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Toward Anomaly Representation in Lithium-Ion Batteries: An Ontology-Based Approach

Marwa Zitouni^{a,*}, Franco Giustozzi^a, Ahmed Samet^a, Tedjani Mesbahi^a

^aUniversité de Strasbourg, 67000, France Institut National des Sciences Appliquées (INSA Strasbourg), 67000, France CNRS, ICube Laboratory UMR 7357, Strasbourg, 67000, France

Abstract

In today's energy-dependent world, ensuring the safety and efficiency of lithium-ion batteries is crucial. Early representation of anomalies becomes essential for optimizing performance, reducing disruptions, and prolonging battery lifetime in electric vehicle applications. This objective necessitates the integration of data from distributed and heterogeneous sources, a challenge traditionally tackled by semantic web technologies. In response, this paper introduces an ontology-based model that capitalizes on representing anomalies in lithium-ion batteries. Ontologies play a vital role in representing knowledge in a machine-interpretable format. Our approach enriches sensor data with contextual information, employing structured concepts, rules, and semantics specifically designed for representing anomalies in lithium-ion batteries.

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Keywords: Lithium-Ion Batteries ; Anomaly Representation ; Ontology.

1. Introduction

Lithium-ion batteries have become integral to the advancement and functionality of a broad spectrum of technologies, from everyday portable electronics to electric vehicles, playing a pivotal role, especially in electric vehicle (EV) applications. Their superior energy density, longevity, and stability over other types of batteries make them the ideal choice for powering electric vehicles. These vehicles, which often require consistent and reliable energy for long-distance travel and efficient operation, necessitate robust and enduring battery solutions. As the electric vehicle market rapidly expands to include a diverse range of models and systems, the reliance on lithium-ion batteries is expected to increase significantly. This burgeoning demand underscores the critical need for advanced battery management and precise fault diagnosis systems. Effective diagnostic techniques that can identify and rectify anomalies in lithium-ion batteries are essential, not merely for the operational efficiency of electric vehicles but also for their sustainability.

* Corresponding author.

E-mail address: marwa.zitouni@insa-strasbourg.fr

In addressing this need, our paper presents an approach not previously explored in the domain of lithium-ion battery, bridging the gap in the application of battery domain ontologies for anomaly representation. We significantly contribute to the field by: (i) conducting a systematic review of contemporary anomaly diagnosis methods, (ii) enhancing the BattINFO ontology [1] with additional properties, (iii) the development of new SWRL (Semantic Web Rule Language) rules for the descriptions of the modules and the semantic model for representing and classifying anomalies. (iv) As we conclude, we emphasize the critical importance of advancing battery technology research, particularly in response to the expanding needs of electric vehicle applications. We also suggest promising directions for future studies.

2. Related Work

In addressing safety and performance concerns of lithium-ion batteries, research has advanced in diagnostic techniques, notably categorized into knowledge-based and data-driven methods, as detailed by [18]. Knowledge-based approaches rely on the fundamental understanding of battery mechanics to predict and identify failures, whereas data-driven methods utilize algorithms and machine learning to analyze operational data for patterns indicating battery health. Together, these strategies aim to enhance battery safety and efficiency, supporting the reliable use of lithium-ion technology across various applications.

2.1. Data-Driven Methods

Data-driven approaches leverage statistical, machine learning, and deep learning algorithms to identify patterns, anomalies, or trends from historical and real-time data of battery operations. Among these techniques, machine learning techniques have been extensively researched and applied. One comprehensive review [16] discusses several key techniques, including Artificial Neural Networks (ANN) as discussed in [10, 16, 24] which is a computing system inspired by the biological neural networks that constitute animal brains. ANNs learn to perform tasks by considering examples, generally without being programmed with task-specific rules. They are particularly effective in identifying nonlinear relationships within large datasets, Support Vector Machines (SVM) as highlighted in the works of Hu et al. [10, 16, 24] is a supervised learning model used for classification and regression analysis. SVMs effectively create a decision boundary, called a hyperplane, that separates different classes of data with as wide a margin as possible, making them powerful for high-dimensional data analysis, Random Forest (RF) is explored by Samanta et al. and Liu et al. [16, 11] as an ensemble learning method for classification, regression, and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the Random Forest is the class selected by most trees. This method is known for its high accuracy, robustness, and ease of use, in the studies by [16, 15] Logistic Regression (LR) despite its name, is used for binary classification rather than regression. It estimates probabilities using a logistic function to model a binary dependent variable, making it suitable for cases where the response variable is categorical, Gaussian Process Regression (GPR) as explored by Samanta et al., Tagade et al., and Zhao et al. [16, 17, 24] is a non-parametric, bayesian approach to regression that provides a probabilistic prediction. GPR is particularly useful for estimating uncertainty about the predicted values, making it powerful for modeling complex phenomena where the prediction includes a measure of uncertainty.

2.2. Knowledge-Based Methods

Conversely, knowledge-based diagnostic methods, referenced in the work of Netzer et al. [14] rely on established rules and domain expertise to interpret system behavior and identify anomalies. Utilizing an understanding and observational analysis, proving particularly effective for complex and nonlinear systems like lithium-ion battery systems, without the need for developing mathematical models. Systems driven by this method facilitate explainability and knowledge sharing across diverse applications and domains. A concise introduction to some key knowledge-based methods follows: according to Hu et al. and Zhao et al. [10, 24] expert systems are computer programs that emulate the decision-making ability of a human expert. By using a set of coded rules that represent the knowledge and processes of the domain, expert systems can make inferences and provide explanations to the users about how the conclusions were derived. Graph Theory (Signed Directed, Fault Tree, Failure Mode and Effect Analysis) this method

uses graphs to model systems in a way that nodes represent entities or concepts, and edges represent the relationships between them. Signed directed graphs, as discussed in Yang et al. [23] specifically consider the direction and nature (positive or negative) of relationships. For Zhou et al. and Gao [25, 3] fault trees are a top-down approach to identify the root causes of failures, depicting the logical relations of system failures and potential faults. Failure Mode and Effect Analysis (FMEA), as detailed by Held et al. [9] systematically evaluates potential failures in a system, their causes, and effects, often visualized through these graphs for better understanding and analysis. Fuzzy Logic as explored in the works of Muddappa and Zhao et al. [12, 24] extends traditional boolean logic to handle the concept of partial truth, where truth values can range between completely true and completely false. It's particularly useful in dealing with uncertainty and reasoning about imprecise data, making it a powerful tool for knowledge-based systems in diagnosis and decision-making processes. Ontologies according to research by Mutz et al., Clark et al., Wessel et al., and Hamouni et al. [13, 2, 21, 8] in the context of knowledge representation provide a formalized representation of concepts, relationships, and constraints within a specific domain. They are used to model domain knowledge in a structured, machine-readable format, employing languages such as RDF (Resource Description Framework) or OWL (Web Ontology Language). Ontologies enable comprehensive understanding and reasoning about the domain-specific anomalies, in this case, lithium-ion battery anomalies. By encapsulating domain knowledge, ontologies facilitate explainability, interoperability, and knowledge sharing across different systems and applications, offering a robust framework for the diagnosis and analysis of complex systems.

2.3. Discussion

A comparison between data-driven approaches and knowledge-based systems highlights fundamental differences in flexibility and explainability. Data-driven methods excel in environments where large datasets are available, offering adaptability and the potential for uncovering unknown patterns or anomalies. However, they may suffer from the "black box" problem, where the decision-making process is not transparent, making it difficult to interpret or justify the results. On the other hand, knowledge-based methods, particularly those employing ontologies, provide a clear reasoning path for diagnoses, making them highly explainable and trustworthy. However, their effectiveness is contingent upon the completeness and accuracy of the underlying knowledge base, which can be challenging to maintain and update.

3. Semantic Model for Representing Anomalies in Lithium-Ion Batteries

This section presents the proposed ontology. First, an introduction and the main goals of the ontology are introduced and then the key ontologies utilized in our approach are also described.

3.1. General Overview

The aim of the ontology is to represent observed anomalies in lithium-ion batteries and their causes. Our ontology is inspired by [4], which entails combining multiple ontologies. Fig. 1 illustrates the key modules of the proposed domain ontology along with their relationships. According to [5] ontologies can be categorized into three main types: core ontologies, domain ontologies, and application ontologies, depending on their conceptual focus. Core ontologies provide general, domain-independent frameworks that are applicable across different fields of knowledge. In our case, these ontologies include time, location, and sensor ontologies, which fall into this category due to their universal applicability meanwhile the domain ontology is a specialized framework that focuses on a specific area of knowledge, defining its unique concepts, relationships, and entities. It provides detailed insights into a particular field, unlike general ontologies, to support interoperability and understanding within that domain in this case BattINFO belongs to this category.

As previously stated, our ontology integrates different ontologies as modules in order to describe lithium-ion batteries anomalies. These modules are Time module, Location module, Sensor module, BattINFO module and we introduce a new module called Anomaly module. This module allows a hierarchical organization of anomaly types and their characteristics. It provides relations to represent the association between an anomaly and its detected location and time as well as the properties that are involved (e.g. temperature, current and voltage).

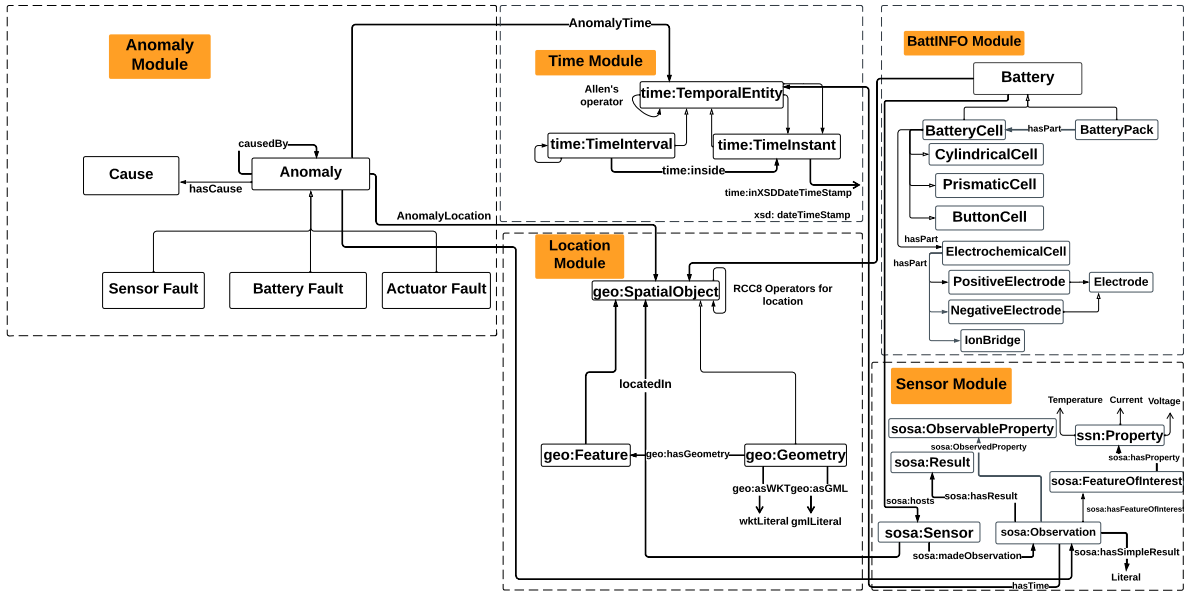


Fig. 1: An overview of the ontology.

The ontology is written in OWL (Ontology Web Language) [19] and is developed in Python using Owlready2¹, a library for ontology-oriented programming. The following subsections describe the different modules of the ontology.

3.1.1. BattINFO module

The BattINFO [1] module is an integral part of our ontology, specifically focusing on the battery domain. It offers a domain-specific ontology for describing lithium-ion batteries. In particular, the concept *Battery* which is defined as assembly of one or more electrochemical cells, used to provide devices with stored electrical energy. It has two sub-concepts: *BatteryCell*, defined as a basic functional unit, consisting of an assembly of electrodes, electrolyte, container, terminals and usually separators, that is a source of electric energy; *BatteryPack*, defined as a battery containing multiple cells and a casing. The relation *hasPart* allows to represent the fact that a *BatteryPack* has a *BatteryCell* as a part. Furthermore, the concept *BatteryCell* has the sub-concepts: *CylindricalCell*, *PrismaticCell* and *ButtonCell* to represent different shapes of lithium batteries. BattINFO enhances data interoperability and supports artificial intelligence workflows. This module is seamlessly integrated with other ontology modules, notably the *Sensor* module, through the *sosa:hosts* relation. This relation enables to state that a sensor is attached to a battery. The example below describes the case of a *BatteryPack* that contains two *CylindricalCell*.

$$\text{BatteryPack}(bp) \wedge \text{CylindricalCell}(cc1) \wedge \text{CylindricalCell}(cc2) \wedge \text{hasPart}(bp, cc1) \wedge \text{hasPart}(bp, cc2)$$

3.1.2. Sensor module

Developed by the W3C’s Semantic Sensor Networks Incubator Group, the Semantic Sensor Network (SSN) ontology and its SOSA (Sensor, Observation, Sample, and Actuator) extension [7] allow to effectively manage heterogeneous data types and metadata.

¹ <https://owlready2.readthedocs.io/en/latest/>

In particular, it allows to integrate sensor data such as current, temperature and voltage in order to represent anomalies of lithium batteries. The properties are critical for monitoring battery health, safety, and efficiency. This process of data interpretation, beginning with `madeObservation`, indicating when a sensor captures data. This data is then associated with specific properties through `observedProperty`. Timestamps for these observations are established with `hasTime`. Subsequently, the straightforward result values are identified with `hasSimpleResult`, and finally, the detailed outcomes are categorized with `hasResult`. The example below makes use of the previous properties to describe that a `BatteryCell(c)` has a `Sensor_t` which measures temperature.

$$\begin{aligned} & \text{BatteryCell}(c) \wedge \text{Sensor}(\text{sensor}_t) \wedge \text{sosa:hosts}(c, \text{sensor}_t) \wedge \\ & \text{sosa:madeObservation}(\text{sensor}_t, \text{obsT}) \wedge \text{sosa:observedProperty}(\text{obs}, \text{"Temp"}) \wedge \\ & \text{hasTime}(\text{obsT}, t) \wedge \text{hasSimpleResult}(\text{obsT}, 30^\circ\text{C}) \end{aligned}$$

3.1.3. Time module

The integration of W3C's [22] Time Ontology into battery behavior analysis enhances the technical capability to timestamp and contextualize data within a temporal window. The ontology has a concept `time:TemporalEntity` with properties `time:hasBeginning` and `time:hasEnd` that link to the temporal instants that define its limits, and `time:hasTemporalDuration` to describe its extent. The `time:TemporalEntity` concept has two sub-concepts: `time:Interval` and `time:Instant`. Intervals are things with extent. Instants are point-like in that they have no interior points, but it is generally safe to think of an instant as an interval with zero length, where the beginning and end are the same. The Time ontology provides Allen's temporal operators [6] to represent relations about time intervals and instants.

Incorporating the Time Ontology into our model allows representing temporal data. It enables the contextualization of fluctuating data, ensuring analyses considering the temporal dimension of changes and anomalies. Particularly, it allows to event timestamping, for precise timestamping of battery-related events, such as measurements of temperature, voltage, and current as well as anomalies. This facilitates the correlation of such events with specific times, enhancing the analysis and understanding of battery behavior over its lifecycle. Furthermore, by the use of Allen's operators such as `time:before`, `time:after`, and `time:during` to establish temporal relationships between events, enabling temporal reasoning about battery behavior. The following example captures the situation.

$$\begin{aligned} & \text{Anomaly}(A_1) \wedge \text{Anomaly}(A_2) \wedge \text{Anomaly}(A_3) \wedge \text{hasTime}(A_1, t_1) \wedge \text{hasTime}(A_2, t_2) \wedge \\ & \text{hasTime}(A_3, t_3) \wedge \text{time:meets}(t_1, t_2) \wedge \text{time:contains}(t_2, t_3) \Rightarrow \text{time:after}(t_3, t_1) \end{aligned}$$

3.1.4. Location module

The Location Ontology represents the architecture of the battery pack by abstracting their physical spaces, allowing for precise spatial representation of cells and sensors. Through this, an interpretation of the values collected by the sensors can be conducted, the ontology provides an overall picture of the condition of the pack. It is integrated with the Semantic Sensor Network (SSN) ontology [20] via the `locatedIn` property, it maps the exact locations of sensors. The `AnomalyLocation` property specifically annotates the positions of anomalies, enabling the identification of location-dependent performance issues.

$$\begin{aligned} & \text{Sensor}(\text{?sensor}) \wedge \text{locatedIn}(\text{?sensor}, \text{?location}) \Rightarrow \text{Cell}(\text{?cell}) \wedge \\ & \text{hasSensorLocation}(\text{?cell}, \text{?location}) \wedge \text{Anomaly}(\text{?anomaly}) \wedge \text{locatedIn}(\text{?anomaly}, \text{?location}) \wedge \\ & \text{affects}(\text{?anomaly}, \text{?cell}) \Rightarrow \text{Cell}(\text{?cell}) \wedge \\ & \text{hasPerformanceIssue}(\text{?cell}, \text{?issue}) \wedge \text{locatedIn}(\text{?cell}, \text{?location}) \end{aligned}$$

3.1.5. Anomaly module

Within the domain of battery system management and maintenance, representing and categorizing anomalies is crucial for ensuring reliability and performance. The centerpiece of our ontology within this domain is the Anomaly module as detailed in 2, a structured framework designed to classify anomalies into three principal fault categories: Battery Faults, Actuator Faults, and Sensor Faults. This module not only aids in the precise identification of the nature of the faults but also lays the foundation for understanding their impact on battery performance.

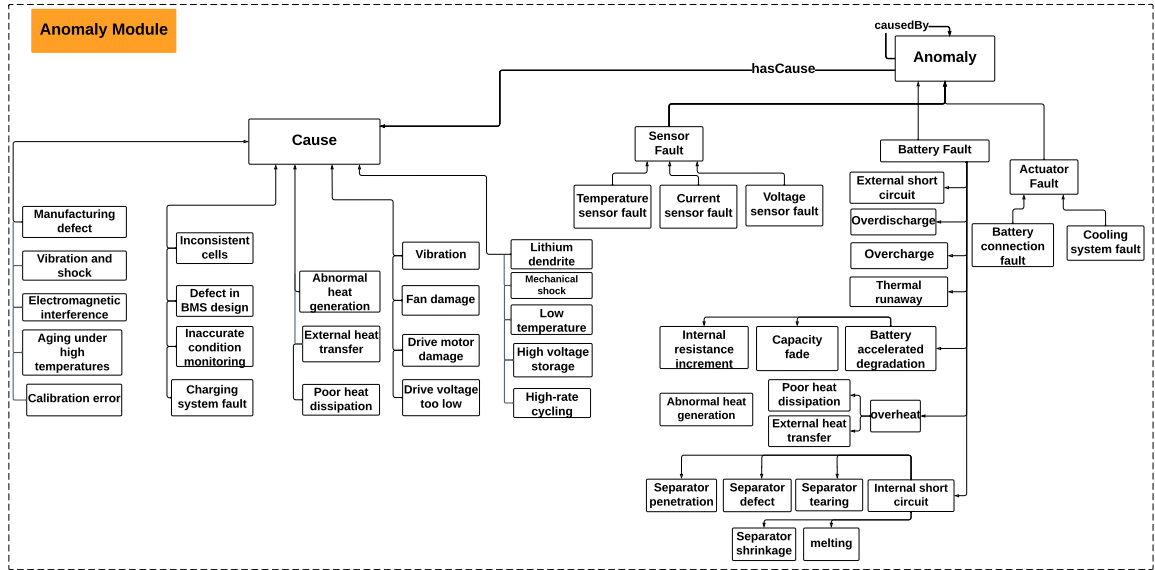


Fig. 2: Detailed view of the anomaly module.

Battery Faults are at the core of this ontology, focusing on issues that are directly related to the battery’s internal components. These faults can range from cell degradation, electrolyte imbalances, to internal short circuits. Such anomalies are intrinsic to the battery itself, often resulting from wear and tear, manufacturing defects, or inadequate maintenance. Actuator Faults represent the problems associated with external components that interact with or impact the battery system. Actuators, essential for the operation of Battery Management Systems (BMS), include components like switches, relays, and other mechanisms that control the charging and discharging processes. Faults in these actuators can lead to improper battery usage, affecting its performance. Sensor Faults encompass anomalies arising from inaccuracies or malfunctions in the sensor readings within the battery system. Sensors play a vital role in monitoring battery parameters such as temperature, voltage, and current. Faulty sensors can lead to incorrect data being relayed to the battery management system, potentially leading to overcharging, undercharging, or other harmful conditions. The example below makes use of the previous properties to describe the faults using description logic.

$$\text{Fault} \sqsubseteq \text{Battery Fault} \sqcup \text{Sensor Fault} \sqcup \text{Actuator Fault}$$

Our approach focuses on the detailed representation of anomalies by analyzing the variations of multiple variables over time. Specifically, it examines how these variables change within defined periods referred to as 'time windows' not in isolation, but in conjunction with changes in the values of other related variables. such variations are quantified using a metric referred to as "delta" which captures the difference in measurements between two time points, denoted as t_n and t_m where $t_m > t_n$. Δx : The change in measurement between consecutive observations is defined as: $\Delta x =$

$x_m - x_n$, where x_m and x_n represent the measurement values at consecutive times t_m and t_n , respectively.

Time Window (Δt): This is a predetermined duration that specifies how long a deviation must persist to be considered an anomaly defined as: $\Delta t = t_m - t_n$. The presence of a significant delta over this window is a critical factor in anomaly representation.

significant changes in measurements 'delta' must persist for a specified 'delta time' window to be considered anomalies. Section 4 provides a concrete example through an illustrative case study, showcasing this method's application.

Integral to our ontology is the concept of the Cause which relates each anomaly to its root cause, providing deeper insights into the origins of the fault. Examples of these causes include **ManufacturingDefects** that refer to any flaw or imperfection that occurs during the production process of the Battery like electrode defects, separator issues and poor welding or joining. **AbnormalHeatGeneration** in a lithium-ion battery occurs when excessive heat is produced due to internal faults or external misuse, **LowTemperature** describes conditions under which the temperature is below the optimal operating range for the battery, **calibration errors** are characterized by inaccuracies or mismatches in the readings and actual states of battery parameters such as charge level, voltage, and capacity.

This classification not only aids in the diagnosis of issues but also in the formulation of targeted interventions. By understanding the underlying causes of **Battery Faults**, **Actuator Faults**, and **Sensor Faults**, engineers and technicians can implement design improvements, refine maintenance protocols, and enhance the overall reliability and efficiency of battery systems.

4. Illustrative Case Study

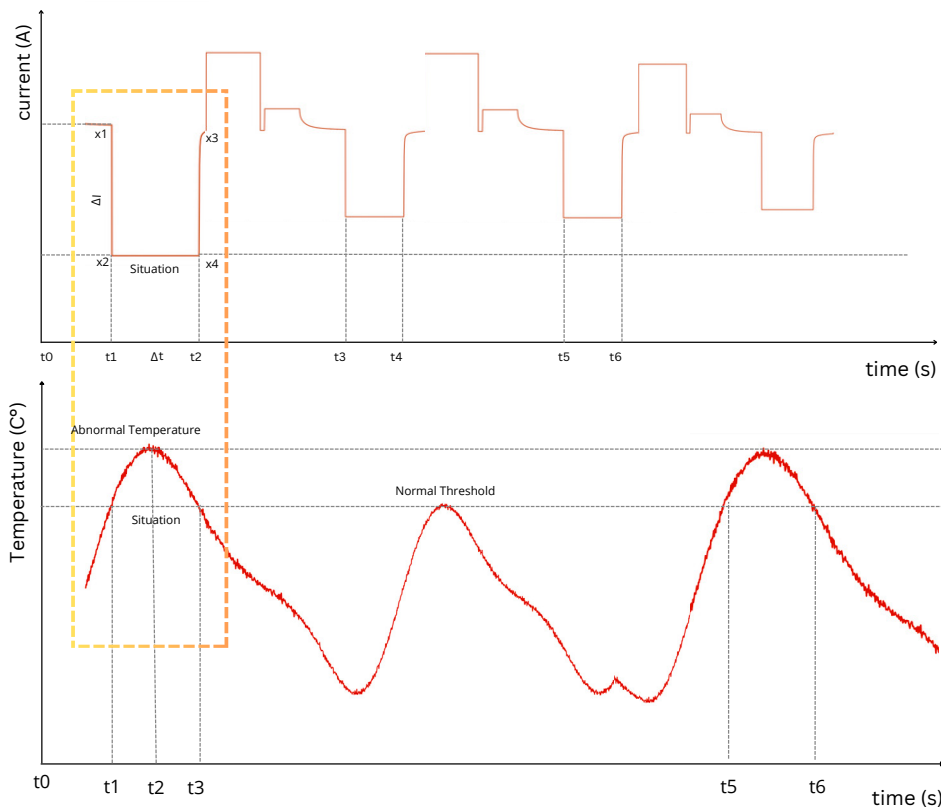


Fig. 3: Current and Temperature profile During Lithium-Ion Battery Charge-Discharge Cycles.

This case study demonstrates the practical application of using the Anomaly ontology for representing anomalies in lithium-ion batteries. We focus on a scenario involving a battery pack of two cells equipped with two sensors as shown in Fig. 4: one for monitoring current and the other for temperature. The case illustrates how the ontology facilitates the representation of an Overheat anomaly, a critical condition that can lead to battery failure or even safety hazards.

System Configuration: the battery pack under consideration contains a cell monitored by two distinct sensors. SensorI 1, dedicated to current measurement, is hosted by the cell and tasked with creating two observations, instances x_1 and x_2 , these observations record the current at two different times, t_1 and t_2 , producing SimpleResults res1 and res2, respectively. Simultaneously, SensorT 1 measures temperature changes within the same cell, generating instances y_1 and y_2 that capture temperature readings at times t_1 and t_2 . These readings are represented as SimpleResults resT1 and resT2. The ontology-based system is designed to represent anomalies by analyzing variations in current and temperature over a specific time window. An Overheat anomaly is identified when two conditions are simultaneously met within the same time interval ($t_2 - t_1$).

- **Temporal Alignment:** This ensures that the detected increases in current and temperature are within the same time window formalized as : $\Delta t = t_2 - t_1$.
- **Current Increase Detection:** An anomaly is flagged if $\Delta I > X$, where X is a predefined current increase threshold and $\Delta I = I_2 - I_1$.
- **Temperature Increase Detection:** An overheat anomaly is identified if $\Delta T \geq Y$, where Y is the minimum temperature increase that indicates overheating and $\Delta T = T_2 - T_1$.

In our analysis, we define the anomaly Overheat as illustrated in Fig. 3, which is derived from real, adapted data. This is done by observing two critical properties. An 'Overheat' is identified when there is an atypical demand for current (as compared to standard cycles) within a specific time window [$t_2 - t_1$], accompanied by a simultaneous temperature increase that breaches a predefined safety threshold. This co-occurrence of events indicates a departure from normal operational parameters, fitting our criteria for an Overheat.

Contrastingly, the time window [$t_6 - t_5$] presents a different scenario. Here, the temperature reaches a similarly elevated threshold; however, the absence of a concurrent spike in current demand means this does not qualify as an Overheat. Instead, it is categorized as an aberration from expected behavior, but it lacks the synchronicity of conditions to meet the stringent definition of an Overheat.

When such an anomaly is occurred, our ontological model, as introduced in Fig. 1, is designed to systematically explore and identify potential causes contributing to the thermal anomaly manifested in the battery cell. The example below describes the Overheatsituation illustrated by cell1 in Fig. 4.

```

BatteryPack(bp) ∧ Cell(C1) ∧ Sensor(Sensor_T1) ∧ Sensor(Sensor_I1)
  ∧sosa:hosts(C1, Sensor_T1) ∧ sosa:hosts(C1, Sensor_I1)
  ∧sosa:madeObservation(Sensor_T1, obsTemp1) ∧ sosa:madeObservation(Sensor_T1, obsTemp2)
  ∧sosa:madeObservation(Sensor_I1, obsCur1) ∧ sosa:madeObservation(Sensor_I1, obsCur2)
  ∧sosa:observedProperty(obs, y_1) ∧ sosa:observedProperty(obs, y_2)
  ∧sosa:observedProperty(obs, x_1) ∧ sosa:observedProperty(obs, x_2)
  ∧hasTime(obsTemp1, t1) ∧ hasTime(obsTemp2, t2) ∧ hasTime(obsCur1, t1) ∧ hasTime(obsCur2, t2)
  ∧hasSimpleResult(obsTemp1, 40°C) ∧ hasSimpleResult(obsTemp2, 55°C)
  ∧hasSimpleResult(obsCur1, 12A) ∧ hasSimpleResult(obsCur2, 20A)
  ∧Substract(resT, obsTemp2, obsTemp1) ∧ Substract(resI, obsCur2, obsCur1)
  ∧greaterThan(resT, Y) ∧ greaterThan(resI, X)

```

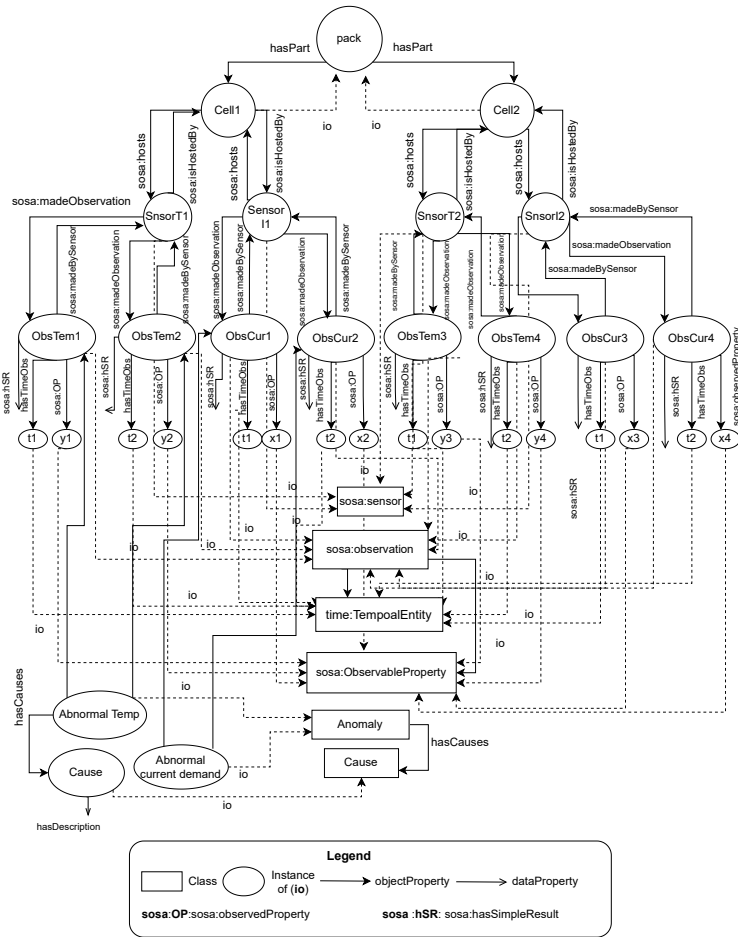


Fig. 4: Representation of the scenario presented in the case study using our model.

5. Conclusions & Future Work

This research has introduced a novel ontology-based approach for representing anomalies within lithium-ion batteries, enhancing data collected from sensors with contextual information to enable the real-time representation of potentially hazardous situations. Through the early identification of these anomalies, our methodology not only mitigates risks but also facilitates more timely interventions for preventive maintenance. In our subsequent research, we will explore the adoption of stream reasoning to seamlessly integrate diverse data streams, each with unique semantic contexts and temporal resolutions, enabling the real-time processing of this information.

In future work, we aim to expand the scope of our ontology-based approach beyond its current application, exploring its effectiveness across different domains and with various types of batteries, such as lead-acid and nickel-metal hydride. This exploration will assess the approach’s flexibility and its potential for adaptation to specific use cases. Additionally, we plan to explore the integration of machine learning and deep learning models to enhance anomaly prediction capabilities, utilizing historical sensor data and recognized patterns to preemptively identify potential issues. This predictive mechanism will be refined through the development of algorithms for real-time adaptive reasoning, enabling the ontology to dynamically update its reasoning in response to new data and emerging patterns. Such advancements will not only improve the system’s anomaly detection but also contribute to optimizing the energy efficiency of lithium-ion batteries. By examining the interplay between detected anomalies and battery

performance, we anticipate uncovering strategies to extend battery longevity and improve overall energy management.

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