A Comprehensive Literature Review of State of Safety (SoS) for Maritime Battery Management Systems (BMSs)

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ABSTRACT

Battery-powered vessels can help reduce greenhouse gas emissions in the maritime industry, which is crucial to achieving the International Maritime Organization's (IMO) ambition of net-zero emissions by 2050. However, batteries also introduce unique safety risks, since failures can lead to catastrophic outcomes such as thermal runaway and onboard fires. Effective Prognostics and Health Management (PHM) is essential for early detection of hazardous states to prevent critical failures or unsafe conditions. This paper investigates the emerging concept of state of safety (SoS), a metric for real-time quantification of battery safety, which is essential for ensuring safe operation of battery-powered vessels. A PRISMA-based literature review is conducted to address three research questions: (1) What are the current definitions of SoS in the maritime and other industries? (2) What are the existing methods to estimate SoS? (3) What gaps remain in defining and implementing SoS in the maritime industry? The review reveals recent advancements in SoS research from the automotive and energy storage domains, while identifying a notable lack of studies addressing SoS in maritime battery systems. Existing estimation approaches and key battery parameters relevant for SoS assessment are reviewed and critically discussed. To advance the practical implementation of SoS, the paper provides a structured overview of the battery parameters required for comprehensive SoS implementation, including measurement methods and associated challenges. Furthermore, safety hazards identified in the European Maritime Safety Agency (EMSA) battery guidance are systematically allocated across the battery management system, SoS, and design levels, thereby positioning SoS as a complementary layer to the safety functions ultimately governed by the Battery Management System (BMS). Finally, future research directions are outlined for advancing SoS estimation in marine applications, focusing on interpretability, granularity, ultrasound-based strain monitoring, and integration in the maritime environment.

1. INTRODUCTION

Global efforts to decarbonize shipping have intensified in recent years, driven by climate commitments and regulatory pressure. In July 2023, the International Maritime Organization (IMO) adopted an updated greenhouse gas strategy, setting the ambitious goal of achieving net-zero emissions from international shipping by 2050 (IMO, 2023). To meet this target, the maritime industry is increasingly exploring battery-based electrification as a key enabler to lower emissions. However, battery failures are associated with severe consequences. A typical example of it is thermal runaway, a condition in which the battery generates more heat than it can dissipate. This imbalance accelerates exothermic reactions, leading to the release of large amounts of heat and toxic gases, and potentially resulting in a fire or an explosion. As maritime vessels face harsher and more isolated operating conditions than electrical vehicles (EVs), the complexity of ensuring safe integration of large-scale battery systems is significantly increased.

To monitor battery conditions, the onboard Battery Management System (BMS) supervises cell-level parameters and estimates key indicators such as the State of Charge (SoC) and State of Health (SoH) as required by class societies (*DNV Rules for Classification of Ships, Part 6 Chapter 2: Electrical Installations*, 2025). SoC is the ratio of current charge to total available charge, while SoH is the ratio of current capacity to initial capacity. Manufacturers typically develop robust SoC and SoH algorithms and establish conservative safety limits based on them through extensive testing. However, safety testing performed by manufacturers may not fully capture the risks that emerge under real-world conditions, especially as batteries age and operate in complex environments (Sethia, Berendes, Kratzing, & Lehmann, 2025). Furthermore, defects that appear harmless during production can evolve into serious

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faults over time (Wenzel, 2023).

Currently, industry practice often assumes capacity loss as an indicator of increasing safety risk and as a result, battery end-of-life (EOL) is typically defined as the point at which SoH declines to 70–80% (Cabrera-Castillo, Niedermeier, & Jossen, 2016; Vanem, Salucci, Bakdi, & Alnes, 2021; Che, 2023). However, SoH is strictly a measure of capacity loss and does not directly reflect safety risks (Koch & Schweiger, 2022). Hazards such as thermal runaway can occur even when SoH values remain high.

To address this gap, (Cabrera-Castillo et al., 2016) introduced the State of Safety (SoS[1]) that is a metric designed to quantify the safety level of a battery system on a scale from completely safe (1) to critically unsafe (0). Unlike SoC and SoH, which focus on energy availability and capacity fade, SoS aims to capture the dynamic risk level of hazardous conditions to ensure vessel safety. SoS provides a direct assessment of safety margins, enabling context-aware operational limits and more sustainable replacement strategies (Sethia et al., 2025). Despite its relevance to many applications, SoS remains an emerging concept that is not well researched and lacks standardized estimation methods for quantification (Vanem & Wang, 2025).

This is particularly critical for maritime applications, where vessels operate in harsh isolated environments with limited emergency response capabilities. Excessive degradation independent of SoH and battery replacement are most likely during the operational life of a vessel. As such, the development and integration of SoS into maritime BMS architectures is essential for improving both the safety and economic viability of battery-powered vessels, and is a valuable contribution to the field of Prognostics and Health Management (PHM) for battery systems in general.

In the last two years, multiple contributions to the PHM Society have predominantly addressed Lithium-ion battery (LIB) reliability and safety within Electric Vehicle (EV) applications. (Jia, Brancato, Cadini, & Giglio, 2024; Jia, Brancato, Giglio, & Cadini, 2024; Z. Zhang, Arrinda, & Perez, 2024) focused on safety diagnostics for Internal Short Circuit (ISC) detection, employing augmented Extended Kalman Filters (EKF) combining electrical and thermal measurements, or supervised machine learning models, respectively. Regarding state estimation, (Badfar, Mohammad, Chinnam, & Yildirim, 2024) tackled SoC generalization across domains using regression-based unsupervised domain adaptation, while (Lee, Yoo, Choi, Sung, & Heo, 2024) addressed robust SoC/SoH co-estimation for deeply degraded hybrid systems via Dual EKF and Fixed-Point Iteration methods. For prognostics, (Alcibar, Aizpurua, & Zugasti, 2024) quantified capacity fade uncertainty using Bayesian ensemble learning, supporting Health-Aware Control strategies by (Spinola Felix, Martinez-Molina, Bérenguer, Kulkarni, & Orchard, 2024) for degradation regulation in Vehicle-to-Grid scenarios.

While these studies significantly advance battery state estimation and behavioral modeling, ranging from observer-based methods like EKF to data-driven approaches such as Bayesian ensemble learning, none explicitly address online safety assessment or the operational implications of SoS, particularly in maritime contexts. Generally, the automotive sector's dominance in battery innovation has strongly shaped both technological development and regulatory focus. As a result, SoS remains only lightly explored within current research. In contrast, maritime applications introduce operational and safety constraints that differ substantially from those in road vehicles, including large-scale battery installations, limited onboard emergency response, and exposure to harsh environmental conditions. These characteristics underline the need for dedicated SoS development to support the safe and broader deployment of battery systems in vessels.(Vanem & Wang, 2025).

To address the above-mentioned challenges, this paper conducts a comprehensive literature review of the SoS concept, aiming to address the following three research questions (RQs):

1. What are the current definitions of SoS in the maritime and other industries?
2. What are the existing methods to estimate SoS?
3. What gaps remain in defining and implementing SoS in the maritime industry?

In addition to addressing these research questions, the paper advances the field of battery SoS through two novel contributions.

First, battery parameters reported in the literature for assessing cell-level safety are systematically collected and synthesized into a structured overview, together with their associated measurement methods and implementation challenges (Table 2). This overview is intended to support practitioners and researchers in identifying the requirements for comprehensive SoS assessment of battery cells.

Second, safety hazards identified in the European Maritime Safety Agency battery guidance are allocated across the BMS, SoS, and system design levels. This allocation clarifies the role of SoS as a dynamic safety evaluator that complements the safety functions ultimately governed by the BMS.

Finally, the paper highlights future research directions, including SoS interpretability and granularity, ultrasound-based monitoring, and testing in maritime environments, to further advance the applicability of SoS in maritime battery systems.

The remainder of this paper is organized as follows. Section 2 provides the necessary background on existing battery state indicators and defines the concept of SoS in detail. Section 3 outlines the research questions guiding this study. Section 4

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[1] State of Safety is abbreviated as both SoS and SOS in the literature. In this paper, we use SoS as the abbreviation of State of Safety consistently except when quoting papers that use SOS.

details the PRISMA-based literature review approach adopted. Section 5 presents the key findings and observations from the reviewed literature. Section 6 discusses future research directions for advancing SoS in the maritime industry. Finally, Section 7 concludes the paper by summarizing the main insights and implications for maritime battery safety.

2. BACKGROUND

2.1. Maritime Battery Safety Context

Ships operate in harsh isolated environments with limited emergency response capabilities. Vibrations, temperature fluctuations, humidity and salt corrosion from the marine environment all contribute to accelerated battery degradation (Mao, 2025; Vanem & Wang, 2025). Simultaneously battery systems introduce significant safety risks such as the thermal runaway risk that could lead to fire and explosion onboard (Mao, 2025), or loss of propulsion leading to collision or grounding (Vanem & Wang, 2025).

Consequently, demonstrating the safety and reliability of the battery system is essential for the safe operation and certification of battery-powered vessels. Currently the SoH level is used to quantify the degradation of the battery and risk level of the battery system (Wenzel, 2023). However it is strictly a capacity fade measurement and is not fully correlated to the safety level of the battery system. For instance an ISC could appear in a battery cell without the SoH varying significantly while the safety of the system drops significantly. In comparison, the SoS introduced by (Cabrera-Castillo et al., 2016) quantifies directly the safety level. By enabling a more accurate, context-aware and interpretable evaluation of risk, the SoS estimation enhances operational safety and allows for early detection of thermal runaway or other failures that would lead to catastrophic outcomes in operation, ensuring the safety and reliability of the vessel.

In addition, SoS evaluation can provide significant economic benefits for maritime battery systems. Real-time assessment of safety conditions can support safety-informed operational strategies that avoid harmful operating regimes, reduce battery degradation, and extend service life. Over the long term, these effects contribute to the reduction of repair costs as well as the prevention of operational disruptions or catastrophic failures, and their associated financial losses. At the same time, enhanced safety monitoring and risk mitigation can support regulatory compliance for battery-powered vessels and improve stakeholder confidence.

Integrating SoS within a PHM framework further enables condition-based maintenance and optimized battery replacement scheduling. This is particularly relevant in the maritime context, whereas battery systems typically have an operational lifetime of approximately 10 years, vessels are expected to remain in service for 25 to 30 years (Vanem et al., 2023). Battery replacements over the vessel lifetime therefore introduce substantial logistical and financial costs. By supporting more informed operational, maintenance, and replacement decisions, SoS has the potential to reduce unnecessary replacements, minimize vessel downtime, and improve the overall economic sustainability of battery-powered maritime systems, while simultaneously enhancing onboard safety.

2.2. Battery Management System (BMS) and EMSA Battery Guidance

A comprehensive maritime battery safety evaluation should first articulate the safety functions of the BMS and the hazard framework defined in the EMSA Battery Guidance (EMSA, 2023).

The BMS is a critical component for ensuring the safe and efficient operation of battery packs. It serves as the primary interface between the battery pack and the Energy Management System (EMS), enabling real-time data exchange and control coordination (Moon, Vennam, Tanvir, & Rahn, 2024).

The BMS continuously monitors key parameters such as cell voltage, temperature, and current. It then computes different SOXs, and finally performs cell balancing and fault detection. Under unsafe conditions, such as overcharging, overheating, or internal faults, the BMS initiates protective actions including current limitation, system isolation, and activation of alarms or fire suppression systems (Haghverdi et al., 2025). Ultimately the safety of the battery system as whole is the responsibility of the BMS. These safety functions are essential for preventing thermal runaway and ensuring compliance with operational safety standards (Cabrera-Castillo et al., 2016).

On the other hand, the EMSA Battery Guidance (EMSA, 2023) provides a broad functional capability recommendation list for the BMS, spanning monitoring, management, alerting, protection, and diagnosis. Specifically, it presents a list of all hazards maritime battery-powered vessels are subject to. However, EMSA's functional categories operate as discrete capabilities without a mechanism for integration into a coherent safety assessment. This fragmentation limits the ability of operators and automated systems to interpret the overall safety status of the battery system in real time. The SoS indicator addresses this gap by encapsulating the possibly unsafe state parameters into a unified, interpretable metric. By doing so, SoS transforms isolated functional checks into a continuous safety evaluation, enabling predictive and system-level decision-making aligned with PHM principles.

2.3. Battery State and Safety Indicators

The introduction already briefly outlined three battery state indicators: SoC, SoH, and SoS. This section presents a detailed definition of the existing battery state and safety indicators that will be referred to in the remainder of this paper.

State of Charge (SoC) The state of charge is the ratio of the current charge of the battery over the full charge of the battery.

$$SoC = \frac{Q_{current}}{Q_{max}} \tag{1}$$

where $Q_{current}$ is the current charge of the battery while Q_{max} is the maximum charge the battery has capacity for. It is important to note that the latter takes into account the capacity fade. The SoC is typically the percentage given on portable batteries indicating the battery charge status.

State of Health (SoH) The state of health is the ratio of the current capacity over the initial capacity of the fresh battery. It reflects thus the capacity fade and the internal resistance increase of the battery due to calendar and cyclic aging (S. Zhang, Guo, Dou, & Zhang, 2020). Calendar aging refers to degradation over time, independent of usage, while cyclic aging is the aging caused by cyclic charges and discharges.

$$SoH = \frac{C_{\text{Available}}}{C_{\text{Nominal}}} \tag{2}$$

where $C_{\text{Available}}$ denotes the battery's current usable capacity, and C_{Nominal} refers to its original rated capacity at the beginning of life (Vanem et al., 2021).

Safe Operating Area (SOA) The safe operating area (SOA) is the range of voltage, temperature and possibly other parameters within the battery is expected to operate safely (Lu, Han, Li, Hua, & Ouyang, 2013; Haghverdi et al., 2025). Conventional SOA is usually defined by the manufacturers themselves based on testing and empirical models relying on external variables (Haghverdi et al., 2025). However the work of (Couto et al., 2022) highlighted shortcomings to this framework by demonstrating charging regimes that were both faster and safer that violated the conservative limits of conventional SOA. These findings have motivated efforts to establish a dynamic SOA framework, although its development is still at an early stage (Haghverdi et al., 2025; Sarkar, Swamy, Amin, El-Halwagi, & Khan, 2024).

State of Safety (SoS) While SOA defines the permissible operating boundaries, it does not provide a real-time quantification of safety. *Calculation of the state of safety (SOS) for lithium-ion batteries* (Cabrera-Castillo et al., 2016) addressed this gap by presenting the first definition of the SoS. It is constructed to build upon the concepts of SOA by (Lu et al., 2013) and State of Function (SOF), that reflects the battery's ability to meet its power demand (Meissner & Richter, 2003) (not presented in detail in this paper), and aims at simplifying the evaluation of the safety of batteries through a unified, interpretable metric.

In (Cabrera-Castillo et al., 2016) the SoS is defined as the metric $SoS(\mathbf{x})$ varying between 0, representing a totally unsafe state, and 1, a completely safe state. Mathematically it is defined as:

$$SoS(\mathbf{x}) := \frac{1}{1 + f_{\text{abuse}}(\mathbf{x})} \tag{3}$$

$$f_{\text{abuse}}(x) \geq 0 \tag{4}$$

$\mathbf{x}$ includes all relevant battery state and control variables at time t, such as electrical, thermal, and mechanical indicators. The abuse function f_{abuse} equals zero under normal conditions and grows with increasing severity of abuse.

(Cabrera-Castillo et al., 2016) define the abuse function as a quadratic expression parameterized by two constants m and d, and a transformation $h(x)$ of the battery state vector $\mathbf{x}$, whose output can be both positive and negative.

$$f_{\text{abuse}} = m\big[h(\mathbf{x}) - d\big]^2 \tag{5}$$

To enable an interpretation of the SoS output, they introduce two reference operating conditions. An output of 1 of the SoS represents a totally safe state of the battery system while an output below $\zeta \in (0, 1)$ indicates a potentially unsafe state of the battery system. Mathematically, these can expressed as:

$$SoS(\mathbf{x}_{\zeta}) = \zeta \tag{6}$$

$$SoS(\mathbf{x}_{100}) = 1 \tag{7}$$

where $\mathbf{x}_{\zeta}$ denotes the operating conditions at which the SoS reaches the predefined lower safety level ζ, and $\mathbf{x}_{100}$ represents operating conditions associated with fully safe operation, giving 1.

Utilizing these new definitions and some basic mathematical operations, they end up with the following formulation of $SoS(\mathbf{x})$:

$$SoS(\mathbf{x}) = \frac{1}{\left(\frac{1}{\zeta} - 1\right)\left[\frac{h(\mathbf{x}) - h(\mathbf{x}_{100})}{h(\mathbf{x}_{\zeta}) - h(\mathbf{x}_{100})}\right]^2 + 1} \tag{8}$$

If the $SoS(\mathbf{x})$ goes below ζ, an alarm should be triggered to indicate probable unsafe state of the battery system.

The authors further simplify the original approach by assuming that variables act independently. Under this assumption, each variable has its own safety function $SoS_k(x_k)$, and the overall $SoS(\mathbf{x})$ is obtained by multiplying these functions.

$$SoS_k(x_k) = \frac{1}{\left(\frac{1}{\zeta} - 1\right)\left[\frac{h(x_k) - h(x_{k,100})}{h(x_{k,\zeta}) - h(x_{k,100})}\right]^2 + 1} \tag{9}$$

$$SoS(\mathbf{x}) = \prod_{k=1}^{n} SoS_k(x_k) \tag{10}$$

While simplifying greatly the computation of the SoS, this assumption disables the SoS to take height of the documented safety degradation due to interacting parameters (Song, Li, & Tang, 2023; Che, 2023). Examples of unsafe combination of parameters are high charging intensity with high SoC, and charging under subzero temperatures (Sethia et al., 2025; Lu et al., 2013).

Concluding Remarks In maritime applications, battery systems are currently required by class societies to compute SOC and SOH (*DNV Rules for Classification of Ships, Part 6 Chapter 2: Electrical Installations*, 2025). These indicators are essential for monitoring charge status and capacity fade, respectively. In contrast, both SOA and SoS remain active areas of research and are not yet widely implemented in commercial maritime systems. While SOA and SoS both relate to safe battery operation, they address safety from fundamentally different perspectives. SOA defines admissible operating regions for relevant variables such as voltage, current, and temperature, and is therefore a boundary-based concept. SoS, on the other hand, provides a continuous and probabilistic real-time quantification of safety, reflecting both the current operating conditions and their temporal evolution. As a result, SOA is primarily used to constrain operation, whereas SoS is intended to assess and track safety margins during operation.

Finally, although the SoS definition presented by (Cabrera-Castillo et al., 2016) conceptually builds on SOA and SOF, these are not directly incorporated into its mathematical implementation. Instead, SoS relies on a separate abuse function that evaluates the deviation from safe operating conditions, where such battery state and safety indicators could be incorporated. Additionally, the choice of a quadratic abuse function and setting of the safety threshold, is rather arbitrary while they are crucial to the SoS evaluation.

3. RESEARCH QUESTIONS (RQS)

This section details the three RQs that guide this study. Each question is accompanied by a brief rationale to clarify its relevance and scope.

3.1. RQ1: What are the current definitions of SoS in the maritime industry and other industries?

Numerous state indicators for batteries exist in the literature, yet their definitions are often fragmented and inconsistent. There is an urgent need for a unified method for quantifying maritime battery safety. The concept of SoS offers the potential to consolidate various state indicators into a single, interpretable safety metric. This RQ seeks to determine which aspects are currently encompassed by SoS, how widely adopted these definitions are, and whether there is precedence for SoS in the maritime industry. Furthermore, it explores how definitions from other industries may inform and support the maritime sector.

3.2. RQ2: What are the existing methods to estimate SoS?

This RQ explores the range of mathematical formulations and computational strategies proposed for SoS estimation. It analyzes the differing approaches in existing literature to real-time safety quantification and to the selection and integration of critical battery parameters. The objective is to capture the diversity of strategies used to represent safety margins and evaluate their suitability for implementation within maritime BMSs.

3.3. RQ3: What gaps remain in defining and implementing SoS in the maritime industry?

The thorough review of the literature required by the two first RQs is expected to also reveal the main challenges hindering the widespread adoption of SoS, as well as potential solutions. This RQ focuses on identifying the barriers to effective definition and implementation of SoS, particularly focusing on BMSs within the maritime industry. The findings will guide a list of future research directions for advancements in this domain.

4. METHODOLOGY

This section details the methodological approach adopted in the study. First, a systematic literature review was performed using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Page et al., 2021) to identify, screen, and classify publications addressing SoS definitions and estimation methods. The resulting evidence base captures both conceptual and practical perspectives relevant to the RQs. To extend this foundation, additional reviews on SoH estimation, BMS capabilities, battery technology trends, and prognostics were examined. Together, these sources provide a comprehensive understanding of current safety-related approaches and inform the identification of advancements that may support future SoS development (RQ3).

4.1. Literature Review Approach

To investigate the current definitions, methods, and gaps related to the SoS in battery systems, a systematic literature review was conducted following the PRISMA framework (Page et al., 2021). This methodology provides a structured approach to identifying, screening, and selecting relevant publications and is illustrated in Figure 1.

4.1.1. Scope and Criteria

The sources reviewed included peer-reviewed journal articles, conference papers, and master theses. The inclusion criteria were:

- Relevance to battery safety, SoS, or safety-state estimation.
- Accessible full-text documents.

4.1.2. Database Coverage

Google Scholar was used as the primary search engine due to its broad indexing of academic content. The initial query `allintitle`: "state of safety" returned 179 results across multiple research fields. To refine the scope to battery-related safety, the query was adjusted to `allintitle`: battery OR lithium OR LiOn OR "Lithium-ion" OR batteries OR BESS AND "state-of-safety" OR SoS OR "state of safety" OR "safety-state"

This refined search yielded 21 results, from which 12 publications were included in the review. Additional databases such as IEEE Xplore and ScienceDirect were consulted for additional material, however, they did not yield any further relevant publications at the time of the search. As such, Google Scholar was retained as the primary source for this study.

4.1.3. Screening Process

The screening process is illustrated in Figure 1. Following title and abstract screening, 7 of the initial 21 records were excluded due to lack of relevance to battery safety or safety-state assessment. Of the 14 remaining publications, 2 could not be retrieved in full text and were therefore excluded. The final dataset comprised 12 publications, all of which met the eligibility criteria and were included in the review.

Notably, several papers included in this review addressed the safety state and not the state of safety or SoS directly. This is voluntary as the review should enlighten us about not only the strict SoS but also about how safety in battery systems is considered. Some papers in the review do therefore not mention SoS at all. Nevertheless they are considered relevant as they present other approaches to the safety state definition of battery systems.

4.1.4. Review

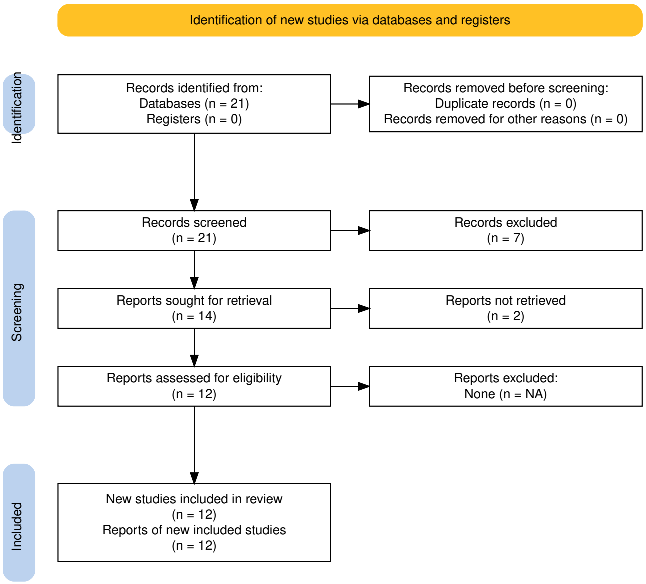

Figure 1. PRISMA flow diagram

Following selection, the papers were critically reviewed and systematically analyzed to enable an objective comparison of approaches to SoS. The analysis focused on predefined dimensions aligned with the research questions (RQ1–RQ3), ensuring coverage of both conceptual and practical aspects. These dimensions are summarized below and form the basis of Table 1:

- **Definition of SoS**
  - D1: Uses Cabrera-Castillo definition (Eq. 3)
  - D2: Extends Cabrera-Castillo definition
  - D3: Proposes new definition
  - D4: Presents different definitions
- **Domain**
  - M1: Automotive
  - M2: Marine
  - M3: Energy storage
- **Validation method**
  - V1: Experimental data
  - V2: Synthetic data
  - V3: Simulation data
  - V4: No validation
- **Objective**
  - S1: Avoid thermal runaway
  - S2: Prolonged lifetime
  - S3: Safe operation
  - S4: Other
- **System Level**
  - C: Cell
  - P: Pack

This structured categorization provides a clear overview of the state of the art and supports the identification of trends and gaps relevant to maritime applications.

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[2] translated from Chinese using `deepl.com`
[3] translated from Japanese using `deepl.com`

Table 1. PRISMA literature review on the state of safety in batteries

Ref.	**Title**	**Year**	**Def.**	**Obj.**	**Domain**	**Validation**	**System Level**
(Cabrera-Castillo et al., 2016)	Calculation of the state of safety (SOS) for lithium-ion batteries	2016	D1	S3	M3	V1	C
(Song et al., 2023)	Research progress on the safety-state assessment of lithium-ion batteries [2]	2023	D4	S1, S2, S3, S4	M3	V4	C
(Gu et al., 2025)	Early warning of thermal runaway based on state of safety for lithium-ion batteries	2025	D3	S1	M3	V1	C
(Wenzel, 2023)	State-of-safety (SoS) data-driven assessment for utility-scale lithium-ion operating BESS	2023	D1	S3	M3	V1	C & P
(Sethia et al., 2025)	Quantitative Assessment of State of Safety of Lithium-ion Batteries	2025	D2	S3	M1	V1	C
(Vanem & Wang, 2025)	Data-driven state of health and state of safety estimation for alternative battery chemistries	2025	D1	S2, S3	M2	V4	C
(Kim & Choi, 2025)	Adaptive Safety Modeling for Improved Battery Protection via Integrated State-of-Safety Estimation	2025	D2	S1, S3	M3	V1	P
(Moon et al., 2024)	State of Safety Assessment in Electric Vehicle Battery Packs	2024	D3	S1	M1	V1	P
(Morita, Tsuruga, Honda, & Koshika, 2024)	Verification of Non-Destructive Diagnosis of Battery Internal State Using Charging Curve Analysis for SOH/SOS Estimation of EV Batteries [3]	2024	D3	S1	M1	V1	C
(Koch & Schweiger, 2022)	Possibilities for a quick onsite safety-state assessment of stand-alone lithium-ion batteries	2022	D3	S3	M1	V1	P
(H. Zhang, Xu, Shi, He, & Liu, 2023)	Fuzzy Comprehensive Safety State Evaluation of Energy Storage Batteries Based on Variable Weight Theory and Combination Weighting	2023	D3	S3	M3	V1	P
(Xia et al., 2024)	Technologies for energy storage power stations safety operation: Battery state evaluation survey and a critical analysis	2024	D3	S3	M3	V4	C

4.2. Existing Reviews

In addition to SoS-specific literature, recent reviews on SoH estimation, BMS functionality, prognostics, and battery technology were examined (Diaz, 2020; Vanem et al., 2021, 2023; Vanem & Wang, 2025; Guo et al., 2024; Lu et al., 2013; Haghverdi et al., 2025; Wei, 2025; Nazaralizadeh, Banerjee, Srivastava, & Famouri, 2024; Che, 2023). These reviews and their cited works provided broader context and helped identify complementary research avenues that could enhance SoS estimation.

4.3. Original Contributions to SoS

This review provides two original and complementary contributions that clarify the operational role of SoS within maritime battery safety architectures:

1. A structured table that identifies the key indicators that an SoS estimation should include, at the cell level, together with their associated measurement methods and the practical challenges linked to each parameter (Table 2). This mapping clarifies which physical quantities are most relevant for real-time safety assessment and highlights the current limitations in sensing, integration, and interpretability.
2. A novel allocation of hazard–mitigation responsibilities across the BMS, the SoS, and the system design (Table 3). Based on the hazard list published by EMSA in (EMSA, 2023), the proposed allocation distinguishes between: (i) discrete or binary fault conditions that remain under the responsibility of the BMS, (ii) dynamically evolving parameters that should be monitored through SoS, and (iii) structural or environmental hazards that must be addressed through design measures. This allocation formalizes a layered safety concept in which discrete fault detection, continuous safety evaluation, and design-level mitigation are treated as distinct but interacting safety functions. Within this framework, SoS is positioned as a complementary safety layer to the BMS. Instead of trying to replace the BMS's fault handling and overall safety responsibility, it augments it by continuously quantifying the evolution of safety margins between normal operation and critical failure.

Together, these two contributions refine the operational scope of SoS, clarify its interaction with existing BMS and design-level safety functions, and establish a practical foundation for integrating SoS into maritime battery systems without redefining established safety responsibilities. This distinction is particularly relevant for maritime applications, where limited emergency response and long service lifetimes demand a clear separation between real-time protection, safety margin monitoring, and preventive design measures.

5. KEY OBSERVATIONS

The methodology outlined in the previous section establishes a consistent foundation for addressing the RQs. The PRISMA-based review and its classification scheme ensure that the evidence base is both systematic and traceable, enabling a structured synthesis of how SoS is defined, how safety-related methods are implemented, and where knowledge gaps persist.

This section synthesizes the key observations derived from the reviewed literature and is organized in alignment with the research questions. First, the results of the PRISMA-based literature review are summarized and supported by an overview of the screened publications (Table 1). Second, existing SoS definitions and associated estimation methods across different application domains are analyzed. As most SoS definitions are tightly coupled with a corresponding estimation approach, RQ1 (Section 3.1) and RQ2 (Section 3.2) are addressed jointly.

Finally, the analysis shifts to maritime-specific considerations to address RQ3 (Section 3.3). This includes the identification of critical battery parameters relevant for SoS estimation together with their measurement methods and practical challenges, as well as a structured allocation of safety responsibilities among the BMS, SoS, and system design based on the hazards listed in the EMSA battery guidance (EMSA, 2023). Together, these observations bridge key gaps identified in the literature and clarify the operational role of SoS within maritime battery safety architectures.

5.1. PRISMA Review on Battery SoS

Table 1 summarizes the reviewed publications according to definition type, objectives, domain, validation approach, and system level.

The key observations from the literature review are:

- (Cabrera-Castillo et al., 2016) is confirmed as the cornerstone of SoS research:
  - Written in 2016, it contains the earliest title mention of SoS, while all other reviewed publications were published after 2022.
  - Cited by seven of the other publications.
  - Three papers directly adopt its definition.
  - Two others extend on it.
- The reviewed publications are distributed across domains as follows:
  - Energy storage is the most represented with seven instances.
  - Closely followed by the automotive industry with four instances.
  - Only one reviewed paper has a link to the maritime industry in its body (Vanem & Wang, 2025).
- Three papers reduce battery safety to thermal runaway avoidance. While most critical risks associated with bat-

teries are linked to the onset of thermal runaway, a battery system that is not in nor close to a thermal runaway state is not necessarily in a safe state either.

- Ten out of twelve papers validated their methodology and all did so through experimental results.
- Seven out of twelve papers do not tackle the SoS of the pack at all and instead focus on the cell level only.

5.2. Current Definitions and Estimation Methods of SoS for RQ1 and RQ2

Building on the PRISMA-based synthesis, this section analyzes how the reviewed studies define and estimate SoS, thereby jointly addressing RQ1 and RQ2. This integrated approach ensures that conceptual interpretations (RQ1) and quantitative estimation techniques (RQ2) are examined in a unified manner, facilitating a clearer understanding of how safety is characterized and assessed across different studies. Grouping these elements provides a direct link between theoretical definitions and practical implementation.

Quantitative Indicators Most SoS formulations discussed in this review are based on quantitative indicators, where safety is expressed as a continuous variable, typically normalized between 0 and 1. In such formulations, the SoS provides a graded and time-varying measure of safety margins, allowing continuous tracking of how operating conditions evolve relative to unsafe states.

Several papers highlight a need for refinement of the SoS definition by Cabrera-Castillo et al. (Eq. (3) to (8)) (Sethia et al., 2025; Kim & Choi, 2025; Vanem & Wang, 2025).

First and foremost, modeling the abuse through the definition of the quadratic f_{abuse} function is non-trivial. Especially considering the concurring and intricate effects of different battery parameters, such as temperature, voltage, and current as well as history.

Already in the foundational paper on SoS (Cabrera-Castillo et al., 2016), a formulation with individual parameters (Eq. 9 and 10) is presented in addition to Eq. 8. There each parameter is treated independently, with individual safety subfunctions, which are then multiplied to yield the overall SoS (Eq. 9 and 10). This approach neglects the documented compound effects of interacting parameters (Song et al., 2023; Che, 2023). For instance charging at subzero temperature is a significant hazard due to increased lithium deposit and is an example of the need of considering several parameters simultaneously for correct risk quantification (Sethia et al., 2025; Lu et al., 2013).

The following papers present various enhancements to the original SoS definition, as identified in the literature.

(Kim & Choi, 2025) proposed a sigmoid-based abuse function, replacing the quadratic form. This yields a piecewise SoS function that is 1 when that the battery pack is under safe conditions, becomes sigmoid in the warning zone, and 0 when unsafe. This formulation mitigates the compound threshold effects that may obscure early warnings.

(Sethia et al., 2025) introduced a sensitivity-weighted approach, arguing that certain abuse conditions are more critical than others, like temperature compared to voltage for instance. They replaced the multiplicative combination of subfunctions with a summation of weighted abuse functions giving:

$$SoS(x) = \frac{1}{1 + \sum_i \alpha_i f_{\text{abuse},i}(x_i)} \tag{11}$$

with α_i the sensitivity parameter that allows to adjust the contribution of the different abuse conditions to the total abuse.

Furthermore they introduce a dynamic safety threshold $\eta(x)$ based only on individual safety thresholds η_i that correspond to the active abuse conditions.

$$\eta(x) = \frac{1}{1 + \sum_i \left(\frac{1}{\eta_i} - 1\right)} \tag{12}$$

This approach reduces threshold levels during high-risk operations such as charging, thereby improving reliability by minimising false alarms under conditions where elevated risk is expected. Sensitivity parameters were determined through fault tree analysis, drawing on the probabilistic degradation modeling framework proposed by (Sarkar et al., 2024).

Other papers choose to redefine the original SoS definition. In *Early warning of thermal runaway based on state of safety for lithium-ion batteries*, (Gu et al., 2025) they construct an evaluation matrix A with all the evaluation indicators normalized for each cell.

$$A = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1m} \\ V_{21} & V_{22} & \cdots & V_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nm} \end{bmatrix}$$

The matrix is of size n×m, where n indicators are monitored across m cells.

In the paper the chosen evaluation indicators are median voltage, temperature rise, SoH, peak power, and strain.

Two reference states are defined: an optimal state (D+), representing the safest operating condition, and a worst state (D-), representing the onset of thermal runaway are defined. The SoS is then obtained as the ratio of the weighted distance from the current state to D- over the sum of weighted distances to both D+ and D-, ensuring the SoS remains between 0 and 1. The weighting coefficients for each indicator are assigned manually. Although not presented here it should also be mentioned that the authors have also defined a specific SoS for charging conditions that is significantly different from the one presented here for discharging conditions. Furthermore, safety here is reduced to the weighted distance from thermal runaway conditions and does not consider other hazards.

Qualitative Indicators The discussion so far has centered on quantitatively defined SoS formulations, but there are also approaches that characterize safety through qualitative indicators. In these formulations, the output of the SoS does not longer vary continuously but switches between levels. Qualitative SoS indicators are typically rule-based or threshold-driven and are primarily intended for classification and alarm generation rather than fine-grained safety margin assessment.

In contrast to quantitative indicators, which support continuous safety evaluation and trend analysis, qualitative indicators provide simpler safety representations that are easier to interpret but offer limited resolution on the evolution of safety margins.

(Moon et al., 2024) propose an SoS assessment method based on deviations in voltage and temperature. At each time step, the difference between an individual cell's voltage or temperature and the pack mean is calculated. This value is then compared to its initial difference to obtain the residual delta. The following equations illustrate the computation, where X represents the voltage V or the temperature T:

$$\Delta X_i[k] = X_i[k] - \frac{1}{n}\sum_{i=1}^{n} X_i[k] \tag{13}$$

$$\Delta^2 X_i[k] = \Delta X_i[0] - \Delta X_i[k] \tag{14}$$

A warning is triggered when the delta residual exceeds three times the standard deviations based on the n-1 previous time steps.

(Morita et al., 2024) define three outputs to the SoS, “Safe state”, “Use with caution”, and “Replacement required”. The status update is triggered by the charge–discharge curve, with lithium deposition detection playing a key role. The kneepoint, where the lithium deposition rate increases significantly, is identified as a reliable indicator of the transition from safe to unsafe conditions.

(H. Zhang et al., 2023) propose a “fuzzy comprehensive safety state evaluation” method for BESS, integrating variable weight theory and combination weighting to enhance assessment accuracy. The fuzzy logic enables a hierarchical index system where the safety state is expressed in levels: serious, remarkable, normal, and good. These are put together using a half-ladder and half-ridge function. Further, the evolution from one level to another is dependent on chosen battery parameters combined with variable weights. This method highlights the non-binary nature of safety, as well as the changing relative importance of certain parameters towards safety, offering as a whole a more adaptive view of safety. It represents an alternative perspective compared to the SoS metric, focusing on interpretability and engineering applicability rather than numerical quantification.

(Xia et al., 2024) present a comprehensive review of battery health evaluation and safety operation technologies for energy storage power stations. They highlight data-driven methods and edge computing platforms to monitor internal and external battery parameters for improved safety assessment. A novel entropy-based approach is proposed to detect inconsistencies based on the idea that failing batteries have increasing presence of unordered data. While not explicitly using the SoS framework, the paper presents new approaches that reflect the inherently multi-faceted nature of battery safety.

(Koch & Schweiger, 2022) describe a practical implementation in an EV of an SoS evaluation algorithm following a decision tree. The evaluation of the SoS follows a series of decision blocks based on thresholds on current, voltage, temperature as well as event check like crash detected, isolation error, etc. The answer to each decision block is either yes or no and the result is either green, orange or red according to the criticality of a threatening condition of the battery.

In summary, the reviewed definitions and estimation methods reveal an absence of implementation in the maritime industry and significant diversity in how SoS is conceptualized and operationalized. This directly addresses RQ1 by highlighting the lack of consensus on what constitutes a safe state, and RQ2 by illustrating the range of mathematical approaches used to quantify safety. These variations underscore the complexity of defining SoS in a way that is both theoretically sound and practically implementable for maritime battery systems. The next section builds on these observations to identify gaps that hinder standardization and robust application in maritime contexts.

5.3. Parameters for Estimating the SoS for RQ3

While definitions and estimation methods clarify how SoS is formulated, practical implementation ultimately depends on the parameters that can be measured or estimated. This section therefore outlines the key parameters that should be included in an implementation of a comprehensive SoS formulation, at the cell level, following RQ3. It presents a summary of the works of (Cabrera-Castillo et al., 2016; Koch & Schweiger, 2022; Song et al., 2023; Wenzel, 2023) in identifying key indicators and discusses the challenges associated with their measurement as well as available measurement methods based on *Advancements, Challenges, and Future Trajectories in Advanced Battery Safety Detection* (Wei, 2025). The findings are presented in Table 2, an original contribution of this paper that systematically maps identified key indicators for cell-level

Table 2. Key parameters for comprehensive cell-level SoS estimation together with associated measurement methods and challenges

Indicator	Measurement Method	Challenge
Voltage	Direct via BMS	Threshold selection
Current / C-rate	Direct via BMS	Context-dependent safety limits
SoC	Coulomb counting / voltage models	Drift over time
Internal Temperature	Fiber optics / thermal models	Cost, invasiveness
External Temperature	Surface sensors	Thermal lag
Strain	Fiber optics / ultrasound	Sensor placement, interpretation, cost
SoH	Model-based / Data-driven	Requires ageing model
Internal Resistance	DC pulse	Interpretation
Electrochemical Impedance	Electrochemical Impedance Spectroscopy	Equipment limitations
Lithium Plating	Relaxation voltage / impedance	Indirect, interference from other effects

SoS estimation to corresponding measurement methods and associated challenges. Eventually it shows that there is no single best indicator nor measurement method, however the combination of the different indicators might help overcome these challenges.

5.3.1. Electrical Parameters

- **Voltage:** Using flexible all-in-one microsensors, optical voltage sensor, or even integrated circuits the voltage can be directly measured. Voltage monitoring is paramount for correct SoS estimation as overvoltage and undervoltage conditions are linked to hazardous outcomes such as electrolyte decomposition or dendrite formation (Cabrera-Castillo et al., 2016).
- **Current and C-rate:** Measured and limited by the BMS. High current rates contribute to Joule heating and lithium plating. However, interpretation depends on context, e.g., a 3C charge may be safe at room temperature but hazardous at subzero conditions (Sethia et al., 2025). Different sensors can be considered; Hall-effect current sensor, shunt resistor, or even fluxgate current sensors (Wei, 2025).
- **SoC:** High SoC corresponds to a large amount of stored energy, which increases the operational stress on the cell and amplifies the severity of events such as thermal runaway. SoC is typically estimated via Coulomb counting or voltage-based models (Cabrera-Castillo et al., 2016). Coulomb counting consists of integrating the current to estimate the capacity of the battery (Vanem et al., 2023). Small deviations causes the SoC estimate by Coulomb counting to diverge eventually, however integrating an EKF on top of it can limit the uncertainty bounds (Plett, 2004).

5.3.2. Thermal Parameters

- **Internal Temperature:** Internal temperature is a critical parameter for detecting early signs of thermal runaway and for avoiding subzero operation, where lithium plating can significantly reduce the safe operational boundaries. Direct measurement is challenging: fiber-optic sensors and thermocouples provide accurate data but are costly and invasive (Wei, 2025). As an alternative, internal temperature can be estimated using observers or thermal models but with a significant lag (Song et al., 2023).
- **External Temperature:** In absence of internal temperature measurement, an external temperature measurement using a thermo-resistive sensor can help evaluating the internal temperature. Contrary to internal temperature, it is easily measured, however it may not reflect internal conditions accurately (Kim & Choi, 2025).

5.3.3. Mechanical Parameters

- **Strain:** Strain has emerged as a promising early indicator of thermal runaway, often preceding temperature rise by several seconds (Gu et al., 2025). It can be measured using strain gauges or external pressure sensors (Wei, 2025) or with ultrasounds (Khan, Gierc, & Hossain, 2025).

5.3.4. Aging Indicators

Aged batteries may exhibit lower thermal runaway onset temperature, increased gas generation, and higher internal resistance (Haghverdi et al., 2025; Song et al., 2023; Morita et al., 2024). Therefore the aging must be included in the state of safety assessment.

- **SoH:** SoH quantifies the capacity fade of the battery from its fresh state and is generally used for establishing the battery's EOL (Cabrera-Castillo et al., 2016; Vanem et al., 2021). There is a variety of SoH estimation methods depending on the battery chemistry and data availability, from model-based approaches to purely data-driven techniques (Vanem et al., 2021, 2023; Vanem & Wang, 2025). It is generally the battery manufacturer's responsibility to provide a reliable SoH estimation algorithm (Vanem et al., 2023).
- **Internal Resistance:** Internal resistance is a key indicator of ageing and degradation. It reflects the battery's ability to transport charge and is influenced by solid electrolyte

interphase (SEI) growth, loss of contact between electrode particles, and passivation of active materials. It is typically measured by DC Pulse Testing which is suitable for in-situ measurement. It involves applying a current pulse and measuring the voltage response (Cabrera-Castillo et al., 2016). The drawback is that it is challenging to interpret the response relatively to other effects (e.g. SoC and temperature).

- **Electrochemical Impedance:** Electrochemical impedance represents the battery's opposition to alternating current across a range of frequencies, capturing both resistive and reactive components. It provides insight into electrochemical processes such as charge transfer and diffusion, making it valuable for advanced diagnostics and aging analysis. Electrochemical Impedance Spectroscopy (EIS) provides detailed insights into charge transfer and diffusion processes. However it requires specialized equipment and is typically used in laboratory settings (Song et al., 2023).
- **Lithium Plating and Dendrite Formation:** Lithium plating is a critical degradation mode linked to overcharge, low temperature, and high C-rate. Detection methods include relaxation voltage analysis, which observes a voltage plateau during post-charge rest; a combination of electrochemical impedance and internal resistance measurement (Pan, Ren, Han, Lu, & Ouyang, 2022); impedance spectroscopy, which detects abnormal changes in charge transfer resistance; and coulombic efficiency, which measures irreversible capacity loss due to plating (Song et al., 2023). These methods vary in complexity and feasibility for online application, with electrochemical techniques being the most promising for integration into BMS according to (Song et al., 2023).

5.4. Maritime Industry Specificity

Although the identified parameters apply across multiple domains, their behavior, measurement feasibility, and safety implications are strongly shaped by the operational environment. The following subsection therefore focuses on the specific challenges associated with maritime battery systems.

5.4.1. SoS in the Maritime Industry

In agreement with the observation by (Vanem & Wang, 2025), our review finds no documented academic implementation of SoS in maritime applications. In contrast, practical applications of a monitoring of the safety of batteries are evident in EV and BESS. The accelerated deployment of batteries in EVs has been a major driver for regulatory evolution in transport safety. China's GB38031 standard Electric Vehicle Traction Battery Safety Requirements illustrates this progression. The 2020 revision mandated that an alarm signal be triggered within five minutes of thermal runaway initiation, while the 2025 update introduced a more stringent requirement which is containment of the event for at least two hours without fire or explosion (Neumann & Stahl, 2025). Unlike land-based contexts, vessels cannot rely on rapid external emergency response. This changes the safety strategy fundamentally, placing a strong emphasis on preventing the onset of thermal runaway and ensuring the containment of fire or explosion in the battery room. Moreover, existing standards, like the GB38031, require testing on fresh battery packs, whereas maritime applications are more concerned with the behavior as the system approaches EOL. Maritime degradation pathways are influenced by operational load profiles, vibration exposure and environmental stressors, all of which make the design of representative test protocols and maritime-specific regulation a research challenge in itself. In this regard, the development of the SoS indicator could support the identification of the most critical degradation mechanisms and clarify their impact on safety margins.

5.4.2. BMS and SoS

These maritime-specific constraints further emphasize the need to clarify the respective roles of the BMS and SoS.

The literature review did not reveal any publication that clearly delineates the respective responsibilities of SoS and BMS, which suggests a gap in the current understanding of maritime battery safety. Although the EMSA battery guidance (EMSA, 2023) provides a comprehensive list of hazards, it does not specify which system should address each hazard. This ambiguity emerged as a critical observation during the review process. Clarifying the scope of SoS and distinguishing its role from that of the BMS is necessary to enable practical implementation of SoS within the maritime industry, answering to RQ3. To respond to this need, this paper proposes a novel categorization of the hazards identified in the EMSA guidance, organized according to the system responsible for mitigation. This categorization, presented in Table 3, constitutes an original contribution of this work and was developed to address the identified gap rather than being derived directly from the literature.

The purpose of this categorization is to define the scope of SoS and clarify its relationship with the BMS and the system design. The SoS, as first defined by (Cabrera-Castillo et al., 2016), quantifies dynamic parameters in relation to safety, while the BMS retains responsibility for real-time operational safety, and design measures address high-level structural and environmental risks. In Table 3, hazards are grouped according to the system responsible for mitigation: discrete or binary fault conditions during operation (e.g., sensor failures) are typically managed by the BMS; dynamic parameters that may evolve into unsafe states (e.g., temperature rise) are monitored and assessed through SoS; and structural or environmental hazards (e.g., flooding of the battery room) are addressed

Table 3. Hazards listed by (EMSA, 2023) allocated to BMS, SoS, and design

BMS	SoS	Design
• Internal short-circuit • External short-circuit • Earth faults • Sensor failure • Leakage (electrolyte, cooling system) • Failure of BMS • Loss of cooling • Loss of communication between battery packs and power management system • Humidity and salt intrusion (maritime application)	• High impedance (cell, connectors, . . .) • Over temperature and mechanical stress • Thermal runaway	• Rupture of the casing of cell, battery module, pack, or system with exposure of internal components • Overpressure • Fire • Explosion • Venting out flammable, corrosive and toxic gases • External ingress • Structural integrity • Water event, flooding • Collision • Emission of combustion gases

through preventive and mitigative design measures.

Deriving indicators from the hazards listed in Table 3 clarifies which parameters are relevant for the SoS computation and which can be excluded. This categorization directly addresses RQ3 by providing a practical foundation for implementing SoS in maritime applications. Table 3 defines the operational scope of SoS, focusing on the online estimation of evolving safety conditions based on dynamic parameters, rather than encompassing the entire safety framework of the battery system, which also includes binary fault indicators and structural design measures. This distinction highlights how the SoS complements the safety functions of the BMS and the design-level protections.

5.5. Summary

In summary, the literature review shows a development of SoS estimation methods in automotive and stationary energy storage sectors, while maritime-specific implementations remain absent. The review highlights wide variation in definitions, heavy dependence on cell-level indicators, and the lack of a clear allocation of responsibilities between SoS and BMS. To address these gaps, we propose a hazard categorization based on EMSA guidelines (EMSA, 2023), presented in Table 3, and a synthesis of required measurements and integration challenges, summarized in Table 2. These findings form the foundation for the research directions outlined in the next section, which aim to improve interpretability, estimation accuracy, integration, and overall feasibility of SoS within maritime BMS.

6. FUTURE RESEARCH

In this section potential future research directions based on the reviewed literature and additional material are presented. The aim of this section is to provide the researchers and practitioners with insights for SoS development aimed at the maritime industry.

6.1. Interpretability

As mentioned in Section 1 Introduction, beyond enabling real-time safety estimation, the SoS should serve as a decision-support tool for determining battery EOL.

One critical gap identified in the reviewed literature is the lack of interpretability in SoS estimation methods. For SoS to become a trusted operational metric and potentially replace SoH, it must be transparent and easily understood by operators. Users should be able to anticipate how SoS behaves under different operating conditions. The original definition of SoS proposed by (Cabrera-Castillo et al., 2016) offers a mathematically straightforward formulation, yet in practice the indicator may fluctuate unpredictably due to the combined effect of multiple abuse functions (Eq. 9 and 10). For instance, during charging, SoS typically decreases because of elevated temperature and charge level, then rises again once charging ends. This behavior reflects the higher risk associated with charging, a phase known to account for a significant proportion of battery-related incidents. Such variations must be communicated clearly to avoid misinterpretation as system faults. (Sethia et al., 2025) introduced a dynamic safety threshold that updates in real time. Communicating it to the operator could potentially improve user understanding of SoS behavior. Alternative definitions, such as the alarm-based method proposed by (Moon et al., 2024), trigger warnings when voltage or temperature deviates significantly (Eq. 13 and 14). While effective for preventing severe degradation, this method provides limited diagnostic insight. A more interpretable approach was suggested by (Gu et al., 2025), which defines SoS as the ratio between the distance to thermal runaway and the total range from optimal to runaway conditions. This formulation offers intuitive insight into safety margins but narrows the scope to thermal runaway only. Future research should therefore focus on developing SoS estimation methods that enhance interpretability without sacrificing diagnostic capability. Achieving this balance is essential for wider adoption and for ensuring that SoS becomes a practical and reliable metric in maritime battery systems.

6.2. Ultrasound Monitoring

A promising research direction for enhancing SoS estimation involves integrating ultrasound-based monitoring techniques. As demonstrated by (Gu et al., 2025), strain monitoring is an effective early indicator of thermal runaway. Ultrasound offers a non-destructive, minimally intrusive solution for in situ state estimation, capable of detecting mechanical changes such as variations in Young's modulus, strain, and density within electrode materials. These changes correlate with internal battery changes such as lithium intercalation, phase transitions, and degradation processes.

Several studies have validated the potential of ultrasound for battery diagnostics. (Yang, 2025) reported a reduction in SoC estimation error from 2.01% (using EKF alone) to 0.63% when ultrasound measurements were incorporated. Similarly, (Renais, 2025) demonstrated ultrasound integration within BMS architectures for structural monitoring and reliable SoH evaluation. Additionally, (Lee, Seo, & Ma, 2025) demonstrated the use of multi-frequency ultrasound monitoring for early warning of thermal runaway on LIB under heating. Their results show an early warning of thermal runaway before occurrence from 270.5 s to 1128.4 s.

Contactless ultrasound techniques based on electromechanical acoustic technology have also proven effective for online state characterization in industrial applications, overcoming the constraints posed by metallic hard-case battery packs common in maritime systems (Li, 2024; Fariñas, 2024). Furthermore, (Binpeng, 2025) highlighted the potential of combining ultrasonic testing with advanced algorithms such as sparrow search and relevance vector machines for SoC and SoH estimation without prior knowledge, enabling periodic recalibration in systems lacking permanent ultrasound equipment. Ultrasound imaging has also been applied to detect lithium plating during cycling, offering valuable insights for maintenance and survey operations (Wasylowski, 2024).

One limitation of ultrasound monitoring is its sensitivity to temperature variations, which can affect measurement accuracy. Nevertheless, its integration into SoS frameworks represents a significant opportunity. By continuously tracking strain and deformation patterns, ultrasound can identify discrepancies between expected and observed mechanical responses based on SoC and SoH predictions. Such deviations may signal abnormal or unsafe behavior, including internal short circuits, gas formation, or lithium plating. Incorporating ultrasound data into SoS estimation could therefore enhance real-time safety assessment, enabling earlier intervention and improved risk mitigation or even failure avoidance in maritime battery systems.

6.3. Granularity

Maritime applications require safety assessment at the pack-level due to the large energy capacity and operational complexity of vessels. Unlike cell-level evaluation, pack-level analysis introduces additional challenges such as heat propagation between cells, fault isolation, and the coordination of safety procedures across modules (Wei, 2025). Nevertheless, inconsistencies among cells within a pack must be incorporated into the estimation process to avoid masking localized hazards (Xia et al., 2024). These aspects are critical for accurate SoS estimation but remain largely unaddressed in current research. Among the five reviewed papers that considered pack-level safety, only (Wenzel, 2023) applied the SoS algorithm simultaneously to cell and pack data. However, this approach did not explicitly account for inter-cell interactions or propagation effects as the algorithm was simply scaled from cell-level to pack-level measurements.

While SoC and SoH are inherently cell-level metrics that can be aggregated to higher levels, SoS is not tied to a specific scale. As such, it can, and should, be defined independently at each level to reflect the unique risk dynamics present at different scales. This is particularly relevant for large maritime battery packs, which often comprise thousands of cells (Vanem & Wang, 2025), making granularity essential for both interpretability and computational efficiency.

A promising research direction could be the development of hierarchical SoS algorithms that integrate cell-level estimations into a unified pack-level metric. Such an approach would enable multi-scale safety assessment, capturing both localized anomalies and systemic risks, and thereby improving predictive maintenance and fault localization capabilities in maritime battery systems.

6.4. Maritime Challenges

The literature review did not find documented SoS integration in maritime applications. Among the reviewed papers, (Vanem & Wang, 2025) is the only one explicitly linked to the maritime domain and it reached the same conclusion that SoS remains underexplored in current maritime battery safety practices.

This lack of documented implementation highlights the need to complement the literature-based findings with insights from maritime practice. Accordingly, future work will involve formal engagement with maritime stakeholders, such as ship operators and battery manufacturers, through structured interviews, to capture practical perspectives on the applicability of

SoS in maritime environments. Such engagement is expected to support the design of relevant real-world case studies by maritime researchers and practitioners, and evaluate the applicability of current SoS estimation methods. Furthermore, as introduced in Section 2.1, SoS estimation is expected to enable an enhanced PHM strategy by supporting safety-informed operation. Real-world case studies are therefore necessary to validate the assumption that SoS-informed battery operation can reduce replacement costs and financial losses due to operational disruptions, while simultaneously enabling safer operation and supporting regulatory compliance.

Beyond stakeholder perspectives and operational practices, maritime-specific environmental and operational conditions introduce additional challenges that directly affect battery safety and SoS estimation. A comprehensive survey by (Mao, 2025) identifies several factors that can accelerate battery degradation and compromise safety at sea, including vibrations caused by wind and waves, humidity within battery rooms, salt intrusion, corrosion, and rapid temperature fluctuations. Although many of these hazards can be mitigated during the design phase through robust safety barriers and mitigation strategies, their combined impact on battery aging and SoS estimation is poorly understood. Certain issues, such as salt intrusion and humidity, can be managed by the BMS, but their interaction with other factors may lead to complex degradation patterns. Understanding these interactions is essential for developing SoS models that accurately capture operational risks and support predictive safety strategies for maritime battery systems.

To address this knowledge gap, testing under realistic maritime conditions should be conducted to quantify how these stressors influence the safety and reliability of battery packs (Mao, 2025). Several methodological considerations can be identified based on the reviewed literature. In particular, experimental campaigns should consider variations in ambient and operating temperatures, significant wave height, and current load profiles, while maintaining other operating parameters as constant as reasonably possible. Such controlled variation would allow isolation of the impact of maritime-specific stressors on safety-related indicators and SoS behavior.

7. CONCLUSION

This paper addressed three research questions on the SoS for battery systems with a specific focus on maritime applications. The objective was to clarify how SoS is currently defined, how it is estimated, and which gaps hinder its adoption in the maritime domain. A PRISMA-based systematic literature review was conducted and complemented by recent work on SoH estimation, BMS functionality and battery safety to build a comprehensive overview of the state of the art.

For RQ1, we did not find any clear maritime-specific SoS definition in the literature, despite active development within the automotive and stationary energy storage sectors. Existing definitions remain centered around the foundational formulation by (Cabrera-Castillo et al., 2016), with several works proposing mathematical refinements or qualitative alternatives. As none of these approaches capture the full breadth of safety concerns relevant to battery systems, the current landscape is characterized by conceptual heterogeneity. For RQ2, estimation methods were found to range from parameter-based formulations to weighted-distance metrics and fuzzy evaluation schemes, each tied to a particular definition of SoS. However, most approaches rely on cell-level indicators and do not consider maritime-specific operational hazards or system-level interactions. Finally, RQ3 revealed several critical gaps including the absence of a common understanding of SoS, the lack of a clear hazard responsibility allocation across safety-critical systems, limited interpretability of holistic formulations and scarce knowledge on the effects of maritime-specific stressors such as vibration, salt intrusion and fluctuating thermal environments.

This paper contributes to the development of SoS for the maritime industry in four ways. First, it provides a structured mapping of SoS definitions, estimation methods and application domains. Second, it identifies and consolidates the key parameters required for a general SoS formulation and discusses their associated measurement challenges. Third, it allocates hazards listed in the EMSA battery guidance among the BMS, SoS and design measures, thereby linking SoS directly to maritime safety requirements and clarifying its operational role. Fourth, it outlines future research directions centered on interpretability, ultrasound-based sensing and multi-level granularity to support robust SoS integration within maritime BMS architectures.

This work is limited to publicly available academic literature and does not address differences across battery chemistries. Nonetheless, the findings highlight the relevance and potential of SoS to support risk-informed, health-aware operation of battery-powered vessels. The results motivate further experimental studies and real-world testing specifically aimed at understanding and quantifying safety margins for batteries operating in maritime environments.

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