statistics that is used to model time-to-event data. If for example a battery's EOL is regarded as the event to be modelled, one could construct probabilistic models for the time until this event, determined by a set of covariates. However, one prerequisite for establishing such models is the availability of sufficient run-to-failure data, where the time until EOL is observed for a number of batteries or battery cells. Such data could typically be collected from similar batteries in operations to reflect realistic load profiles. For an introduction to such models, reference is made to textbooks such as [201].

Survival analysis modelling is applied to lithium-ion batteries for end-of-performance modelling in [202]. A trend-renewal process is used on accelerated testing data to predict end of performance. Results are compared to results from a linear regression model with time-series errors and other well known models including an exponential model, a second-order polynomial model, an exponential and polynomial model and a simple linear regression model, and the accelerated trend renewal process model is found to compare well in obtaining robust estimates of end of performance. However, this model relies on observed capacity ratios, which will typically not be available for maritime battery systems, for projecting capacity fade and estimate end of performance.

3.6. Cumulative damage models

Cumulative damage models are often used for modelling of structural fatigue, where the structural deterioration is modelled as a cumulative sum of different load cycles. Fatigue life of a structure is typically given in terms of number of stress cycles of a specific amplitude. For structural components exposed to a complex, random sequence of loads, the fatigue damage can be estimated by reducing the complex loading to a series of simple cyclic loadings using techniques such as rainflow counting [203] and then form a fatigue damage spectrum as a histogram of cyclic stresses. The effect of individual cycle contributions can be combined using the Miner's rule under a linear damage hypothesis,

$$\sum_{i=1}^{k} \frac{n_i}{N_i} = C, \tag{5}$$

where k denotes the number of different stress magnitudes in the spectrum, n_i is the number of experienced stress cycles of magnitude i, N_i is the number of stress cycles of magnitude i that would lead to failure and C is the cumulative fatigue damage. Hence, in order to apply such an approach, there is a need for counting the number of equivalent stress cycles from a complex loading profile, n_i, and to determine the number of cycles until failure for each stress amplitude, N_i. The former is often found by rainflow counting, and the latter is typically obtained from an S–N curve, where the cyclic stress amplitude (S) is plotted against number of cycles to failure (N). Such curves are typically established based on tests of samples of the material counting the number of cycles until failure and will typically be declining curves with lower stress amplitudes for increasing number of cycles until failure. Often, simple parametric functions can be fitted to the test data to allow interpolation on the S–N curve.

More elaborate methods can be used to extend this simple rule in order to account for the effect of different loading sequences as well as the effect of temperature, loading frequency and mean stress. However, the underlying idea of cumulative damage models is appealing, i.e. that one may assume an additive contribution to fatigue damage from individual cycles of loading. For battery cells, if one is able to construct curves or surfaces similar to S–N curves that determine the contribution to battery degradation from individual charge/discharge cycles of specified DOD/SOC range, temperature and C-rate, this could be used to calculate SOH based on experienced load profiles and some form of cycle counting such as rainflow counting. However, an extensive set of laboratory tests would presumably be needed, where run-to-failure tests would need to be performed for a number of different cycle amplitudes and conditions.

The rainflow counting technique is used on SOC time-series in [204] to generate rainflow load collectives from operational profiles. Additional load collectives for temperature/current and SOC/temperature are generated from the data. These are used as features to train a support vector regression model for the relationship between the load the battery has experienced and the corresponding capacity fade. SOH estimation based on such load collectives is compared to a similar SVR model based on more conventional features (e.g. throughput, SOC, temperature, …) and found to perform better, with lower mean squared training error and a significantly lower mean squared testing error. In addition, prognostics can be performed by assuming previous load history as representative for future battery loads. An extension of the load collectives approach using nested collectives is proposed in [205], where also a relevance vector machine is applied in order to obtain uncertainty estimates. A similar approach presented in [148] uses the joint distribution of current, voltage and temperature and divides this into a number of subregions using a clustering technique for generating features to train a neural network model to estimate SOH.

Another cumulative damage model is proposed in [206], where an empirical model is established that combines models for calendar and cycle ageing described by number of cycles, SOC, DOD, cell temperature and elapsed time. The rainflow counting technique is used to extract cycles from irregular operational data profiles with corresponding cycle amplitudes, mean values and start/end times and the cycles are converted into the various stress factors that are used in the model. Specific experiments are needed to estimate the model parameters.

A rainflow cycle counting algorithm is applied to batteries in [207] and a cycles to failure profile versus DOD is established based on experimental data. This curve is extended to also account for *crate* and a cycles-to-failure surface over DOD and crate is established. A battery ageing factor for a cycle k, $\eta(k)$, is defined as the reciprocal of the cycles-to-failure associated with a specific cycle, and a total battery ageing index is defined as the sum of this factor over all experienced cycles. In analogue with the Miner's rule for fatigue, when the value of this index approaches 1, the battery approaches its EOL. Based on the battery ageing index model and a rainflow cycle counting algorithm, the battery degradation state information is determined for collected battery operational data. This labelled battery operation data are then analysed by a Deep Stacked Denoising Auto Encoder (DSDAE) algorithm to deeply excavate the degradation features and improve the accuracy of the battery model considering terminal voltage, current, SOC and temperature. Finally, the total battery ageing index is used in an ageing considered battery model to model the battery terminal voltage and SOC.

3.7. Empirical/analytical models

Some methods for SOH estimation are based on fitting empirical models to various measurement data. The aim of such models is to capture relationships between battery SOH and various stress factors, such as operation time, temperature and operational loads. These models are typically based on test data and the empirical relationships can be used during operation to model SOH and capacity loss of the battery.

One such approach, reported in [208], is based on measuring the current over time during the constant voltage phase of a CCCV charging process and to model the current as a function of time during this phase as a parametric exponential function on the form $I(t) = Ae^{-Bt} + C$, where A, B and C are model parameters that change as the battery degrades. It is observed that the B parameter has a linear relationship with capacity loss and it is proposed to use this for SOH estimation. One attractive feature of this approach is that it is only based on the charging phase, in particular on the CV part of the charging, and one can assume that charging during normal operations is more controlled than discharging with respect to constant or known temperatures. Hence, in cases where a CV charging phase, just before the battery is fully charged, occurs often, this is a promising method. The method was demonstrated to work well for NMC, NCA and LMO cells, and an even more simplified method was found sufficient for LFP cells, involving only the duration of the CV step of the CCCV charging phase.

Also focusing on the constant-voltage charging phase, [102] proposes to model the capacity as a function of a current time constant, τ_I, that is determined from a set of battery model parameters estimated by assuming a first order equivalent circuit model (1RC model). The normalized capacity is then found to exhibit a linear relationship with the τ_I, where slope and intercept can be determined by curve fitting. One advantage of this method is that it does not require a full constant-voltage charging phase to be completed, and it can estimate the current time constant also from partial CV charging data.

Simple empirical models for capacity fade based on number of cycles/time have been proposed in different forms: i.e. linear ageing [209], square-root ageing [210], power-law ageing [211,212], exponential ageing [109,213] and polynomial ageing [214], or a combination of these [215]. The sum of two exponential functions is proposed in [216] to model capacity degradation and a sigmoid function is suggested in [217]. Various factors such as temperature and SOC can be accounted for by letting model parameters vary. A simple linear model for SOH estimation based on the fitting of a curve to data of voltage at the beginning of discharge and cycle number is presented in [218]. A model for SOH estimation based on measuring internal resistance and establishing an exponential function for the relationship between SOH and number of complete cycles, taking the effect of temperature, DOD and discharge rate is proposed in [219]. A semi-empirical model for SOH taking number of cycles and discharging current as input is proposed in [220], where different coefficients depending on operating conditions such as temperature and C-rate are included. An empirical model for combined calendar and cycle ageing is proposed in [206] based on rainflow cycle counting.

A migration scheme is proposed in [213,221] to establish an accelerated ageing model based on accelerated testing data and then migrate it as a new model to describe normal-speed ageing behaviour. The base method assumes an exponential function of number of cycles, and the migration factors are estimated by Bayesian Monte Carlo methods. This approach is extended with a migration neural network in [222] to enhance the model's nonlinear transfer capability. An empirical model for capacity fade based on moved charge, q (in Ah), is proposed in [16], where capacity fade is modelled as the sum of a square root, a linear and a quadratic function of q.

A number of parametric models for OCV as a function of SOC are reviewed in [85], which could be used to estimate IC/DV curves and inform about battery degradation. However, a model based on a Gaussian function mixture is proposed and found to perform better than the other alternatives. Such a model is characterized by parameters corresponding to the amplitude, location and steepness of peaks on the IC curve, and changes in these parameters over time correspond to changes in the peaks of the IC curve. Hence, the variation of some of these parameters are used to build the relationship with SOH and hence to estimate SOH, assuming a linear relationship. A 1RC equivalent circuit model is assumed to determine the open circuit voltage and the OCV curves used for fitting the parametric OCV model.

State of health monitoring based on measuring the battery open-circuit voltage after a brief relaxation time (30 min) after full charge and then assuming a linear relationship between this measure and SOH is presented in [223]. The linear model has two parameters that can be estimated and calibrated from accelerated ageing tests. Typically, the parameters will vary by battery technology and chemistry and also by load profile and temperature. Different relationships between characteristics of the Ah–V curve and capacity or usable energy are established in [92] and used for estimating SOH.

An analytical model for actual capacity taking both calendar and cyclic ageing into account is proposed in [7] as a function of time, t and throughput, $Ah_{throughput}$ (in Ampere-hours), as follows: $C_{actual} = C_{BOL}\left(100 - \alpha t^{\beta} - \eta Ah_{throughput}\right)$. The model parameters, α, β and η are determined using a support vector machine and experimental data. A model for capacity fade as a function of Ampere-hour throughput, DOD and number of cycles is used in [224].

A semi-empirical model for battery capacity, which models calendar and cyclic ageing separately, is presented in [225]. The calendar ageing is modelled as the square root of time, with a stress factor that is dependent on temperature and SOC. The pure cycle ageing is modelled by first subtracting the calendar ageing and then using a superposition of three models for high temperature, low temperature and low temperature/high SOC, respectively. The high and low temperature models are functions of the square root of charge throughputs, with stress factors dependent on temperature and (for the low temperature part) charge current. Finally, the low temperature/high SOC part is modelled as a linear function of charge throughput, with a stress factor depending on temperature and charge current, if SOC is above a fixed SOC limit.

See also combined empirical modelling of calendar and cyclic ageing as a superposition of separate models in [226,227]. Empirical capacity fade models for both calendar and cyclic ageing are proposed in [228], where SOC and temperature are stress factors in the calendar ageing model with a power law function of time, and temperature and current are stress factors in the cycle ageing model with a power law function of throughput. They also suggest to switch between the calendar and ageing models during operation to account for what kind of ageing is taking place and uses a threshold on the current to determine which ageing model to apply.

A semi-empirical model for calendar ageing based on the Eyring law is presented in [229], where the capacity loss over time is modelled to follow the Lambert W function dependent on temperature, time and available capacity.

The coulombic efficiency (CE) is used to establish a model for actual reversible capacity in [210]. It is assumed that the coulombic efficiency describes the decrease in reversible capacity in successive cycles, $C_k = C_{k-1}CE_k$, where C_i denotes the reversible capacity at cycle i and CE_i is the coulombic efficiency of cycle i. Then, assuming that the coulombic efficiency is constant over cycles, one arrives at the following, by iterating over cycles since the initial capacity C_0: $C_k = C_0\left(CE_1CE_2 \cdots CE_k\right) \approx C_0CE^k$, see also [94]. Hence, they propose the following parametric model for reversible capacity:

$$C_k = \alpha_0 CE^k + \alpha_1, \tag{6}$$

where α_0 and α_1 are considered model parameters, and also CE is regarded as a model parameter, reflecting that it is difficult to measure CE accurately. This model is compared to a simple empirical model based only on cycle number, $C_k = \beta_0\sqrt{k} + \beta_1$, and is found to perform better. In order to apply the method as an online application, the model is formulated as a state-space model and a particle filter is used to update state parameters. The effects of ambient temperature and DOD are not accounted for, and this is an important topic for further research. Furthermore, it has been shown that coulombic efficiency is influenced by the C-rate, with higher efficiency for lower current rates [230]. An extension of the model above that also takes into account the capacity increase that can be observed during rest periods between cycles is proposed in [94], and the parameters are estimated using particle filter with resampling.

Relationships from a simple equivalent circuit model are combined with a polynomial-based relationship between OCV and SOC in order to obtain a function of voltage with only charged capacity as variable in [99]. The parameters of this model, only one of which is temperature dependent, can be fitted to a defined voltage window of the charging/discharging profiles at different levels of ageing in order to estimate the present maximum capacity and hence the SOH. It is indicated that a polynomial of order three can be suitable for some battery chemistries, whereas for example LFP requires a polynomial of order greater than 10. Hence, the generality and adaptability of such methods across different chemistries is a drawback with this approach.

A cycle life model for LFP batteries is proposed in [231], where different empirical models are fitted to describe the dependencies between cycle life and working temperature (third-order polynomial model), discharge current rates (exponential model), DOD (exponential model) and charge current rates (exponential model).

3.8. Other approaches

Some other approaches to SOH estimation that do not directly belong to any of the categories above have been suggested in the literature. A discrete wavelet transform (DWT) based approach is proposed in [232], where the SOH is related to the standard deviation of the approximation component and the detail components of the transformed voltage signals. Discrete wavelet transform has also been used for battery SOH estimation in [233] (for lead–acid batteries) and in [234] (employing a fast discrete wavelet transform and combined with a cross D-Markov machine).

A geometrical approach to lithium-ion battery capacity estimation is presented in [235], which can reflect the intrinsic degradation of the batteries. Four geometrical features that are sensitive to changes in the degradation of batteries are extracted from current curves during charging and voltage curves during discharging. Next, the Laplacian eigenmap method is applied to establish an intrinsic manifold where geodesic distances are calculated and used as a metric for the estimated capacity.

Rather than training a data-driven model to estimate SOH based on sensor data, a multidimensional look-up table is introduced in [236], where several features of interest are extracted from incremental capacity curves, and their evolution along the battery degradation paths is used to construct a look-up table for capacity estimation under any operational scenario. The idea is that this can be used very efficiently when IC curves corresponding to batteries in operation are collected.

A visual cognition approach to battery capacity estimation is proposed in [237]. With this approach, charging current and discharge voltage data for each cycle are arranged to form a two-dimensional image, which is then decomposed into multiple spatial-frequency channels with a set of orientation subbands, imitating the human visual system. Several indicators are then extracted to form an initial high-dimensional feature vector and manifold learning is used to construct a low-dimensional intrinsic manifold that can reveal the capacity degradation in the extracted features. Finally, battery capacity degradation is estimated using the geodesic distance on the manifold between the initial and the most recent features.

Data-driven SOH estimation methods will be an important ingredient in battery digital twins. Battery data, models, control, and diagnostics tools are fused with battery knowledge and emerging machine learning techniques towards creating battery digital twins where SOH and capacity estimation models are essential. The building components of battery digital twins are reviewed in [238], and [239] discusses the applications of battery digital twins in manufacturing and production phase and the operation stage. In this direction, cloud-based battery management systems were considered in [240] through cloud computing using combinations of diagnostic algorithms and digital twins built using Internet of Things (IoT). SOC and SOH estimation algorithms are developed using respectively H-infinity and particle swarm optimization techniques based on equivalent circuit models and measurement data. Using empirical capacity and resistance ageing models, [241] develops a deep deterministic policy gradient approach for a cloud-based energy management system in a hybrid high-energy and high-power battery pack to increase electrical and thermal safety and reduce energy losses and ageing costs.

4. Discussion

4.1. Data availability and requirements

Data-driven models need training data to learn relationships between input variables and responses, and the availability of data determines both what types of models can be used and the accuracy of the model predictions. Often, training data are gathered by laboratory experiments and used to train a model that can be used in an operational setting, and it is not obvious how representative such data are. However, if a sufficient amount of operational data is available, it may also be possible to train models based on such data without requiring extensive laboratory testing, as suggested by e.g. [183,184]. The origin of the training data notwithstanding, available training data needs to be of sufficient quality and quantity, sufficiently representative, sufficiently complete and sufficiently relevant in order to train usable data-driven models, and the availability of such data is a crucial prerequisite for relying on data-driven models for battery capacity estimation. A recent review of publicly available battery data is presented in [242].

The type of data that are available will determine what types of data-driven methods can be developed, and the extent of requiring collection of specific data for the purpose of model training. For example, if cell-specific training data are needed to train the models it may be a requirement that specific accelerated testing are carried out prior to, or in parallel with, starting up operation of the actual battery system. On the other hand, if more generic training data are sufficient, it may be possible to train models based on previous tests on similar battery cells. However, different types of models may not need prior training, so the training data requirements needs to be assessed based on what models will be used and what data are available.

Also, it will be important to understand what type of operational data will be available throughout the lifetime of the battery system. What are the resolution at cell, module and pack level and which features will be available. One may not necessarily assume that data collected routinely by the BMS will be available for the SOH algorithms, such as various current, voltage and temperature measurements, and temporal and spatial resolution may vary. Furthermore, the reliability and accuracy of derived quantities such as the SOC will need to be assured. It remains to be determined whether the data automatically collected are sufficient, or if additional specific measurements are required, e.g. periodic tests with set load patterns and fixed conditions with respect to C-rate, temperature and SOC range where one can perform Coulomb counting, or particular tests such as pulse tests and impedance or resistance measurements. From a practical point of view, it may be desirable to only rely on continuously measured data streams, but results could be improved if additional tests are carried out.

Moreover, it is important to consider how to handle missing data and the extent and effect of this on the SOH diagnostics. For example, for models such as cumulative damage models where the complete operational history is needed in order to estimate SOH, missing data and data interruptions may not be tolerated, but other approaches based on snapshots of the batteries, for example regression models relating features of the charge/discharge curves to SOH, would not suffer much from missing data. Imputation techniques could also be explored to remedy the problem of missing data [159]. These considerations need to be taken when selecting a data-driven approach for SOH modelling. Another aspect of missing data is that data streams will typically not contain capacity or SOH for all data points. Hence, models that can be applied with no or limited labelled data may be needed, indicating that methods from unsupervised or semi-supervised learning could be relevant [143].

The data quality is a crucial issue for data-driven methods, and results can only be as good as the data allow. Many of the continuous variables will most likely be discretized in both time and measurement value, and additional measurement noise will always be present. This could influence results in different degrees, and some denoising and preprocessing of the data will probably be needed. For example, methods based on ICA/DVA relying on the differentiation of discrete signals will certainly need some type of smoothing to perform well. Hence, proper approaches to preprocessing and denoising of the data signals will need to be considered as well as the actual data-driven models.

Moreover, additional factors that may be relevant for maritime batteries have not been well studied in the literature, such as the effect of humidity, airborne salinity, vibrations and the constant movement of the ship. Such information may not be available and it should be investigated to what extent such factors influence battery degradation.

As mentioned above, some data-driven methods require extensive amount of training data in order to train the models properly. Possibly, specific tests may be required for the particular battery cells in each case, or test results from similar cells could be exploited. A combined approach utilizing transfer learning could also be envisioned [172], where models are pre-trained on publicly available data before they are re-trained more specifically for the application in question. A methodology for synthetically generated battery data for big data training are discussed in [243].

4.2. Synthetic and realistic load profiles

Some approaches to SOH modelling assume that batteries are used in a controlled way, at near-constant temperatures, with constant charge and discharge C-rates and systematically cycled between minimum and maximum SOC. Indeed, training data obtained from laboratory tests will often be collected under such controlled situations. However, for maritime battery systems, this is hardly the case and batteries are typically cycled only partially and under highly variable loads and environments [148]. This must be taken into account, and methods that are able to account for these variations are needed. For example, proper calibration of SOC estimates may be difficult for batteries that rarely experience fully charged or fully discharged conditions, but are partially cycled around an uncertain SOC level. This may cause SOC estimates to drift over time which may again influence SOH and capacity estimates. A methodology for generating synthetic training data by simulation is presented in [243], and such approaches could be useful to expand available training data.

For data-driven methods that have been trained using laboratory test data or synthetic data, it will also be important to have data from dynamically varying loading tests, where the effect of varying temperature and C-rates are included. As noted in [244], there is no guarantee that data-driven methods that are perfected for constant loading profiles perform well on variable loading cases. However, several authors have noted that the charging process of batteries in actual operation tend to be less variable than the discharging process. Often, charging is performed with a constant current constant voltage procedure, with deterministic rather than stochastic current and voltage profiles in the different steps [76,102,134,135]. Hence, methods that consider features from charging profiles may be preferred to methods relying on discharge features. However, typical charging patterns may vary and extensive use of partial fast-charging may deviate from normal charging routines under very similar conditions.

The fact that realistic load profiles expectedly will exhibit only partial charging and discharging cycles means that methods that rely on e.g. Coulomb counting through a complete cycle will not be accurate, as these situations hardly ever occur in actual operation of the battery. Hence, methods based on partial charging/discharging information are more attractive. This review has shown that several approaches are proposed that extracts features from partial charging curves, including incremental capacity information from specific voltage ranges, information extracted from the constant voltage step of a CCCV charging process and information related to battery response to short-term current pulse tests, and use these to estimate battery degradation and SOH. Hence, such features are believed to be useful and could be used to estimate SOH for maritime battery systems. However, the effect of dynamically varying temperatures and currents must be taken into account also for features based on partial cycling data, and this may not be straightforward.

4.3. Statistical and machine learning models

One often distinguishes between statistical models and machine learning models, and different types of models have been reviewed in this paper. In regression problems such models are used to establish a relationship between a response variable, in this case the SOH or capacity of the batteries, and one or more explanatory variables. In this context, statistical models are often referring to more simple models, where linear or simple functional relationships are fitted to the data, whereas machine learning models yield more complicated relationships.

Some aspects to consider when selecting a statistical or a machine learning model are predictability and interpretability. Typically, more advanced machine learning models are more flexible and can accommodate complicated relationships between the input and output variables and may have higher predictive power. However, such models are often referred to as black box models in the sense that it is difficult to understand the predictions and difficult to interpret the relationship. On the other hand, simple statistical models are more interpretable and intuitive, but may have slightly poorer predictive performance. Furthermore, complicated models may fail to generalize and are more prone to overfitting than more simplistic models.

Another aspect is to what extent uncertainty is taken into account and whereas some models provide predictive distributions, most machine learning model only give point estimates. Obviously, estimation of the uncertainty can be useful but often comes at a computational cost [245]. Uncertainties can also be accounted for by an ensemble of point predictions from different models, and ensemble models may also increase the robustness of the data-driven models. Hence, selecting a statistical or a machine learning model for SOH estimation is a trade-off between accuracy, generalizability, interpretability and computational cost.

Notwithstanding, for the purpose of developing data-driven models for SOH verification, it is believed that other aspects of the data-driven methodologies are more important than the exact type of regression model, i.e. related to selection of features, data pre-processing and the overall modelling approach. It is also mentioned that the required accuracy may depend on the usage of the data-driven models. Typically, OEM may require higher accuracy than the classification society, who only need independent modelling to verify the SOH estimates from the BMS in order to validate that the battery systems is fit for further use.

4.4. Feature extraction and selection

There are different definitions of SOH, and two common approaches are to consider SOH in terms of the actual capacity of the battery and the internal resistance of the battery [6]. In this paper, it is assumed that the capacity-based SOH is the most important one, and this obviously influences the modelling choice.

Different modelling techniques require different types of features to explain battery degradation and different training data. For models to be useful it is also important that the selected features will be collected during operation. Hence, there is typically a need for features that can be extracted from data readily available from the battery management system, such as current, voltage and temperature measurements. From such raw data, derived features such as SOC, number of cycles and rest time at different SOC/voltage level can also be extracted. This review has showed that there are countless approaches to extract features, sometimes referred to as health indicators, for SOH modelling, and which features are used to train the data-driven models may typically be more important than the actual type of statistical/ML model to employ.

Feature extraction for SOH estimation is addressed in [135] and it is proposed that six features that can be extracted from charging profiles are informative on SOH, i.e. time intervals, charging capacities and temperatures in CC and CV steps of a CCCV charging process, respectively. Moreover, they propose to validate the relevance of features using grey relational analysis (GRA) and possibly remove features that are found to have low relational grade. An optimized feature extraction method based on a genetic algorithm (GA) is proposed in [136]. It uses the charging time for a fixed voltage range from partial charging data to determine SOH and optimizes the charging voltage range to be used as features to achieve best accuracy at the lowest computational cost.

4.5. Models based on complete loading history vs. snapshot methods

Some of the models reviewed in this paper rely on the whole operating history of the battery cells in order to estimate SOH, whereas others estimate SOH based on brief snapshots. Cumulative damage models and empirical/semi-empirical models relating SOH to number of cycles and other stress factors such as temperature, C-rate and SOC swing are examples of the former. Regression models on features extracted from partial charging curves or incremental capacity curves are examples of the latter. Both approaches have some advantages and disadvantages.

Cumulative damage models are attractive, since they can be used to model the accumulated degradation effect from the experienced operational profile. In essence, such models establish a relationship between the load profile or individual cycle and the change in SOH, the ΔSOH. The actual SOH after n cycles can then easily be estimated as $SOH_n = SOH_0 + \sum_{i=1}^{n} \Delta SOH_i$, where SOH_0 is the initial capacity, typically 100%.[2] Moreover, if a future duty cycle can be assumed, such an SOH estimation model can also be used for prognostics and RUL prediction. However, one disadvantage of this approach is that the complete operational profile is needed. Periods of missing data will effectively render such models inaccurate. Possible remedies could be to impute values for missing data, but this is probably only possible for relatively short periods of missing data. Some situations where longer period of missing data for maritime battery systems can be envisioned, e.g. short- or long-term system down-time of interrupted data transfer capabilities, periods when the vessel is temporarily laid up and the battery system has not been in use (although not in use, calendar ageing continues and will typically be dependent on SOC, temperature, etc...), and if the ship changes owner or class society with possibly lost access to previous operational data. Such approaches would presumably also be vulnerable to deliberate data tampering and it would be possible to remove data from unintended periods of abusive conditions.

On the other hand, methods based on regular snapshots of the data streams are very attractive in the sense that it does not require access to continuous data streams, or alternatively, accumulated data in the form of histograms or collectives representing the complete operation history. With such models, it would suffice to get batches of data at certain intervals, and if the models are able to reliably extract battery capacity and SOH from such snapshots, the cumulative effect since the previous batch would implicitly be estimated. Thus, if such models are found to perform well enough, they may be the preferred approach for SOH verification of marine battery systems.

Possibly, a hybrid approach could also be envisioned, where for example a crude cumulative damage or empirical type of model runs on system level, supplemented by snapshot-type models on cell level at regular or irregular intervals. Notwithstanding, the choice of modelling approach will have implications on the data requirement and this aspect need to be considered.

4.6. SOH estimation and RUL prediction

Estimation of SOH and prediction of RUL of batteries can be considered as two sides of the same coin. SOH estimation aims at describing the current degradation state of the battery, whereas RUL predictions projects future degradation of the battery until it reaches its EOL. Hence, both depend on a method for describing ageing as a function of various factors such as calendar time, cycle time and operating conditions related to temperature, C-rate and SOC levels. However, for RUL there is the additional need of predicting future conditions and usage patterns. For battery systems operating under variable loads, this may be challenging and some additional assumptions need to be made. Another issue is that inherent uncertainties exist, which get compounded and can easily grow out of control when predicting many steps ahead, making RUL prediction less accurate than SOH estimation [244].

Some of the methods described above for SOH estimation cannot easily be adopted to predict RUL, and all methods based on direct measurements such as Coulomb counting, electrochemical impedance spectroscopy and ICA will be difficult to apply in a prognostics setting. However, other methods will typically be more relevant for RUL

[2] An initial capacity test will be relevant for ships in order to verify that the battery is working as it should, and even in a future class framework perspective where annual test requirements can be waived such initial tests could be required.

prediction than for SOH estimation, for example different time series models and survival models. Cumulative damage type of approaches, where degradation is modelled based on cumulative effects of the load histories, on the other hand, could presumably be adopted and used also for RUL prediction, under some assumed future loading conditions. Also, many of the empirical capacity fade models could in principle be extended to predict remaining useful life of batteries, i.e. to predict when capacity crosses a predefined threshold.

The duty cycles and operating conditions of maritime battery systems will typically be varying and unpredictable, and depend on factors such as weather and sea state conditions, loading conditions and possibly different voyage lengths and routes or different operations. However, one plausible assumption could be that past operating history is representative for the future. Hence, one solution is to merely repeat historical usage patterns into the future to predict RUL based on a degradation model. This approach was suggested in [204].

4.7. Cell vs. module vs. pack level

When establishing diagnostics methods for SOH estimation one needs to consider whether to apply these on cell, module or pack (string) level. Both approaches may be useful, but the choice of level might influence the modelling choice. For maritime battery systems in particular, which are large-scale installations consisting of numerous cells, SOH at system level is highly relevant. The heterogeneity of the different cells within a module or a pack is a challenge, and even though the BMS tries to balance the cells, some imbalance and differences between the cells seem unavoidable [246]. Moreover, there are different balancing approaches, e.g. active and passive balancing, and the heterogeneity will be design-dependent. This will influence the degradation and cells within a battery system will typically not degrade uniformly. Hence, methods to identify cell differences are relevant. There will also be varying temperatures between cells in a module and from module to module. Variations will typically depend heavily on design aspects such as the cooling system, and e.g. air cooled systems may be expected to entail larger variations than liquid cooling systems. A classification approach to determine relative self-discharge rates in a battery system is presented in [247]. An approach to evaluate cell-to-cell variations for batteries in electric vehicles based on charging data stored in the cloud is proposed in [248].

It is suggested in [249] that the capacity of a battery pack connected in series is determined by the two worst cells, i.e. the cell that first reaches fully charge state during charging and the cell that first reaches fully discharge state during discharge. Hence, given SOC and capacity for all cells in the pack, the capacity of the pack, C_{pack}, can be found from

$$C_{pack} = \min_{1\le i\le n}\left\{SOC_i \times C_i\right\} + \min_{1\le i\le n}\left\{(1-SOC_i)\times C_i\right\}, \tag{7}$$

where C_i and SOC_i are the capacity and SOC, respectively, for cell i, $i = 1,\dots,n$, and n is the number of cells connected in series in the pack. A so-called capacity–quantity diagram is introduced as a graphical illustration of this relationship that can be used to estimate the capacity of the battery pack. Moreover, it is demonstrated that the estimation error of pack capacity is influenced more by estimation error of the individual cell's SOC than the estimation error of individual cells capacities. However, as pointed out in [250], this approach needs to be extended to account for variations in C-rate and temperature.

In principle, one could assume that SOH estimation at cell level are easily aggregated to pack level. For example, for cells connected in series with passive equalization, the available capacity of the entire string will be determined by the capacity of the single cell with the minimum capacity, and for series-connected cells with active equalization, the available pack capacity is given by the average of the cell capacities [251]. For parallel-connected cells the available capacity will be given by the average cell capacity times the number of cells. However, earlier studies have shown that battery pack lives are typically shorter than single cell life due to other degradation mechanisms [21]. Moreover, individual cells may not be monitored and for example measurements of the current going through individual cells may not be available. Compared to degradation of individual cells, the degradation of battery modules and packs are influenced by additional factors such as battery topology, inhomogeneity and cell balancing approach. Whereas most papers study capacity modelling at cell level, there are some studies that addresses capacity estimation at pack level [22,252–256].

An incremental capacity peak tracking approach is proposed in [22] for online SOH monitoring of battery modules consisting of cells in parallel with different ageing histories. They demonstrate that ICA methods developed for single cell capacity may also be used for modules with cells connected in parallel, even considering non-uniformity of the cells, and based on terminal measurements only. Their results indicate that correlations between the peak of the IC curve and capacity obtained from single-cell data are generalizable to battery modules, and may be used to model module capacity and for health monitoring. A similar approach was validated for a battery pack with cells in series in [254], even though they employ a strategy where SOH is estimated on each cell in order to detect the weakest cell in the module.

State of health estimation for battery packs based on a simplified equivalent circuit model is proposed in [253]. They propose a simplified ECM in order to reduce complexity, but this introduces a significant amount of noise and errors. In order to deal with this noise, a state-space model is developed based on the simplified ECM and a genetic resampling particle filter is applied to estimate SOH. A serial-connected battery pack model based on a second-order equivalent circuit model is proposed together with a multi-time scale extended Kalman filter in [255] to estimate all the cell's capacity. A "special and difference" model is employed where one of the cells in the pack is selected as a special cell, and the difference between the remaining cells in the pack and this special cell is modelled in order to estimate the battery pack output. An ECM is also used for battery pack modelling in [257].

System-level SOH of battery packs are assessed based on knowledge of individual cell SOH, pack topology and a voltage equalization approach in [251]. A battery pack model is constructed based on three interconnected submodels, composed by electrical, thermal and ageing models for individual cells. A similar set of models are used in [258] to model individual cell capacity fade as well as cell-to-cell variations within a battery system. They conclude that estimation considering the cell-to-cell variation within a battery system is more accurate than assuming identical behaviour of all cells. In [259] a battery pack model is constructed based on a series of ECMs for individual cells in series, and a nonlinear predictive filter is used to estimate the states of both individual cells and the battery pack and to estimate capacity and power SOH. The energy SOH of a battery pack is proposed in [252] as an alternative to SOH definitions based solely on capacity or internal resistance. It is defined as the ratio between the current maximum available energy (MAE) in the battery pack and the rated total energy of the battery pack. They assume an equivalent circuit model and estimate the MAE considering the inhomogeneous capacities and internal resistances of the cells in the pack.

Techniques from systems reliability analysis have been used to analyse the reliability of battery systems as a series or parallel system of individual cells as components in a system in e.g. [260,261]. Degradation tests for cell and pack level, for a selection of simplified pack configurations, are presented in [261] and it is suggested to model the dependencies among cells degradation using copulas. Degradation tests for battery packs with similar configurations are also presented in [262], where the Pearson correlation coefficient is used to evaluate the dependence between different cells in the pack and between the cells and the overall pack.

Although several papers have been published that deal with SOH estimation at battery pack level, generic and robust estimation of battery SOH remains a challenge. Many of the approaches discussed above rely on complicated equivalent circuit models. It is questionable how generic these are and to what extent a model constructed for one battery system can be applied to others. The approach based on ICA on pack level is interesting, but it is dependent on charging/discharging in controlled environments and typically with constant and low C-rates. Moreover, the availability of data on cell or pack level will be important to consider for deciding whether to estimate SOH on cell or pack level. This relates both to the availability of test data for model training, which is typically obtained for single cells only, and the operational data that may typically only be available on module or pack level.

Whether one opts for a modelling based on a complete loading history or a snapshot method may also influence, and to require high-resolution data on cell level corresponds to requiring vast amounts of data. If a snapshot method is used, detailed data on cell level might be feasible, whereas if data for the complete loading history are needed, then low-resolution data on module or pack level might be the only realistic option from the perspective of amount of data required. Possibly, hybrid methods could be developed, where high-level data on system level approximates system SOH based on complete operational data, whereas snapshot methods are applied at cell level at regular intervals.

4.8. Generalization

The idea of identical cells is important for modelling SOH, and one may typically assume cells to be identical if they have the same chemistry and belong to the same production line. Moreover, different cells may be assumed to be similar, if they share some common features, such as the same type of chemistry, the same cathode or anode materials, the same form factor or the same producer. One important question that is relevant both for the modelling of battery packs consisting of several cells believed to be identical, and also to the applicability of basing SOH monitoring on operating cells based on laboratory test data for identical cells, is to what extent results obtained from one cell are generalizable to other similar or thought-to-be identical cells. A study on four different cells presented in [121] reports that a model built using data from one single cell was able to simultaneously estimate SOC and SOH of the three other cells with reasonable error.

However, several studies have demonstrated that the variability in degradation and capacity fade is large even for nominally identical cells [263]. Furthermore, identical cells in one battery pack may experience significant cell-to-cell variations in experienced temperatures, currents and voltages, which will influence degradation [258]. Such cell-to-cell variation may be important and adds to the uncertainty of battery degradation modelling. Furthermore, it may limit the extent to which results obtained for a specific cell can be generalized to other similar or even identical cells. A cells-in-series approach is proposed in [264] to detect cell-to-cell variation with high precision, based on voltage measurements only, since cells in series experience the same current. A logistic regression classifier was used in [265] in order to quickly, during a few early cycles, dichotomize cells into low-lifetime and high-lifetime groups of cells.

One issue that has been raised as a major challenge in battery capacity and SOH estimation is the effect of varying operating conditions. More specifically, degradation rates of batteries are known to be highly sensitive to variations in temperature, C-rates and range and levels of SOC during cycling and storage. If models are trained on laboratory data that do not exhibit the same variation in operational conditions as what could be expected during operation, it is an open question how the model generalizes to predict actual capacity under typical loading. Hence, the effect of such varying loading and operational conditions is an important aspect that needs to be considered when developing data-driven methods.

4.9. Effect of battery chemistry and degradation mechanisms

In this review of data-driven methods for battery SOH estimation, modelling approaches for a range of different battery types and chemistries have been reviewed, without a lot of emphasis on what type of batteries the various methods have been applied to. It has tacitly been assumed that the data-driven methods are agnostic to battery chemistry, in most cases, and that different chemistries can be handled by changing the model parameters or re-training models with appropriate training data. However, it should be noted that some methods may not be easily transferred to other battery chemistries, so care should be taken when selecting a modelling approach for a particular battery type. For example, it is generally known that LFP batteries exhibit a flat plateau in the SOC–OCV curve that renders voltage-based algorithms and ICA difficult to apply to such types of batteries [56]. Such considerations have not been made in the generic review presented in this paper, but obviously need to be made carefully in an actual application.

It is also known that different battery chemistries can have very different degradation mechanisms and that the degradation response to various abuse factors vary significantly across battery chemistries, and even between batteries with the same or similar chemistries from different production lines [266].

When adopting a data-driven approach to degradation modelling, it is implicitly assumed that detailed knowledge of the various degradation mechanisms are not needed beyond what is implicit in the data. Hence, this paper does not review the degradation mechanisms in detail, but it should be kept in mind that different batteries degrade differently and that this needs to be accounted for in the models. Some of the most important causes of battery degradation are loss of active material at the electrodes, SEI growth, electrolyte degradation, lithium plating at the anode, increase of internal resistance and possible dendrite formation, but the rate of degradation varies significantly.

Another issue that should be taken into account is that some degradation mechanisms may not be completely irreversible and some capacity recovery can occur, for example after extended periods of rest.

4.10. Verification and validation

One important question for data-driven SOH estimation methods is to what extent they can be verified and validated to perform satisfactorily for the intended battery system. This question is at the core of the objective of this review, where one of the main goals is to provide means for an independent verification of the SOH estimates provided by the battery management system (BMS). One obvious approach is to establish an independent SOH estimator that can run in parallel to the BMS to provide a real-time second opinion on SOH, and report large discrepancies. Another option could be to have an off-line model that can run on batches of data at regular intervals and compare with the estimates obtained from the BMS. Notwithstanding, there will still be a need for verification and validation of the independent SOH estimation method. This may require a standardized platform and extensive testing data from actual degrading batteries.

The preferred solution would be to have a generic SOH estimation approach that could be adopted and used for all types of battery systems; for all common chemistries, for all battery sizes, for all operational profiles (e.g. fully electric, peak shaving, spinning reserve, …) and in all environments. However, even with such a generic approach, there would still be a need to adjust the model and possibly re-train it on a case-by-case manner. Hence, verification and validation of the model may not be possible once and for all, and it would need to be, somehow, verified and validated particularly for each case.

It is noted that some particular methods may be prone to systematic under- or overestimation of actual capacity. For example, as indicated in [51], SOH estimation based on Coulomb counting of partial cycles – a technique that is utilized for maritime battery systems today – is likely to underestimate the capacity fade and thereby overestimate the actual capacity. It is important to understand and account for such systematic biases for specific approaches, in order to obtain reliable estimates of SOH and capacity.

Some publicly available battery data are available for the purpose of providing a benchmark for battery diagnostics and prognostics approaches, and these may be utilized, to the extent that they are found relevant, for testing different SOH estimation methods. One example is the data available at the NASA Arnes Prognostic Data Repository [186]. However, it is questionable if such data are sufficient for a full verification of SOH estimation methods for maritime battery systems.

The literature survey presented in this paper has reviewed a number of different modelling approaches, and results in the reviewed papers are often accompanied with some measure of accuracy or uncertainty, e.g. in terms of root mean square error or similar metrics. Hence, in principle one should be able to compare and rank various approaches based on reported performances. However, since the different models are applied to different datasets, such comparison is futile, and it is deemed difficult, if not entirely impossible, to verify claims of accuracy reported in the literature and use this to rank models. In order to do this in any sensible way, a comparative analysis where different approaches are explored on the same dataset would need to be performed. This is out of scope of this state of the art survey, but will be important in future work.

5. Summary and conclusions

The main objective of this paper is to understand the various approaches one could take on SOH estimation of maritime battery systems, and to guide the selection of promising methods and models to explore further. The focus has been on capacity-based SOH.

Data-driven methods for SOH modelling can be categorized into a few groups of approaches, i.e. direct measurement techniques, state-space models with observers, regression type models, time-series models, survival type models, cumulative damage models and empirical/analytical models. However, the distinction is not crisp, and several types of approaches are often combined. Notwithstanding, based on the review presented in this report, it is assumed that some of these approaches are more relevant for maritime battery systems than others. One desired feature of the selected modelling technique is that it only needs information contained in operational data. For example, time-series models and survival type models are not believed to be optimal. Time-series models typically describe the temporal evolution of a variable, such as the SOH and capacity and require time-series of capacity measurements that will not be available. However, such approaches may be interesting in a later stage, for prognostics based on time-series of accurate SOH estimation. Also, survival type models need extensive lifetime data that cannot be expected to be available. Hence, it is believed that a combination of direct measurement techniques, regression models, empirical models and cumulative damage models will be most relevant for further study.

State-space models, either electrochemical models or equivalent circuit models require a battery specific model which may be difficult to validate. However, it is noted that current battery management systems for maritime battery systems typically rely on a battery model such as an ECM for battery monitoring and capacity estimation. Hence, such models are highly relevant. Nevertheless, from a class perspective the aim is to develop means for independent verification of capacity/SOH estimation made by the BMS, and it may therefore be advisable to consider alternative modelling approaches.

Direct measurement techniques include some approaches that require particular hardware and might not be suitable for verification of SOH estimation. Moreover, direct capacity estimation based on Coulomb counting requires specific reference charge and discharge cycles between fully charged and fully discharged batteries, under specific conditions (e.g. temperature and C-rate) which will not be observed during normal operations. However, techniques based on partial charge or discharge information could be useful and will be explored further.

A large number of regression type models, ranging from simple linear regression, to empirical/analytical models, to highly complex machine learning models have been proposed, establishing a relationship between capacity and different features extracted from the data. Perhaps more important than what type of regression model to use is the selection of features to use. Two fundamentally different approaches can be taken, herein referred to as snapshot and cumulative approaches. The cumulative approaches establish a relationship between various stress factors (temperature, C-rate, SOC, DOD, etc.) and *capacity degradation*, ΔC, whereas the snapshot approach establishes a relationship between observed features and *actual capacity*, C. They both have their advantages and it is recommended to explore both approaches in further work.

One disadvantage of the cumulative models is the need for the full operating history of the batteries. Even if a perfect model were able to estimate the capacity degradation under various stress-factors, if parts of the history are missing it would not be possible to estimate actual capacity at a particular time. On the other hand, such models may be sufficiently accurate and may not require very high temporal resolution data. Another possible disadvantage of this approach is the need for extensive training data and possibly such models would be accompanied by requirements of laboratory degradation testing prior to the actual operation phase.

A huge advantage of snapshot models is that capacity can be estimated based on parts of the continuous data-stream only. This is believed to be a very promising feature for a method employed for regular verification of online capacity estimation. However, such methods may require higher temporal resolution in the data in order to extract the necessary features. If such models can be established reliably, SOH can be verified based on regular batches of data. However, it remains to be seen if reliable and accurate models can be established without the need for reference operation under specific conditions. Possibly, information collected from partial charging processes can be used to estimate capacity via a suitable regression model. Presumably, charging operations will be less susceptible to highly variable conditions compared to discharge and there are several suggestions in the literature about how information from partial charging curves can be used to estimate capacity. However, challenges remain with respect to how the influence of temperature, variations in SOC etc. can be incorporated in the models. Moreover, such models also need training data in order to estimate the relationship between the actual capacity and the features.

Another approach presented in [124], where capacity is estimated as the regression coefficient between integrated current and differences in SOC, is believed to be interesting and will be explored further. This approach has the advantage of not requiring training data, but it needs reliable and continuous current measurements and SOC estimates.

Other aspects of capacity estimation need to be further explored in future work, such as whether to model capacity on cell level or system level and the effect of different battery chemistries or differences in the battery production line. Possibly, a hybrid approach can be taken, where different models are used on cell-, modular- and system level, and where a set of models can be applied to different groups of chemistries. Notwithstanding, the available data (what variables are measured, data quality, resolution, etc...) will determine what types of models can be exploited.

CRediT authorship contribution statement

Erik Vanem: Conception and design of study, Drafting the manuscript, Revising the manuscript critically, Approval of the version of the manuscript to be published. **Clara Bertinelli Salucci:** Conception and design of study, Revising the manuscript critically, Approval of the version of the manuscript to be published.

Azzeddine Bakdi: Conception and design of study, Revising the manuscript critically, Approval of the version of the manuscript to be published. **Øystein Åsheim Alnes:** Conception and design of study, Revising the manuscript critically, Approval of the version of the manuscript to be published.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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