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BPO—A battery production ontology for traceable, transparent, and sustainable electric vehicle batteries

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ABSTRACT

The growing demand for lithium-ion batteries (LIBs) in industries such as electric vehicles (EVs) and renewable energy storage underscores the need for tools that ensure transparent, sustainable, and compliant production processes. This paper presents the Battery Production Ontology (BPO), a comprehensive framework designed to standardize the representation and traceability of LIB production lifecycles. By modeling key aspects such as material flows, energy consumption, carbon emissions, and production activities, the BPO supports environmental impact assessments, supply chain transparency, and process optimization.

The BPO is aligned with existing standards, including the EU's digital battery passport requirements, ensuring interoperability across diverse systems. Developed using a structured methodology, the ontology underwent rigorous validation. Real-world case studies demonstrated its capacity to model emissions, trace materials, and represent production sequences, while quantitative assessments confirmed its scalability, reasoning efficiency, and accuracy for industrial applications. Additionally, the ontology integrates seamlessly with external standards like BONSAI, FOAF, Schema, and OWL Time, fostering semantic reuse and interoperability.

By addressing the critical need for transparency and sustainability in LIB production, the BPO provides stakeholders with a robust tool to drive the green energy transition and achieve global sustainability goals.

1. Introduction

With the global push toward carbon neutrality and the transition to renewable energy sources [1], the electrification of transportation has accelerated dramatically. EVs are at the forefront of this movement, contributing significantly to cleaner urban environments. This shift has led to an exponential increase in demand for LIBs, which power not only EVs but also energy storage systems and portable electronics [2–4]. Recent estimates project that global demand for Li-ion batteries will exceed 4900 GWh by 2030, a substantial rise from approximately 800 GWh in 2022 [5,6]. However, this heightened demand poses challenges, particularly with regard to critical raw materials such as lithium, nickel, and cobalt [7]. Despite a 180% increase in lithium production since 2017, demand outpaced supply in 2022, with EV batteries consuming nearly 60% of lithium, 30% of cobalt, and 10% of nickel [8]. Additionally, the energy-intensive processes required for mining and refining these materials often rely on fossil fuel-based power systems, adding to the overall carbon footprint of EV batteries [9].

To address these concerns, the European Union (EU) recently introduced comprehensive battery regulations that enforce strict standards for sustainability and traceability in battery production [10]. A cornerstone of this regulation is the Digital Battery Passport (DBP), an electronic record designed to track key data on the material composition, carbon footprint, and recycling potential of each battery [11]. The DBP aims to provide consumers, manufacturers, and regulatory bodies with a transparent and accessible record of each battery's life cycle: from raw material sourcing to end-of-life recycling, thus promoting responsible energy production [12]. Starting in 2027, DBP will become mandatory in Europe [13].

As battery production scales, the challenges of ensuring traceability, sustainability, and regulatory compliance in manufacturing continue to grow [14–17]. LIB production is a complex multistage process that involves diverse raw materials, intricate chemical processing, and significant energy inputs. To manage and optimize these processes, industry stakeholders need a robust framework capable of capturing and analyzing data on material flows, emissions, energy consumption, and production outputs. Meeting regulatory standards for environmental transparency and life cycle assessment (LCA) has become essential given the considerable carbon footprint and resource intensity of battery production. Recently, battery data acquisition and management have gained importance, as researchers have extensively explored data-driven methods to ensure higher performance and lower economic

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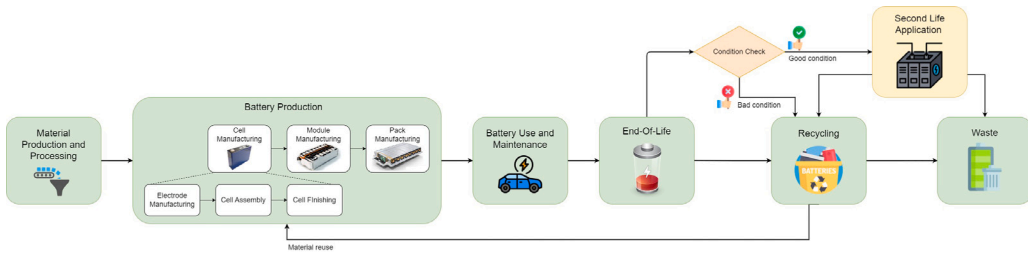


Fig. 1. Life cycle of a LIB including the materials' production, battery manufacturing, usage life and either a second life or recycling of materials after the end of the first life.

and environmental impacts [18,19]. These approaches underscore the importance of tracing materials, intermediate products, and all related process data throughout the manufacturing chain. Furthermore, as research increasingly focuses on smart factory developments, robust traceability data management in complex process environments is crucial to achieving a competitive edge in areas such as process optimization, product quality, and error-proofing.

This paper introduces the Battery Production Ontology (BPO), an ontological framework specifically designed to address these needs. By structuring data related to production processes, materials, energy consumption, and emissions, BPO serves as a comprehensive tool for assessing environmental impacts and ensuring traceability throughout the Li-ion battery production life cycle. Aligned with LCA principles, BPO facilitates data interoperability, enhances transparency, and supports compliance with evolving standards for battery production and sustainability. Through this structured approach, BPO contributes to a sustainable and accountable battery manufacturing industry capable of meeting the growing demand for Li-ion batteries while minimizing environmental impacts. Unlike existing solutions that combine physical identification with heterogeneous data silos, **BPO** provides a hierarchy-aware semantic model enabling end-to-end provenance, formal constraint checking, and a native traceability–sustainability link; a feature-by-feature positioning is provided in Section 3.5 (Table 2). This research paper is organized as follows. First, the theoretical background introduces the concepts of traceability, the battery pack life cycle, and ontology. Second, a thorough literature review identifies existing ontology-based models for LIB production to highlight research gaps. Third, we present an ontology-based model for LIB battery production aimed at facilitating traceability and sustainability assessments. Fourth, qualitative and quantitative validations are performed to ensure the viability of the model. Finally, the conclusion summarizes key findings and discusses directions for future work.

2. Theoretical background

2.1. Traceability in manufacturing systems

Traceability, as defined by ISO 9000, is "the ability to trace the history, application, or location of that which is under consideration (an object)" [20]. This definition emphasizes the importance of tracking the origin of raw materials, the processes involved, the distribution pathways, and the final location of the product. Effective traceability systems are essential across various industries to ensure quality, safety, and regulatory compliance. A comprehensive traceability system consists of two components: forward tracking and backward tracing [21]. Forward tracking involves identifying, acquiring, and storing information as the product moves from upstream to downstream. Backward tracing, on the other hand, is the process of recreating or extracting the history of a product from the recorded data, moving downstream to its origins [22]. A traceability system is composed of five core elements: identification, data acquisition, data linking, communication of data, and verification. Identification assigns a unique identifier to each trace object [20]. Data acquisition involves collecting relevant information at each stage of the product's life cycle. Data linking associates collected data with the corresponding trace object. Data communication ensures that data are accessible and shareable throughout the value chain. Finally, verification involves regularly checking the integrity and accuracy of the data within the system.

2.2. Battery pack life cycle

A holistic cradle-to-cradle representation of a battery life cycle helps identify all the sources of data acquisition. Fig. 1 illustrates the typical LIB life cycle in EV applications, starting with raw material extraction, followed by material processing, electrode manufacturing, cell assembly, cell finishing, module assembly, and finally, pack assembly. The supply chain of a LIB system is a complex and multifaceted network involving several steps and components. This section aims to demystify the manufacturing process to facilitate better data modeling. The production of LIB is typically divided into three phases: electrode manufacturing, cell assembly, and cell finishing. However, when considering the complete life cycle of a battery pack, these phases are preceded by upstream material production (mining and refining) and followed by downstream processes such as module and pack integration, use-phase operation, second-life applications, and recycling or disposal. Electrode manufacturing begins with mixing active materials with additives and binders to create a slurry, which is then coated onto metal foils; typically copper for anodes and aluminum for cathodes. After coating, materials are dried and cooled, followed by calendering, where coated foils are compressed using rollers to achieve the desired porosity and density. The foils are then cut into smaller electrode sheets or coils and subjected to a final drying process under vacuum to remove residual solvent and moisture [23]. During cell assembly, the anode, cathode, and separator are stacked or wound together, depending on the cell type. Cylindrical and prismatic cells generally follow a winding process, whereas pouch cells are assembled through stacking. This is followed by tab welding, cell packaging, and electrolyte filling. Cells are then hermetically sealed, and subjected to formation cycling, during which the initial charge–discharge cycles create a stable Solid Electrolyte Interphase (SEI) on the anode surface. Following testing and quality control, cells are graded based on capacity, internal resistance, and other performance metrics for EV applications [24]. The entire cell manufacturing steps are depicted in Fig. 2.

Subsequently, individual cells are connected in series and parallel configurations to form modules, which are equipped with electrical interconnections, mechanical housings, and safety components. Several modules are then integrated into a complete battery pack that includes additional subsystems such as the Battery Management System (BMS), cooling and thermal management units, electrical control units, and structural supports [25]. This pack-level integration phase is critical because it determines the overall energy density, safety, and lifetime of the system, while also representing a major source of traceability and environmental data within the production chain. Beyond the production stage, batteries enter the use-phase, where performance data (e.g., temperature, voltage, and state of health) can be monitored through embedded sensors and BMS telemetry. After their first life in

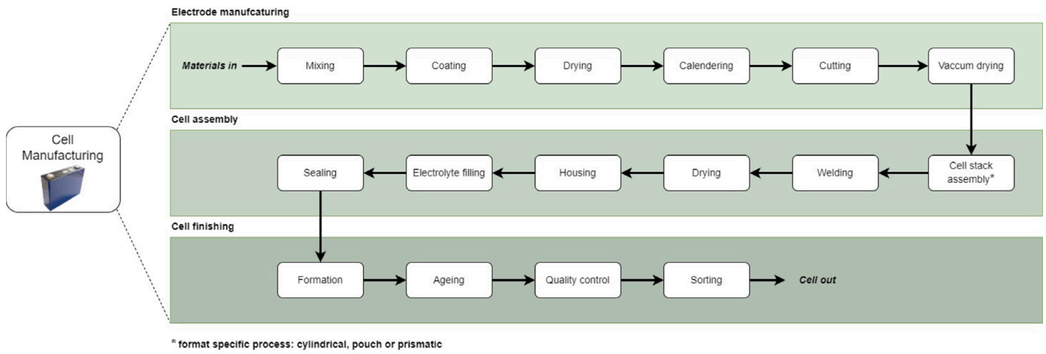


Fig. 2. The detailed steps of the battery cell manufacturing supply chain.

EVs, many packs are repurposed for stationary energy storage applications, extending their functional lifespan before entering recycling or material recovery stages, which closes the life cycle loop.

2.3. Ontology and data modeling

Battery manufacturing companies manage extensive and complex sets of product-related data daily, often stored in heterogeneous formats, which creates significant challenges for data interoperability and integration across different systems. Ontologies play a crucial role in this context by providing a structured framework for organizing and harmonizing data and knowledge, enabling coherent representation and easier retrieval of information throughout the stages of battery production.

The most cited definition of an ontology is attributed to Gruber, who described it as “an explicit specification of a conceptualization” [26,27]. However, this definition is often considered too broad, as it could also encompass database schemas. Consequently, it has served as the foundation for more precise interpretations of ontology. Studer et al. (1998) refined Gruber’s definition, stating that “an ontology is a formal, explicit specification of a shared conceptualization” [28]. In this formulation, conceptualization refers to an abstract representation of reality or a phenomenon, a simplified model expressing the relevant concepts of a specific domain. The term explicit indicates that the concepts, their constraints, and the relationships between them must be clearly and fully defined. For example, within medical domains, concepts may include diseases and symptoms, with causal relationships and constraints ensuring that a disease cannot cause itself. Formal implies that the ontology must be machine-readable, while shared emphasizes that it captures consensual knowledge accepted by a community of experts rather than private, individual understanding. For instance, in a hospital’s disease ontology for breast cancer, the defined concepts and relationships should reflect a consensus among medical professionals. Finally, specification refers to an exact and unambiguous definition of concepts and relations.

Building on early formulations, Guarino et al. frame an ontology as a logical theory that captures the intended models of a conceptualization and excludes unintended ones, thus supporting inference and consistency checking in a principled way [29]. Complementing this, realist accounts describe an ontology as a representational artifact whose units (classes, relations) are intended to designate domain universals and their interrelations, with explicit axioms and constraints that enable shared understanding and data integration [30]. From an engineering perspective, contemporary ontology practice emphasizes formal, explicit, machine-interpretable specifications of a domain, typically implemented in OWL 2 and aligned to upper ontologies/standards like BFO for interoperability across heterogeneous sources [31].

In summary, contemporary ontology engineering regards an ontology as a formal, explicit, and machine-interpretable theory of a domain. It defines the entities, relations, and constraints that enable coherent reasoning, data integration, and shared understanding.

3. Related works

3.1. Traceability and traceability systems

Various technologies have been employed across research and industries to enable effective traceability. Radio Frequency Identification (RFID) and the EPC global Architecture Framework have been introduced to provide generic traceability services, as demonstrated in the chemical sector, to comply with the European REACH regulations [32,33]. Intelligent traceability systems improve real-time monitoring and decision-making capabilities by integrating statistical control, fault-tree analysis, wireless sensor networks, and IoT technologies to achieve instant visibility into manufacturing processes [34–38]. Additionally, blockchain technology is gaining traction for its ability to offer tamper-proof and continuous data records, as illustrated in a blockchain-based approach by Koustas et al. [39] to trace electrical system components across companies and countries, improving quality and reducing failures. However, blockchain’s high computational demands present ongoing challenges.

Traceability systems are especially prevalent in the food industry to meet consumer demands for high quality, ensure product safety, minimize recalls, and protect brand reputation [32,40]. They also play a critical role in pharmaceutical industries to prevent counterfeiting and authenticate products [41,42], and are increasingly applied in other sectors like the wood industry [43]. In the mobility sector, the shift toward electrification has increased traceability requirements for critical components, especially batteries, to ensure safety, reliability, and performance throughout their life cycle [44]. For instance, Northvolt has implemented telemetry and data collection throughout its production chain processes, from manufacturing to deployment, to optimize battery performance and lifespan [45]. This data-driven approach tags materials with metadata for traceability, gathers performance metrics, and employs machine learning for predictive maintenance and optimization [46]. These methods enable efficient battery management, reduce degradation, and introduce new business models such as usage-based warranties. However, achieving comprehensive traceability down to individual batteries remains a challenge due to the complexity of the battery production chain. This process involves multiple stakeholders, including the electrode manufacturer, cell manufacturer, module manufacturer, and pack manufacturer, along with the converging and diverging material flows throughout each stage.

3.2. Traceability systems in battery production

Traceability in the context of battery production has been addressed in only a few studies, most of which focus on high-level frameworks for tracking and identifying material and process flows up to the cell level. For instance, Sommer et al. introduced a tracking and tracing system that investigates the practical implementation of technologies, such as

Table 1
Comparison table of related work on LIB ontologies.

Criteria	References								
	[49]	[50]	[51]	[52]	[53]	[54]	[55]	[56]	[57]
Battery cell level	✓	✓	✓	✓	✓	✓	✗	✗	✓
Battery module level	✗	✗	✗	✗	✗	✗	✓	✗	✗
Battery pack level	✗	✗	✗	✗	✗	✗	✓	✗	✗
Level of investigation									
Conceptual framework	✓	✗	✓	✗	✓	✗	✗	✗	✗
Process representation	✓	✓	✓	✗	✓	✓	✗	✗	✗
Material properties	✗	✓	✗	✓	✓	✗	✗	✗	✗
Context of ontology use									
Knowledge management	✓	✗	✓	✓	✓	✗	✗	✗	✗
Interoperability and data sharing	✗	✓	✗	✓	✓	✓	✗	✗	✗
Process optimization	✓	✓	✓	✗	✓	✓	✗	✗	✗
Standardization and compliance	✓	✗	✓	✓	✓	✗	✗	✗	✗
Traceability and environmental impact	✓	✓	✓	✓	✓	✓	✗	✗	✗

Table 2
Comparison of traceability approaches (capabilities vs. scope).

Criteria	Legacy MES/DBs	Ontology-based dataspaces	BPO (this work)
Hierarchy coverage	Mainly cell-level	Mostly cell-level	Cell → Module → Pack
Semantic interoperability	Ad-hoc, weak	Schema harmonization	Domain-level semantics (process, material, agent, time/space)
Provenance reconstruction	Step-wise logs	Requires mappings	Native genealogy + inference/queries
Quality/sequence validation	Custom scripts	Limited	Formal constraints/rules (SHACL-like, reasoning)
Traceability–sustainability link	Out of scope	Partial	Native linkage to energy/emissions within same graph
Explainability	Raw logs	Metadata	Relations + justifications (queryable digital thread)

laser and ink marking, for identifying electrodes throughout the battery manufacturing chain [46]. Riexinger et al. proposed a conceptual framework centered on product serialization, comparing several marking approaches and concluding that laser engraving and ink marking were the most viable for cell-level identification [47]. Wessel et al. developed a methodology for designing a tracking and tracing system using morphological analysis [44]. This method was implemented within the Battery LabFactory Braunschweig to cover the entire manufacturing process of LIB cells, to support future data-driven applications. The resulting system facilitates automated process identification and integrates all product-specific data. In a more recent contribution, Wessel et al. expanded this concept by introducing feature-based and marker-free tracking methods, enhancing the robustness of the physical identification layer. Instead of relying solely on external markings, the updated framework exploited inherent product and process characteristics, such as electrode surface microstructures, as digital fingerprints to enable continuous, non-invasive tracking [48]. Through image analysis and inline measurements, each electrode could be recognized by its unique "fingerprint", supporting seamless traceability without physical modification. This advancement moved traceability systems closer to real-time process monitoring, supporting virtual quality gates and data-driven feedback mechanisms.

3.3. Ontology-based traceability systems

The advent of Industry 4.0, has made digital traceability increasingly desirable across various industries, leading to a growing interest in ontology-based traceability systems [58]. Ontology-based approaches aim to establish semantic models for traceability, enabling the reuse of information resources while enhancing the accuracy and efficiency of information management. Early research in this field has focused on developing general frameworks and sector-specific applications, particularly in the agri-food industry. For example, Salampasis et al. proposed TraceAll, a traceability system that uses semantic web technology to formalize knowledge representation for pasteurized milk [59]. Similarly, Pizzuti et al. introduced an ontology-based system tailored for the meat supply chain, structured around processes and actors involved in production [60]. In a related study, Pizzuti et al. developed the Food Track and Trace Ontology (FTTO), a reference model designed to support quality assurance and facilitate critical queries during foodborne disease outbreaks by linking data across the food supply chain [22]. Furthermore, the TOVE Quality ontology logically formalizes quality-related concepts, incorporating traceability as a specialized subdomain [61]. In the context of battery manufacturing, several studies have advocated for the adoption of ontology-based traceability systems to improve data management [44,47,48,51,62]. These studies highlight the potential of such systems to improve traceability throughout the production process, address multiple use case scenarios, and enhance data output, such as in the form of a battery passport [63]. Ontology-based models offer significant advantages by enabling manufacturers to integrate heterogeneous data, enhance system interoperability, and achieve precise tracking of materials and processes across the production life cycle. Despite these advances, a comprehensive ontology-based traceability system specifically tailored for battery production systems has yet to be proposed or developed.

3.4. Battery ontologies

A comprehensive literature review was conducted to compare existing studies on battery ontologies, highlighting their strengths, limitations, and potential research needs. Table 1 summarizes this comparison, using check marks (✓) and crosses (✗) to indicate whether each criterion is fulfilled or not, providing a clear comparison of each study's coverage across multiple criteria. The *Scope* criteria assess each ontology's applicability across the different levels of battery structure and production, including cell, module, and pack, indicating which aspects the ontology frameworks effectively address within the structural and production hierarchy. The *Level of Investigation* criteria examines the depth and specificity of the studies, including conceptual framework, process representation, and material properties. This category reflects the theoretical and technical coverage each ontology provides for modeling battery systems. Finally, the *Context of Ontology Use* evaluates the functional utility of each ontology approach across domains such as knowledge management, traceability, data sharing and interoperability, process optimization, and environmental impact assessment. This section highlights the maturity and flexibility of each study's methodology in meeting industry needs, regulatory compliance, and traceability goals in battery manufacturing. Currently, two significant works when it comes to knowledge representation within the

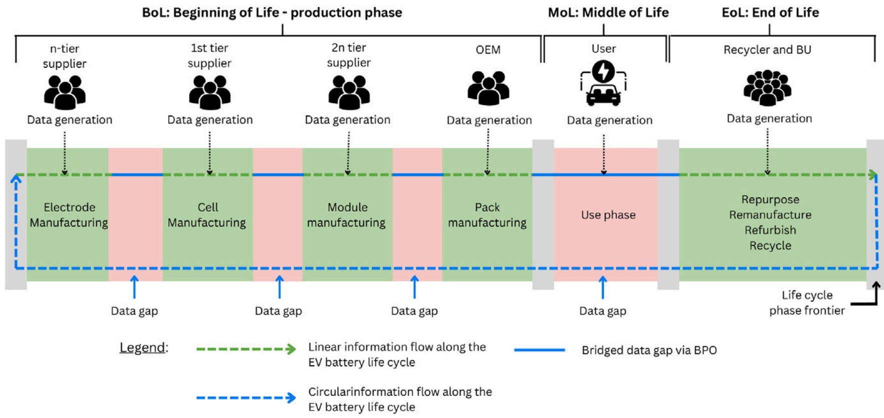


Fig. 3. Data gap in the EV battery life cycle.

battery domain: the Battery Interface Ontology (BattINFO) and the Battery Value Chain Ontology (BVCO). BattINFO is a domain ontology based on the top-level European Materials and Modeling Ontology (EMMO), focusing on detailing batteries at the level of individual cells and below, including components, materials, their interactions, as well as electrochemical mechanisms, models, and data related to characterization [52]. BattINFO aims to formalize the current state of knowledge on physical and chemical processes based on accepted standards and reference literature. In contrast, BVCO focuses on various aspects of the battery value chain, with particular emphasis on battery cell production and recycling [53]. It extends on BattINFO concepts (and, by extension, EMMO) and applies the basic definition of the battery as a system established therein. BVCO also interacts with the General Process Ontology (GPO), which defines terms commonly used across different process engineering domains [64]. Mutz et al. proposed an ontology that describes the LIB cell production process, linking a material-oriented and a process-oriented view [49]. This ontology consists of three main entities: the item entity, the step entity, and the characterization-methods entity, connecting information about applied analytical methods applied to items. Each entity contains several defined properties. Stier et al. presented a unified framework for integrating ontology and graph-based data spaces with data acquisition and analytics within the LIB production chain to enhance data consistency, workflow documentation, and result reproducibility [50]. This framework employs open-source web services to create an ontology-based data space, representing physical and virtual process chains via a semantic information network. The framework's feasibility was demonstrated in a lab-scale LIB cell production facility, where AI was applied to two data analytics use cases. Ismail et al. developed a comprehensive battery ontology that includes several small taxonomies, such as primary and secondary batteries, their properties, and applications [54]. This ontology was designed to integrate battery knowledge for practical applications and to establish a knowledge graph for battery management systems. Although these studies primarily focus on representing the LIB at the cell level, little research has investigated the entire LIB pack, especially concerning structural and production aspects. To address this gap, Yu et al. proposed an ontology-based disassembly task planning method for automotive power batteries [55]. This method features an EV battery semantic model that includes parts information, hierarchical structure, assembly structure, and connection relationships. This comprehensive model facilitates a more detailed and integrated understanding of the entire battery pack but still lacks integration of the production-related understanding [56,57].

3.5. Positioning BPO against existing traceability approaches

Existing research and industrial practice can be broadly seen as two complementary layers: (i) a *physical identification* layer (direct part marking, marker-free fingerprints, sensing) that serializes and recognizes items across the line, and (ii) a *digital or semantic* layer that acquires, integrates, and interprets data. While significant progress has been made in the physical identification layer (e.g., robust serialization, marker-free tracking), the digital layer still suffers from fragmented schemas, proprietary formats, and weak interoperability, limiting end-to-end provenance, cross-station queries, and higher-level reasoning [65–67]. Ontology-based solutions mitigate these issues by providing a shared vocabulary and machine-interpretable relations; however, many "dataspace-style" frameworks primarily act as semantic metadata for harmonization and analytics rather than a full computational domain model [50,51]. As summarized in Table 2, legacy MES/DB solutions and ontology-based dataspaces cover parts of the problem, whereas BPO provides a computational domain model enabling end-to-end provenance, constraint checking, and a native traceability–sustainability link.

The proposed BPO ontology is not merely a metadata layer; it is a *computational knowledge model* of the production domain. It explicitly represents processes, materials/flows, equipment, agents, and spatiotemporal relations across the cell–module–pack hierarchy, enabling (i) semantic interoperability, (ii) automated provenance reconstruction and constraint checking (e.g., sequence validation, genealogy completion), and (iii) native linkage of traceability with sustainability indicators in a single, auditable graph.

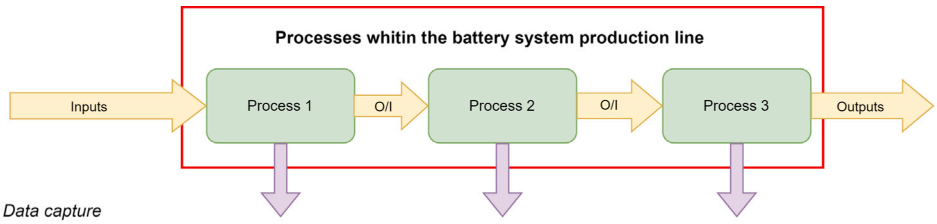
3.6. Research gap

Despite significant advances in battery traceability, substantial gaps remain prominent in existing research, particularly regarding the complete traceability of the entire LIB pack. As mentioned earlier, current studies focus mainly on traceability at the cell level or specific components within the production chain. Methodologies and frameworks for marking and tracking have been developed within lab-scale production facilities. However, these studies fail to address the full spectrum of the battery pack's lifecycle, especially in integrating data from the production and assembly stages. Moreover, although initiatives such as BattINFO and BVCO have made progress in detailing battery components and value chain processes, their scope remains limited to a general overview of the battery system production chain, focusing on the individual cell and material interactions. There is a notable lack of research that encapsulates the entire production and structural aspects of the LIB pack, leading to incomplete data integration and traceability across different manufacturing stages and among stakeholders.

4. Semantic model for representing EV battery production chain

4.1. General overview

The BPO has been conceived as a semantic framework that unifies three complementary dimensions of the electric-vehicle battery



KDE	CTE1	CTE2	CTE3	Ontology
Who	Actor/Agent	Actor/Agent	Actor/Agent	FOAF ontology
Where	Location, origin	Location, origin	Location, origin	Schema ontology
What	Item (input or output)	Item (input or output)	Item (input or output)	Battery Production Ontology (BPO)
When	Date, beginning time, end time, duration	Date, beginning time, end time, duration	Date, beginning time, end time, duration	Time Ontology
Why	Process	Process	Process	Battery Production Ontology (BPO)

Acronyms

KDE: key data elements
CTE: critical traceability event
O/I: output/Input

Fig. 4. Critical tracking events within the battery production line.

domain: traceability, environmental assessment, and manufacturing knowledge. By integrating these layers within a single interoperable model, BPO enables end-to-end data sharing, automated reasoning, and transparent sustainability assessment across the battery value chain, as illustrated in Fig. 3. The following subsections describe how the ontology represents each of these dimensions and how they interact to support both operational traceability and life-cycle analytics.

4.1.1. Traceability model

BPO adopts the 5 W traceability principle which are Who, What, Where, When, and Why to capture the complete provenance of battery-related processes and products. This multidimensional approach models every Critical Tracking Event (CTE) occurring along the supply chain, providing the contextual information required for transparency, accountability, and regulatory compliance as demonstrated in Fig. 4 [21, 44].

- **Who - Actors and agents:** Each CTE is associated with an organization, an individual, or a machine responsible for its execution, thereby establishing a clear accountability chain. This dimension reuses the FOAF ontology to describe companies, facilities, personnel, and machinery as agents capable of performing actions, ensuring a standardized and extensible representation of all entities involved in production [68].
- **What - objects and materials:** The inputs and outputs of each process such as raw materials, intermediate products, and finished components, are represented using BONSAI's FlowObject class, which is further specialized in BPO into subclasses for materials, intermediate products, finished products, and auxiliary components [69]. This structure enables consistent tracking of material flows and transformations throughout the manufacturing chain.
- **When - Temporal context:** Time-stamped data (start, end, and duration) are represented using the W3C Time Ontology, providing a temporal backbone for sequencing, synchronization, and performance analysis of manufacturing events [70].
- **Where - Spatial context:** Locations of production, storage, and transportation are modeled using Schema.org and Geo vocabulary terms, ensuring interoperability with geographic information systems (GIS) and supply-chain databases [71].
- **Why - Process purpose:** The rationale and intended function of each process are captured through BPO's process hierarchy, which links operational goals to higher-level manufacturing and sustainability objectives. This dimension reflects the business or operational context of each event, specifying whether an activity was executed for production, quality inspection, maintenance, or logistics, thereby connecting every CTE to its underlying purpose.

By integrating these five facets into a single semantic layer, BPO produces a comprehensive digital record of all events and their interrelations. This traceability model allows provenance data to be exchanged seamlessly with Digital Battery Passport systems and regulatory platforms, supporting transparent and auditable supply-chain management.

4.1.2. Life cycle assessment model

The second core dimension of BPO formalizes the environmental assessment perspective by embedding the data structures required for Life Cycle Inventory (LCI) and Life Cycle Impact Assessment (LCIA) [72,73]. Each process instance in the ontology links its inputs (materials, energy carriers, and utilities) to its outputs (products, wastes, and emissions), following ISO 14040/44 principles as illustrated in Fig. 5.

Within this model, BPO captures:

- **Quantitative resource consumption and energy use:** For each manufacturing step, the ontology formalizes the amount and type of materials and energy required for production. This information provides the foundation for constructing process inventories and evaluating resource and energy efficiency along the manufacturing chain.
- **Associated emission and waste flows:** BPO represents the environmental outputs of each process, including greenhouse gas emissions, solvent releases, and solid waste. Capturing these flows within a unified model supports the aggregation and comparison of environmental impacts across multiple production stages and facilitates transparent reporting of sustainability metrics.
- **Contextual and operational parameters:** In addition to material and energy balances, the ontology includes contextual information such as equipment characteristics, process efficiency, and

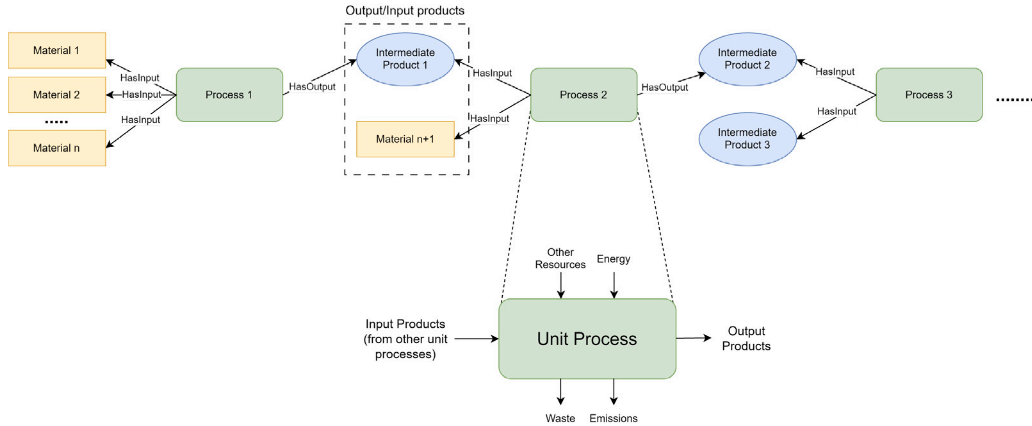


Fig. 5. Supply chain model.

operating conditions. These parameters allow the differentiation of environmental performance according to production technologies or facility-specific conditions, enabling more accurate and contextualized life cycle assessments.

The ontology aligns these representations with external environmental databases such as Ecoinvent, enabling the semantic integration of primary factory data with background datasets. Through these mappings, users can automatically compute environmental performance indicators, such as global-warming potential, energy intensity, and resource depletion, directly from the production knowledge graph. This explicit coupling between traceability data and LCA parameters provides a consistent basis for sustainability reporting, hot-spot analysis, and regulatory compliance under initiatives such as the European Digital Battery Passport.

4.1.3. *Battery manufacturing model*

The third dimension constitutes the process-centric backbone of the ontology, representing detailed knowledge of lithium-ion battery manufacturing. BPO extends GPO to model the hierarchical organization of the production chain from material preparation and electrode fabrication to cell assembly, formation, and testing [64]. Each manufacturing stage is described as an individual process characterized by its specific inputs and outputs, energy consumption, and environmental exchanges. Processes are semantically connected through material and information flows, forming an end-to-end representation of the production line. Operational parameters such as temperature, duration, and throughput are encoded as data properties, which will allow quantitative integration with IoT sensors and Manufacturing Execution Systems (MES) in future implementations. This manufacturing layer serves as the structural core linking the traceability and LCA models: each process provides contextual events for traceability while simultaneously contributing inventory data for environmental assessment. Because the ontology follows a modular design, each production stage, such as electrode manufacturing, cell assembly, or recycling, can evolve independently while remaining semantically interoperable within the same framework.

The modular organization of BPO is reflected not only in its semantic structure but also in how it aligns with the physical hierarchy of the battery production chain. Fig. 6 illustrates this multi-layered architecture, showing how the ontology maps successive manufacturing stages such as electrode production, cell assembly, cell finishing, module manufacturing, and pack integration into interconnected semantic layers. This representation highlights how each layer reuses common ontology patterns while maintaining distinct data contexts, ensuring interoperability and traceability across all stages of production.

To illustrate this hierarchy in more detail, Fig. 7 presents the ontology representation of the electrode manufacturing stage. It shows how individual processes such as mixing, coating, drying, calendering, and cutting are modeled as discrete yet interconnected activities linked through shared material and information flows. Each process is associated with specific material inputs, energy exchanges, and temporal relations, providing an integrated view of process dependencies and data provenance within the sub-cell level of production.

Building upon the same pattern, Fig. 8 demonstrates how the ontology scales upward to represent the pack manufacturing stage. At this level, the same conceptual structure captures the integration of cells and modules into complete battery packs, linking material, energy, and structural relationships across the entire assembly process. This multi-scale representation underscores the modularity and extensibility of BPO, enabling consistent reasoning and data interoperability from component-level processes to full system integration.

Together, these figures illustrate how the ontology provides a comprehensive semantic framework for modeling the entire production chain of lithium-ion batteries, ensuring a unified representation across different manufacturing scales.

4.1.4. *Integration and outcome*

Together, these three complementary models establish an integrated semantic architecture that unifies traceability, environmental assessment, and manufacturing knowledge into a single interoperable system. BPO thus functions simultaneously as a traceability knowledge graph, an LCA data hub, and a digital twin of the production chain, enabling comprehensive visibility and intelligent data analytics across the entire battery value chain. This design advances transparent, data-driven sustainability management and supports the transition toward a fully traceable and environmentally accountable EV battery production system. To ensure that this conceptual architecture is formally implemented and semantically consistent, the following section details the ontology's conceptualization process, describing the development methodologies, modeling strategies, and reuse of existing ontological standards that guided the construction of BPO.

4.2. *Ontology conceptualization*

The development of BPO follows an integrated engineering methodology that combines three established approaches: case-based, reuse-based, and middle-out. This hybrid strategy ensures that the ontology remains application-driven while maintaining strong semantic interoperability with recognized standards and upper ontologies. The conceptualization process translated complex industrial knowledge drawn from manufacturing, LCA, and traceability domains into a coherent and machine-interpretable model.

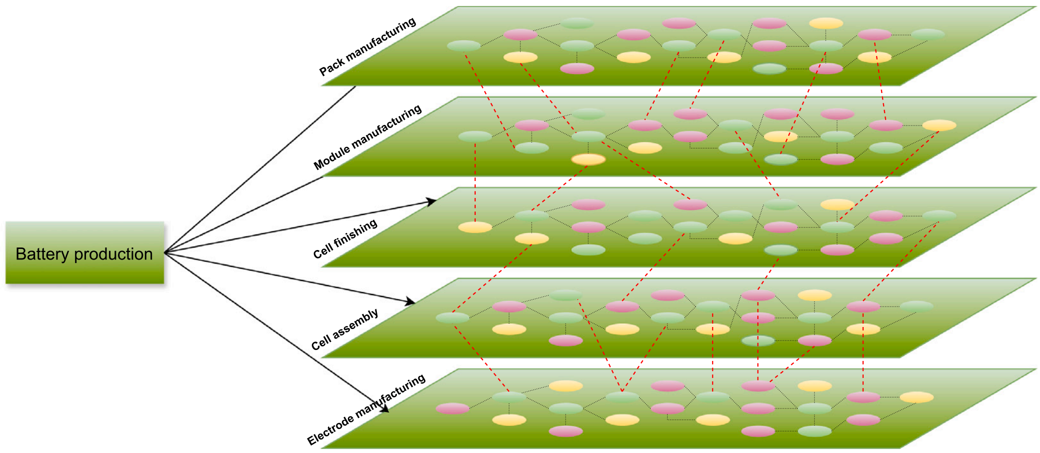


Fig. 6. BPO high-level architecture across LIB manufacturing stages (electrode → cell → module → pack). The layered view shows how common ontology patterns (process, material/flow, agent, time/space, energy/emissions) are reused while keeping distinct data contexts for interoperability.

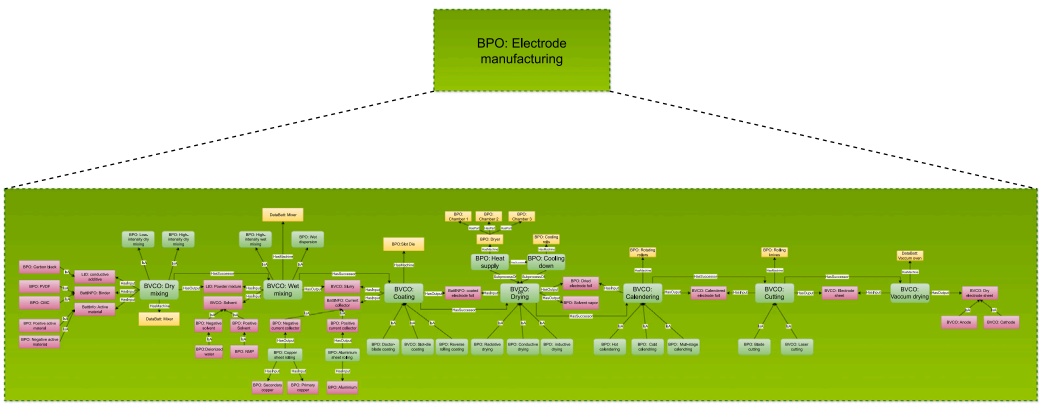


Fig. 7. Electrode manufacturing ontology view: mixing, coating, drying, calendering, cutting. Each process is linked to inputs/outputs, equipment, parameters, energy exchanges, and temporal constraints, enabling fine-grained provenance.

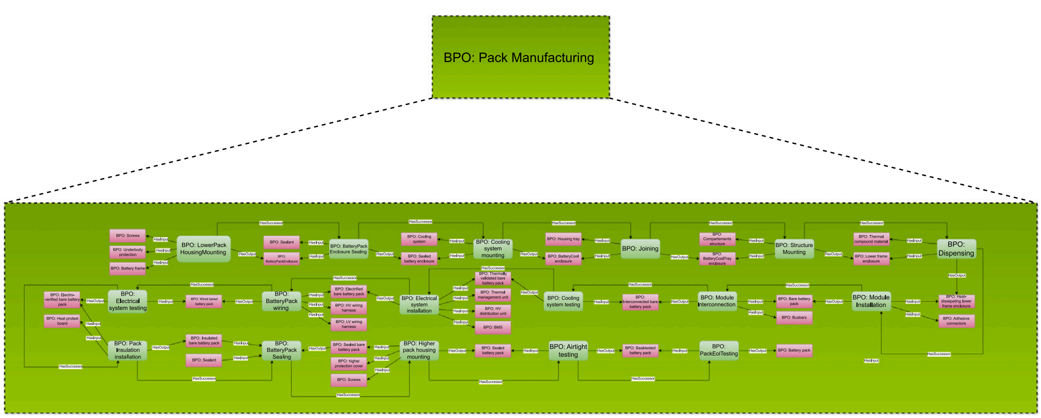


Fig. 8. Pack manufacturing ontology view: integration of cells/modules into packs; composition, assembly relations, test/inspection, and energy/footprint aggregation across the hierarchy.

4.2.1. Methodological approach

1. **Case-based approach** The development began with a use-case-driven analysis focusing on key applications in environmental impact assessment and traceability. Representative scenarios such as evaluating the CO_2 footprint of cathode manufacturing or tracing the provenance of battery materials were selected to ensure that the ontology design aligned with real analytical and reporting requirements. This approach guaranteed that the resulting ontology captures the data flows, process dependencies, and semantic relations actually encountered in industrial contexts. It also enabled iterative validation of BPO's conceptual structure against concrete use cases, ensuring both practical relevance and semantic completeness.

2. **Reuse-based approach** To maximize interoperability and avoid duplicating established concepts, BPO systematically reuses and integrates concepts from existing domain ontologies and vocabularies. These include BattInfo and BVCO for battery-specific terminology and supply chain relations, BONSAI for environmental and flow modeling, FOAF and Schema.org for actor and location descriptions, and the W3C Time Ontology for temporal representation [52,53,68–70]. Reusing these well-defined ontologies provides semantic alignment with broader knowledge ecosystems, accelerates development, and ensures that BPO remains interoperable with datasets and systems already using these standards. Where necessary, terms were extended or specialized within the BPO namespace to ensure compatibility with battery-specific requirements while maintaining original semantics.
3. **Middle-out approach** The conceptualization followed a middle-out design that combines top-down and bottom-up methodologies. Development began with mid-level concepts central to battery production (e.g., *ElectrodeManufacturing*, *CellAssembly*, *CellFinishing*) and then expanded:

   - **Upward**, by linking to higher-level ontological frameworks such as GPO and BVCO for generalized process semantics, and
   - **Downward**, by introducing detailed, domain-specific elements such as slurry mixing parameters, coating energy demand, or formation cycle profile.

   This balanced approach ensured that BPO remains both conceptually coherent and sufficiently granular to model real production data and environmental indicators.

Together, these three methodologies support a development process that is both iterative and extensible, capable of integrating new data sources, evolving manufacturing practices, and emerging sustainability regulations.

4.2.2. Structured development phases

The ontology conceptualization followed four structured phases, adapted from standard ontology engineering lifecycles (METHONTOLOGY, NeOn, and OntoClean principles) [74–76]:

1. **Domain definition:** The domain and scope of the ontology were clearly delineated to identify the key concepts, relationships, and goals of BPO. The focus was set on modeling LIB manufacturing processes with an emphasis on supporting traceability and environmental impact assessment. This phase defined the essential production steps, material hierarchies, and process transformations occurring at the cell, module, and pack levels, ensuring a coherent multi-scale representation of the manufacturing supply chain.
2. **Domain analysis:** A detailed analysis was conducted to identify all relevant concepts, entities, and relationships necessary to capture the battery production system accurately. Both material-centric and process-centric perspectives were examined, providing insight into how inputs (materials, energy) are transformed into outputs (intermediate and final components) across production stages. This step included the identification of key relations such as `BPO:HasInput`, `bpo:HasOutput`, and `BPO:hasEnergyUse`, which form the backbone of BPO's knowledge graph.
3. **Structured modeling:** Identified concepts were organized into a formal conceptual model defining classes, attributes, and interconnections. For BPO, this involved mapping production processes and establishing predecessor–successor relationships between each manufacturing step. Each process and subprocess was represented as a distinct entity with defined inputs, outputs, resources, and machinery. The model was enriched by reusing and aligning concepts from BattINFO, BVCO, and industrial reference materials such as the RWTH Aachen University and VDMA guidelines on LIB cell, module, and pack manufacturing [23–25]. This structured modeling phase provided the logical scaffold for semantic reasoning, enabling automated validation of process dependencies and material flows.
4. **Ontology formalization:** The final phase involved implementing the conceptual model in the OWL 2 language using Protégé [77]. Formalization allowed BPO to support computational reasoning, inference, and querying through SPARQL and rule-based logic. In this stage, class axioms, object and data properties, and restrictions were encoded, enabling the ontology to function as a computable representation of the battery production domain. This step ensures that BPO is not only a conceptual framework but also a machine-interpretable model capable of supporting automated analyses, such as deriving process–material dependencies or aggregating CO_2 equivalent emissions along manufacturing chains.

4.2.3. Reuse, alignments, and compatibility of BPO with upper ontologies

To ensure semantic interoperability beyond the battery domain, BPO reuses and aligns concepts from neighboring ontologies. We adopt a conservative strategy: *equivalence* when the intension matches, and *subsumption* when BPO specializes an external term. Table 3 summarizes representative alignments used in our implementation.

Below, an excerpt of some selected axioms used in BPO:

```
bpo:MaterialFlow  owl:equivalentClass  bonsai:FlowObject .
bpo:Agent         owl:equivalentClass  foaf:Agent .
bpo:Organization  owl:equivalentClass  schema:Organization .
bpo:occursAt      rdfs:subPropertyOf   schema:location .
bpo:hasTime       owl:equivalentProperty  time:hasTime .

#example SHACL shape (instance-level constraint)
bpo:PorocessExecShape a sh:NodeShape ;
  sh:targetClass bpo:ProcessExecution ;
  sh:property [ sh:path bpo:occursAt ; sh:class bpo:Station ;
  sh:minCount 1 ] ;
  sh:property [ sh:path time:inXSDDateTimeStamp ; sh:datatype
  xsd:dateTime ; sh:minCount 1 ] .
```

We adopted a *middle-out* approach to prioritize immediate industrial applicability (competency questions, queries, SHACL constraints). Accordingly, BPO was not built *on top of* a specific upper ontology, but it remains *compatible* with established frameworks. Conceptually, BPO aligns most closely with **DOLCE+DnS Ultralite (DUL)** for its process- and participation-oriented patterns that fit manufacturing activities, roles, and event contexts. In practice, optional bridging axioms allow adopters to plug BPO into DUL (or alternatives such as BFO) without altering the core model, e.g.:

```
bpo:Process rdfs:subClassOf dul:Process .
```

This avoids over-commitment to a single philosophical stance while keeping a clear path to upper-ontology compliance when required by downstream ecosystems (e.g., DBP, Catena-X, OPC UA profiles).

4.2.4. Conceptualization outcome

This combined methodology and structured workflow ensure that the BPO effectively captures the complexity and interdependence of modern battery production systems while maintaining semantic interoperability with existing ontologies and industrial vocabularies. The resulting conceptual model provides a solid foundation for integrating traceability, manufacturing, and environmental data, supporting advanced queries, reasoning, and analytics across heterogeneous sources.

Ultimately, this conceptualization phase ensures that BPO evolves as a modular and extensible ontology, adaptable to emerging battery

Table 3
Representative BPO alignments to neighboring ontologies.

BPO term	External term	Mapping & rationale
`bpo:MaterialFlow`	`bonsai:FlowObject` (BONSAI)	**owl:equivalentClass**: both denote flow-like entities carrying quantities/impacts.
`bpo:Agent`	`foaf:Agent` (FOAF)	**owl:equivalentClass**: generic actor; BPO adds roles and station-specific context.
`bpo:Organization`	`schema:Organization` (Schema.org)	**owl:equivalentClass**: organizational actor reused for supplier/OEMs.
`bpo:occursAt`	`schema:location` (Schema.org)	**rdfs:subPropertyOf**: BPO refines location to manufacturing stations.
`bpo:hasTime`	`time:hasTime` (W3C Time)	**owl:equivalentProperty**: temporal anchoring of events/executions.

technologies, evolving regulatory frameworks, and future digital battery passport implementations. The next section presents the ontology architecture and class hierarchy, describing how these conceptual foundations were translated into formal modules and semantic relationships that structure the implemented BPO model.

4.3. Battery Production Ontology (BPO)

The conceptualization of BPO was guided by a modular and reuse-oriented methodology, combining case-based, reuse-based, and middle-out design principles. The goal was to translate domain knowledge from battery production, traceability, and LCA into a formal ontology capable of representing the complex interrelations between processes, materials, energy, agents, locations, and time. The conceptual model, illustrated in Fig. 9, structures these dimensions into six tightly connected modules, Object, Time, Energy, Agent, Location, and Activity. Each module can function independently while remaining semantically linked through shared object properties, ensuring interoperability across applications such as traceability management, environmental performance evaluation, and digital battery passports. The BPO is thus designed to align closely with LCA methodology and the structure of the battery production chain, enabling integrated analysis of traceability and sustainability information across manufacturing stages. To provide a synthetic overview, Table 4 summarizes the core ontological concepts and their definitions integrated into the BPO model. It highlights how BPO reuses foundational classes from established ontologies such as BONSAI, OWL Time, Schema.org, and FOAF, while introducing domain-specific extensions to represent battery manufacturing activities, flows, and energy exchanges.

4.3.1. Core architecture

At the heart of the ontology lies the `bont:Activity` class, adapted from the BONSAI ontology and specialized as `BPO:Process` [69]. This class embodies the fundamental concept of a production activity, representing each discrete operation in the battery manufacturing chain. Processes are hierarchically organized to reflect the structure of the production line, from electrode manufacturing (mixing, coating, calendering, drying, and cutting) to cell assembly, formation, and pack integration. Each `BPO:Process` instance is semantically connected to its inputs, outputs, energy consumption, agents, location, and temporal context, enabling both material traceability and environmental impact quantification. Through the object properties `BPO:HasInput` and `BPO:HasOutput`, each process instance is linked to one or more instances of the `bont:FlowObject` class, which specializes into a hierarchical material taxonomy that distinguishes between external inputs, in-process materials, and final outputs. This differentiation allows the ontology to model both supply-chain and in-factory transformations, aligning with the LCA distinction between foreground and background systems.

- `BPO:Material`, generalized superclass for all physical inputs that comes from outside the battery production chain with subclasses `BPO:RawMaterial`, and `BPO:ProcessedMaterial`.

Table 4
Main classes used in the BPO ontology. The prefix "`BPO:`" denotes the namespace for the Battery Production Ontology IRI, while "`bont:`", "`time:`", "`schema:`", and "`FOAF:`" represent the namespaces for BONSAI ontology IRI, OWL Time ontology, Schema ontology, and Friend of a Friend ontology, respectively.

Concepts	Definition
bont:Activity	Refers to making or doing something within specific spatial and temporal boundaries. It is a key identifying dimension of a datapoint and defines properties related to the type and direction of flows.
bont:FlowObject	Represents an input or output of an entity to or from an instance of an Activity, or a directional exchange of an entity between two instances of Activity.
BPO:Energy	Represents energy consumed or required during various battery production processes. Includes attributes such as energy type (e.g., electrical, thermal), source type (e.g., renewable, fossil), and intensity (a numeric value quantifying the energy magnitude).
FOAF:Agent	Denotes an entity (e.g., person or system) that performs an Activity. An Agent may have a location distinct from the location of the Activity being performed.
BPO:Machine	Describes a tangible device or tool that facilitates tasks or activities within manufacturing processes. It applies energy or manipulates materials to achieve specific transformations or outcomes in production.
Schema:Place	Identifies a specific spatial location where processes, activities, or operations occur. This may include physical locations (e.g., factories, workstations) or virtual spaces (e.g., digital workspaces).
Time:TemporalEntity	Represents a temporal interval or instant within a timeline.
Time:Instant	A specific temporal entity with zero extent or duration, marking a singular point in time.

- `BPO:RawMaterial` represents unprocessed natural or primary industrial inputs that originate outside the battery value chain and enter it as base materials. Typical examples include lithium carbonate, cobalt oxide, nickel sulfate, aluminum foil, or copper foil. These materials are not modified within the battery production system before being consumed in upstream processes such as precursor synthesis or electrode manufacturing. Modeling raw materials separately enables the ontology to capture supply-chain provenance and environmental burdens originating from resource extraction and refining stages. They are usually linked to external databases such as Ecoinvent or BattINFO for emission factors and upstream data [52,78].
- `BPO:ProcessedMaterial` refers to semi-finished substances that result from industrial processing of raw materials, typically before entering the direct battery manufacturing line. Examples include NMC precursors, polyvinylidene fluoride (PVDF), or N-methyl-2-pyrrolidone (NMP). These materials represent converted

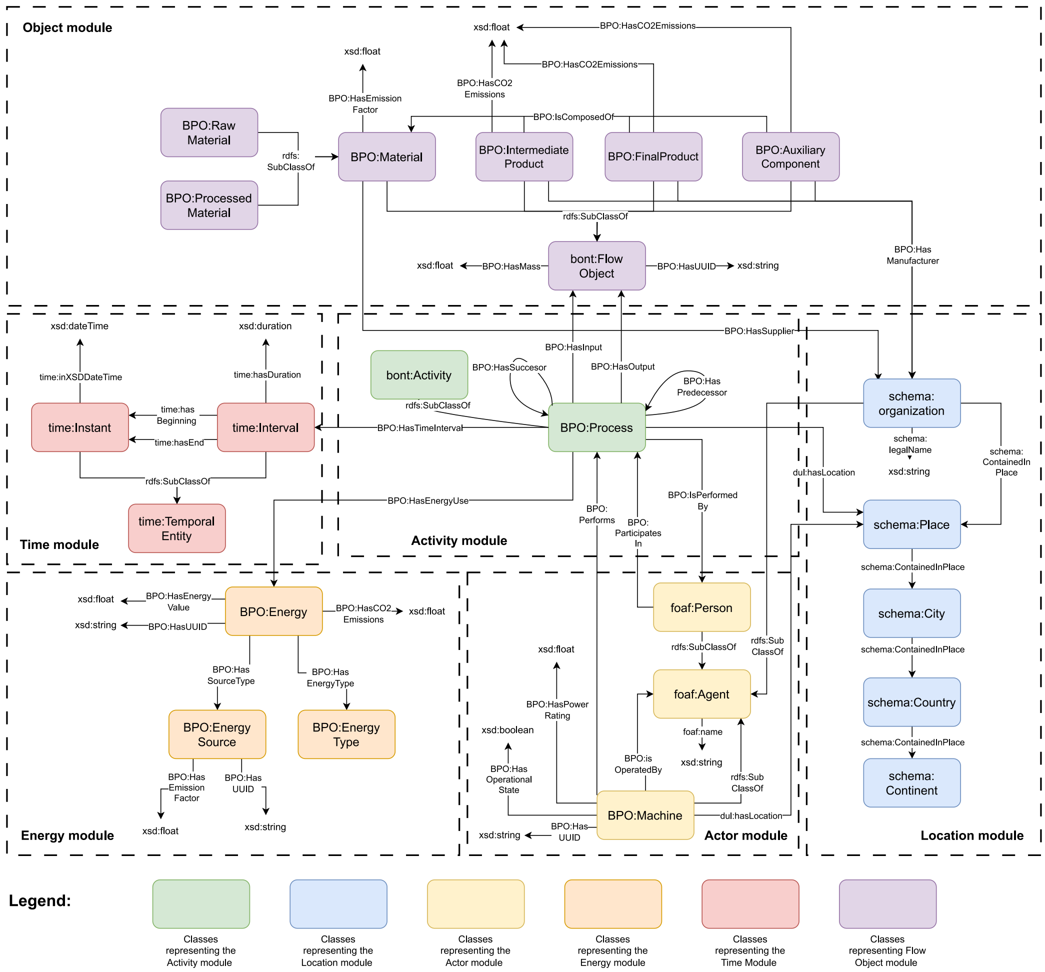


Fig. 9. High-level BPO conceptual model.

or refined forms that bridge upstream material production and in-factory usage. Their explicit distinction from raw materials allows more granular traceability of the upstream-to-factory interface, improving allocation of embedded energy and emissions.

- `BPO:IntermediateProduct` designates materials produced and transformed within the battery value chain itself, representing in-process outputs between consecutive manufacturing steps. Examples include powder mixtures, electrode slurry, coated electrodes, dried foils, or cell casings. These are outputs of one manufacturing stage and inputs to the next, forming the backbone of process interconnection in the ontology. By modeling these as distinct entities, BPO enables recursive reasoning over process dependencies, allowing full traceability and mass-balance validation across stages (e.g., from slurry → coated foil → assembled cell).
- `BPO:FinalProduct` captures the end products of the manufacturing chain, such as battery cells, modules, or packs, which exit the factory as ready-to-use components. They are used as reference flows in LCA evaluations and represent the primary entities for digital battery passport reporting.
- `BPO:AuxiliaryComponents` encompasses externally sourced subsystems and parts that are not manufactured within the battery production line but are assembled into the final product to fulfill structural, electrical, or thermal functions. Examples include battery management systems (BMS), cooling systems, thermal management units, screws, connectors, and housing components. By distinguishing auxiliary components from in-house intermediates, BPO allows the representation of system integration activities and cross-domain traceability, bridging the battery manufacturing ontology with external supply networks.

This refined categorization reflects the multilayered structure of the battery value chain, enabling queries that differentiate between:

- Upstream inputs (raw and processed materials),
- In-factory transformations (intermediate and final products), and
- External subsystem integration (auxiliary components).

Beyond defining their hierarchical roles, each `BPO:FlowObject` is further characterized by a set of data properties that capture its quantitative, identification, and provenance attributes relevant for traceability and environmental assessment:

- `BPO:hasMass` records the object's mass (kg). Supports mass-balance validation across processes and integration with LCA reference flows.
- `BPO:HasUUID` Assigns a unique identifier for cross-system traceability (MES, ERP, or digital passport linkage).
- `BPO:HasEmissionFactor` Specifies emission intensity ($kgCO_2eq/kg$). Used to calculate process-level carbon intensity when combined with mass data.
- `BPO:HasCO2Emissions` Quantifies total CO_2eq associated with the full mass of the object. Enables aggregated emission accounting through SWRL rules or imported LCI data.
- `BPO:IsComposedOf` Captures hierarchical composition (e.g., cell → electrodes → active materials), supporting recursive structural and environmental reasoning.

- `BPO:HasSupplier` Identifies the upstream provider, facilitating provenance reasoning and supplier-specific impact assessment.

4.3.2. Integration of energy, agents, and equipment

Energy consumption and related emissions are captured through the Energy module, which models both energy carriers and their source characteristics. Each `BPO:Process` instance links to one or more `BPO:Energy` instances via the property `BPO:HasEnergyUse`. Energy entities act as semantic containers linking three core concepts, their quantities and carbon intensities (via data properties), their source type and their energy type. These distinctions allow the ontology to reason about energy composition, for example, differentiating grid electricity from on-site solar electricity, or natural gas from steam.

Energy-related object properties:

- `BPO:hasSourceType` links an `BPO:Energy` instance to a member of the class `BPO:EnergySource`, which specifies the form of energy carrier used in the process. Typical instances include Electricity, Natural Gas, Steam, or Thermal Oil. This property enables the ontology to classify and group processes by carrier type, supporting analyses such as *"total emissions from natural-gas-based heating processes"*.
- `BPO:hasEnergyType` connects an `BPO:Energy` instance to the class `BPO:EnergyType`, which characterizes the origin or generation pathway of that energy source. Examples include Grid Electricity, Renewable Electricity, Hydropower, On-site Solar, or District Heating. This relation allows comparative reasoning on the basis of supply-chain decarbonization scenarios e.g., *"emission difference between renewable and grid electricity use"*.

Together, these object properties make it possible to represent both the physical nature and origin of energy inputs in a machine-interpretable way, aligning with ISO 14044 recommendations for energy source differentiation in LCA modeling.

Energy-related data properties: Beyond categorical relations, quantitative properties provide the analytical foundation for carbon and efficiency assessments:

- `BPO:HasEnergyValue` Specifies the amount of energy consumed (kWh). Enables energy balance computation and benchmarking of process efficiency.
- `BPO:HasEmissionFactor` Provides the carbon intensity of the energy source (kgCO_2eq /kWh), typically region-specific. Used to compute the climate impact of electricity or thermal use.
- `BPO:HasCO2Emissions` Quantifies total emissions (kg CO_2eq) derived from the consumed energy. Supports automated carbon-footprint aggregation across processes.

By combining categorical (`BPO:HasSourceType`,`BPO:HasEnergyType`) and quantitative (`BPO:HasEnergyValue`,`BPO:HasEmissionFactor`,`BPO:HasCO2Emissions`) relations, the Energy module enables integrated reasoning across multiple analytical dimensions. Queries such as *"Which processes rely on non-renewable grid electricity?"* or *"What share of total process emissions comes from natural-gas heating?"* can be executed directly through SPARQL, supporting both LCA alignment and energy-efficiency optimization.

The Agent module, based on the FOAF ontology, models both human and non-human actors involved in production. The class `foaf:Agent` is specialized into `foaf:Person` and `BPO:Machine`. The property `BPO:IsOperatedBy` captures the relationship between machines and their operators, while `BPO:IsPerformedBy` links each process to its executing agent. Machines include data properties such as `BPO:HasPowerRating`,`BPO:HasOperationalState`, and `BPO:HasUUID`, enabling detailed tracking of equipment performance and responsibility.

4.3.3. Temporal and spatial context

The Temporal and Spatial Context modules of BPO provide the necessary dimensions to represent when and where each manufacturing activity occurs. These modules enrich the ontology with event chronology and geographical granularity, both of which are essential for traceability, process optimization, and spatially differentiated environmental assessment.

Temporal Representation: Temporal information is modeled using the W3C Time Ontology, which ensures alignment with established web standards for event-based data. Each `BPO:Process` instance is linked to a temporal entity through the object property `BPO:HasTimeInterval`, referencing either `time:Interval` or `time:Instant`. This allows the ontology to represent both continuous processes (e.g., coating, drying) and discrete events (e.g., inspection, transport, or assembly). Temporal entities are further described using the following data properties:

- `time:hasBeginning` records the starting timestamp (xsd:dateTime) of a process or event.
- `time:hasEnd` indicates the completion time (xsd:dateTime).
- `time:hasDuration` captures total elapsed time (xsd:duration), derived automatically when beginning and end times are provided.

Modeling process duration and sequence in this way enables a variety of reasoning capabilities. The combination of `time:hasEnd` and `time:hasBeginning` supports process-sequence validation, ensuring chronological consistency between successive activities connected through `BPO:HasPredecessor` and `BPO:HasSuccessor`. By reasoning over `time:hasDuration`, the ontology can also identify production bottlenecks, such as the longest or most energy-intensive stages within a cycle, allowing for performance optimization and scheduling analysis.

Spatial Representation: Spatial data in BPO are modeled through the Location module, which reuses classes from Schema.org and DOLCE+DnS Ultra Lite (DUL) to describe production sites, facilities, and organizational entities [71,79]. Each `BPO:Process` instance is connected to a spatial entity via the object property `dul:hasLocation`, linking it to a corresponding `schema:Place` or `schema:Organization`. This hierarchical representation supports spatial reasoning across different geographical scales:

- `schema:Place` the generic location concept representing physical sites, such as factories or laboratories.
- `schema:City`, `schema:Country`, `schema:Continent` progressively broader geographical entities connected via `schema:ContainedInPlace`, allowing reasoning from local to global contexts.
- `schema:Organization` captures ownership and operational control of a facility, enabling association of manufacturing activities with specific corporate entities.

The integration of spatial information within BPO enables multiple analytical capabilities. By linking every process, material, and supplier to a defined location, the ontology supports geospatial traceability, allowing the reconstruction of complete geographical supply chains, an essential requirement for regulatory transparency in the battery sector. Spatial relations also facilitate regionalized environmental modeling, as connecting processes to their `schema:Country` or `schema:Region` enables alignment with geographically differentiated LCA datasets, such as regional electricity mixes or emission intensities.

Together, the temporal and spatial dimensions ensure that every manufacturing activity in BPO is contextually grounded in both time and space. This dual contextualization transforms the ontology from a static description of processes into a spatiotemporal knowledge graph, enabling complex reasoning such as: *"Which electrode batches produced in France during Q2 2025 were processed using renewable energy sources and emitted less than 5 kg CO_2eq per kWh?"*

Such queries illustrate how BPO's temporal and spatial modeling bridges the gap between traceability, process analytics, and geo-temporal environmental intelligence, reinforcing its role as a semantic backbone for digital battery passports and dynamic sustainability monitoring.

4.3.4. Integration and reasoning

By interconnecting the Activity, Flow Object, Energy, Agent, Time, and Location modules, BPO constructs a coherent semantic graph of the entire battery production system. This integrated architecture supports both forward and backward traceability and enables diverse reasoning operations:

- **Process-chain reasoning:** infers upstream or downstream dependencies using `BPO:HasPredecessor` and `BPO:HasSuccessor`.
- **Environmental reasoning:** aggregates energy use and CO_2 emissions across process networks through linked data properties.
- **Accountability reasoning:** identifies responsible agents, machines, and facilities associated with specific production events.

This modular interconnection allows BPO to act as a digital twin of the manufacturing chain, linking operational, environmental, and organizational data within one interoperable framework.

5. Ontology evaluation and validation

The BPO ontology has been validated using both qualitative and quantitative approaches. This process aims to confirm its logical consistency, expressivity, and applicability to real-world scenarios, particularly in promoting transparency and sustainability within the battery production lifecycle.

5.1. Qualitative validation

The qualitative validation of the ontology was conducted using a set of SWRL rules to test the ontology's logical consistency and comprehensiveness. The validation focused on instantiating the first level of the LIB production chain, specifically targeting electrode manufacturing with an emphasis on cathode production.

This instantiation integrates two key data types: *foreground data* and *background data*. Foreground data includes the material composition of the cathode (e.g., mass share or material inputs required for production) and the energy consumption associated with the manufacturing process. The cathode's mass share was derived from the life cycle inventory of an NMC battery cell detailed in the study by Peters et al. [80], while the energy consumption was modeled using the findings of Von Drachenfels et al. [81]. Background data, sourced from the Ecoinvent database, provides emission factors essential for calculating the carbon footprint of materials and processes [78].

The SWRL rules were employed to validate that the ontology's relationships, properties, and constraints align with expected real-world behaviors, ensuring its practical applicability to electric vehicle battery traceability.

5.1.1. Case study 1: emissions from energy use in a specific process

Scenario. To demonstrate the ontology's capability to model environmental impacts, a case study rule was designed to calculate CO2 emissions resulting from energy consumption during a production process. This rule incorporates various energy sources, such as electricity and gas, along with their unique emission factors.

Rule. The SWRL rule below determines the total CO2 emissions by multiplying the energy consumption value by the emission factor for the specific energy type.

CO2 emissions from energy use

BPO:Process(?p) ∧ HasEnergyConsumption(?p, ?e) ∧ BPO:Energy(?e) ∧ HasEnergyValue(?e, ?ev) ∧ HasEmissionFactor(?e, ?ef) ∧ swrlb:multiply(?co2, ?ev, ?ef) → BPO:HasCO2Emissions(?p, ?co2)

Results. The ontology successfully calculates the CO2 emissions for various production processes based on energy consumption data. For example, an electrode manufacturing process consuming 100 kWh of electricity with an emission factor of 0.5 kgCO2/kWh results in total emissions of 50 kgCO2. These results validate the ontology's ability to integrate energy data with environmental impact assessments.

5.1.2. Case study 2: CO2 emissions from material and process contributions in intermediate and final products

Scenario. This case study demonstrates the calculation of total CO2 emissions for a final product. The emissions are aggregated from material inputs and production processes. For instance, raw materials and intermediate products are considered alongside the energy consumed during the production of the final product.

Rules. Two SWRL rules are used:

1. To compute emissions for each material based on its mass and emission factor:

CO2 material emissions calculation

BPO:Materials(?M) ∧ BPO:HasMass(?M, ?m) ∧ BPO:HasEmissionFactor(?M, ?ef) ∧ swrlb:multiply(?co2, ?m, ?ef) → BPO:HasCO2Emissions(?M, ?co2)

2. To aggregate emissions from materials and processes into the total emissions for the final product:

CO2 total emissions calculation

BPO:Product(?outputFlow) ∧ BPO:IsComposedOf(?outputFlow, ?inputFlow) ∧ BPO:HasCO2Emissions(?inputFlow, ?co2_input) ∧ BPO:IsOutputOf(?outputFlow, ?p) ∧ BPO:HasCO2Emissions(?p, ?co2_process) ∧ swrlb:add(?totalEmissions, ?co2_input, ?co2_process) → BPO:HasCO2Emissions(?outputFlow, ?totalEmissions)

Results. The BPO accurately computes the total CO2 emissions for a final product. For example, a battery module composed of materials with a combined emission of 30 kgCO2 and a production process emitting 20 kgCO2 results in a total footprint of 50 kgCO2. This confirms the ontology's capability to model cumulative emissions effectively.

5.1.3. Case study 3: Tracing of input components in manufactured products

Scenario. This case study evaluates the ontology's ability to track input components throughout the production process. By defining the relationships between input materials and output products, the ontology supports detailed traceability within the supply chain.

Rule. The SWRL rule formalizes the composition of each product based on its input materials:

Input traceability

BPO:Process(?p) ∧ BPO:HasOutput(?p, ?output) ∧ BPO:HasInput(?p, ?input) → BPO:IsComposedOf(?output, ?input)

Results. The ontology enables detailed tracking of input materials. For example, if a cathode is produced using lithium and nickel, these inputs are traceable through the production process to the final battery pack. This supports enhanced traceability and aligns with regulatory requirements for supply chain transparency.

5.1.4. Case study 4: Sequencing of process steps in electrode manufacturing

Scenario. This case study ensures the logical sequencing of process steps within the electrode manufacturing stage by propagating successor relationships to the overall manufacturing process. Specifically, it states that if a process step (e.g., mixing) belongs to an electrode manufacturing sequence and has a defined successor step (e.g., coating), then this successor step is also considered part of the electrode manufacturing sequence. This rule enables a complete representation of the manufacturing workflow, ensuring that all connected steps are captured within the ontology.

Rule. The SWRL rule establishes the sequencing of manufacturing steps:

Process sequencing

BPO:ElectrodeManufacturing(?s) ∧ *BPO:HasProcessStep(?s, ?step1)* ∧ *BPO:HasSuccessor(?step1, ?step2)* → *BPO:HasProcessStep(?s, ?step2)*

Results. The BPO ontology successfully models sequential steps, such as mixing followed by coating in electrode manufacturing. This ensures a complete representation of the workflow, supporting both traceability and process optimization.

5.1.5. Discussion

Beyond confirming logical consistency, the qualitative validation demonstrates how the ontology directly addresses key challenges in the battery manufacturing value chain. First, Case studies 1 and 2 resolve the long-standing difficulty of linking process-level operational data with environmental performance metrics. By computing emissions from both energy use and material contributions within the same semantic framework, BPO bridges the gap between production monitoring and LCA, enabling consistent and automated environmental impact calculations. Second, Case study 3 tackles the issue of fragmented traceability, where material provenance is often lost as components move across production stages. By formalizing the relationships between inputs and outputs through the `BPO:IsComposedOf` relation, the ontology ensures that each product, such as a cathode, cell, or battery pack, can be traced back to its constituent materials and corresponding emissions. Finally, Case study 4 addresses the challenge of workflow fragmentation in electrode manufacturing. By enforcing sequential dependencies between production steps through successor relations, BPO reconstructs a coherent digital workflow, enabling process optimization and alignment with real production logic. Together, these use cases demonstrate how BPO functions not only as a knowledge representation model but also as a semantic integration layer capable of improving traceability, transparency, and sustainability assessment within lithium-ion battery manufacturing.

5.2. Quantitative validation

The quantitative validation assesses the performance of the BPO ontology in terms of *reasoning efficiency*, *scalability*, and *accuracy*. This is essential to ensure that the ontology can handle realistic, large-scale datasets while delivering timely and accurate output. The reasoning efficiency of the ontology was evaluated using the Pellet reasoner within the Protégé environment. Additionally, SPARQL queries were executed to test common use cases, such as retrieving material emissions, energy consumption, and traceability data.

SPARQL query 1. Retrieve process inputs, outputs, and production stage.

```
PREFIX BPO: <http://www.semanticweb.org/csoufi01/
     ontologies/2024/5/BPO#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-
     ns#>

SELECT ?process  ?stage
  (GROUP_CONCAT(?input; separator=",") AS ?inputs)
  (GROUP_CONCAT(?output; separator=",") AS ?outputs)
WHERE {
    ?process rdf:type BPO:Process .
    ?stage BPO:HasProcessStep ?process .
    ?process BPO:HasInput ?input .
    ?process BPO:HasOutput ?output .
}
GROUP BY ?process ?stage
ORDER BY ?stage ?process
```

Results. The results of the SPARQL query presented above provide a structured overview of the production processes within the LIB production chain. Each process is associated with its respective production stage and details the specific inputs and outputs involved. As shown in Table 5, the query effectively consolidates data, listing key resources such as processed materials (e.g., Carbon black additive, PVDF binder, and NMP solvent) and outputs (e.g., NMC electrodes) critical to different stages of the battery manufacturing workflow.

These query results can be applied in real-world scenarios to track material flows across production stages, identify bottlenecks in resource utilization, and pinpoint inefficiencies in the manufacturing process, enabling industries to optimize production workflows and reduce material waste while maintaining sustainability goals.

SPARQL query 2. Aggregation of CO2 emissions and energy consumption for each process.

```
PREFIX BPO: <http://www.semanticweb.org/csoufi01/
     ontologies/2024/5/BPO#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-
     ns#>

SELECT ?process (SUM(?co2) AS ?total_co2)
       (GROUP_CONCAT(CONCAT("Energy:", STR(?energy),
            ",Amount:", STR(?amount), ",CO2:", STR(?
            co2)); separator=",") AS ?energy_details)
WHERE {
  ?process BPO:HasEnergyUse ?energy .
  ?energy BPO:HasEnergyValue ?amount .
  ?energy BPO:HasCO2Emissions ?co2 .
}
GROUP BY ?process
```

Results. The SPARQL query presented above aggregates CO2 emissions and energy consumption for each process within the battery production chain. By adding CO2 emissions and grouping energy details, the query provides a consolidated view of the environmental impact of each process. Table 6 summarizes the results, presenting the total CO2 emissions for each production process (e.g., *Calendering1*, *Coating1*) along with detailed information on energy use. For instance, the Coating1 process emits a total of 50.4 kg of CO2 per kWh of energy consumed, derived from multiple energy sources, such as *Electricity2* and *Gas1*. This structured representation facilitates a comprehensive understanding of energy use patterns and associated emissions, which are critical to identifying high-impact processes in the manufacturing chain.

These results can guide sustainability strategies by identifying the processes with the highest environmental impact, such as *Coating1* and *Calendering1*. Industries can use these data to prioritize cleaner energy sources for *coating1* or enhance efficiency in *Calendering1*, reducing overall emissions and energy consumption while aligning with sustainability goals.

SPARQL query 3. Trace the provenance of all base materials used in the final product.

Table 5
Results of the SPARQL query 1 applied to the production of an NMC electrode sheet.

Process	Stage	Inputs	Outputs
Calendering1	Cathode manufacturing	NMC_slurry electrode_foil	NMC_calendered_foil
CellStack Assembly1	CellAssembly	NMC_calendered_foil	NMC_cell_stack
Coating1	Cathode manufacturing	NMC_slurry Positive_Current_Collector	NMC_coated_electrode
DryMixing1	Cathode manufacturing	Carbon_Black NMC_Hydroxide PVDF	NMC_powder_mixture
VacuumDrying1	Cathode manufacturing	NMC_electrode_sheet	NMC_dry_electrode
WetMixing1	Cathode manufacturing	NMC_powder_mixture NMP	NMC_slurry
Drying1	Cathode manufacturing	NMC_coated_electrode	NMC_electrode_sheet
Cutting1	Cathode manufacturing	NMC_calendered_electrode_foil	NMC_cut_electrode

Table 6
Results of the SPARQL query 2 applied to the production of an NMC electrode sheet.

Process	Total CO_2 emissions ($kgCO_2eq/kWh$)	Energy details (kWh and $kgCO_2eq/kWh$)
DryMixing1	6.8	Electricity1, Quantity: 10, CO_2 emissions: 6.8
WetMixing1	6.8	Electricity1, Quantity: 10, CO_2 emissions: 6.8
Coating1	50.4	Electricity2, Quantity: 45, CO_2 emissions: 30.6 Gas1, Quantity: 495, CO_2 emissions: 19.8
Drying1	33.6	Electricity3, Quantity: 30, CO_2 emissions: 20.4 Gas2, Quantity: 330, CO_2 emissions: 13.2
Calendering1	40.8	Electricity4, Quantity: 60, CO_2 emissions: 40.8
Cutting1	30.6	Electricity5, Quantity: 45, CO_2 emissions: 30.6
VacuumDrying1	11.8	Electricity6, Quantity: 5, CO_2 emissions: 3.4 Gas3, Quantity: 210, CO_2 emissions: 8.4

```
PREFIX BPO: <http://www.semanticweb.org/csoufi01/
    ontologies/2024/5/BPO#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>

SELECT DISTINCT ?finalProduct ?material ?materialType
     ?uuid ?supplier
WHERE {
  # Final product
  ?finalProduct a BPO:FinalProduct .
  # Recursively trace back from final product to base
       materials
  ?finalProduct (^BPO:HasOutput/BPO:HasInput)+ ?
      material .
  # Only retain actual base materials
  ?material a BPO:Material .
  # Exclude anything that's an output of a process
  FILTER NOT EXISTS { ?anyProcess BPO:HasOutput ?
      material }
  # Optional label for the materials
  OPTIONAL { ?material rdfs:label ?materialType }
  # Optional UUId and supplier
  OPTIONAL { ?material BPO:HasUUID ?uuid }
  OPTIONAL { ?material BPO:HasSupplier ?supplier }
}
```

Results. This query recursively retrieves all raw and processed materials that compose a given final product (e.g., an electrode sheet), while excluding any intermediate products generated within the production line. The results, summarized in Table 7, provide a transparent view of material provenance, linking each base input to its supplier and unique identifier. Such traceability enables manufacturers to verify supplier compliance, ensure responsible sourcing, and meet EU Battery Regulation requirements for material disclosure.

SPARQL query 4. Retrieve hierarchical spatial information for each process.

```
PREFIX BPO: <http://www.semanticweb.org/csoufi01/
    ontologies/2024/5/BPO#>
PREFIX schema: <https://schema.org/>

SELECT ?process
(GROUP_CONCAT(DISTINCT STR(?room); separator=", ") AS
     ?rooms)
(GROUP_CONCAT(DISTINCT STR(?facility); separator=", "
    ) AS ?facilities)
(GROUP_CONCAT(DISTINCT STR(?city); separator=", ") AS
     ?cities)
(GROUP_CONCAT(DISTINCT STR(?country); separator=", ")
     AS ?countries)
(GROUP_CONCAT(DISTINCT STR(?continent); separator=",
    ") AS ?continents)
WHERE {
  ?process a BPO:Process ;
           BPO:dul:hasLocation ?room .
  OPTIONAL {
    ?room schema:containedInPlace ?facility .
    OPTIONAL {
      ?facility schema:containedInPlace ?city .
      OPTIONAL {
        ?city schema:containedInPlace ?country .
        OPTIONAL { ?country schema:containedInPlace ?
            continent. }
      }
    }
  }
}
GROUP BY ?process
```

Results. This query demonstrates how BPO enables spatial reasoning by aggregating hierarchical location data across manufacturing facilities. As shown in Table 8, each process is linked to multiple spatial levels, from room to facility, city, country, and continent, through

Table 7
Results of SPARQL query 3 applied to the production of an NMC electrode sheet.

Final Product	Material	Material type	UUID	Supplier
NMC cathode	NMP	Positive solvent	Mat-001	BASF_SE
NMC cathode	NMC active material	Positive active material	Mat-002	Umicore
NMC cathode	PVDF	Binder	Mat-003	ARKEMA_SA
NMC cathode	NMC current collector	Positive current collector	Mat-004	Orion engineered carbons
NMC cathode	Carbon black	Conductive additive	Mat-005	Hydro extrusion Europe

Table 8
Results of SPARQL query 4 applied to the production of an NMC electrode sheet.

Process	Room	Facility	City	Country	Continent
DryMixing1	Material prep zone	BMZPlant	Karlstein	Germany	EU
WetMixing1	Class D clean room	BMZPlant	Karlstein	Germany	EU
Coating1	Coating bay	BMZPlant	Karlstein	Germany	EU
Drying1	Coating bay	BMZPlant	Karlstein	Germany	EU
Calendering1	Electrode finishing zone	BMZPlant	Karlstein	Germany	EU
Cutting1	Electrode finishing zone	BMZPlant	Karlstein	Germany	EU
VacuumDrying1	Moisture control clean room	BMZPlant	Karlstein	Germany	EU

the integration of *Schema.org* and DUL ontologies. Such reasoning supports region-specific sustainability assessments and compliance with geographically differentiated environmental standards.

SPARQL query 5. Calculate total CO_2 emissions for final products by combining material and process contributions.

```
PREFIX BPO: <http://www.semanticweb.org/csoufi01/
    ontologies/2024/5/BPO#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd:  <http://www.w3.org/2001/XMLSchema#>

SELECT ?finalProduct
       (GROUP_CONCAT(DISTINCT ?material; separator=",
           ␣") AS ?materials)
       (SUM(xsd:float(?materialCO2)) AS ?
           totalMaterialCO2)
       (SUM(xsd:float(?energyCO2)) AS ?
           totalProcessCO2)
       ((SUM(xsd:float(?materialCO2)) + SUM(xsd:float
           (?energyCO2))) AS ?totalCO2)
WHERE {
  ?finalProduct a BPO:FinalProduct .
  ?finalProduct (^BPO:HasOutput/BPO:HasInput)+ ?
      material .
  ?material a BPO:Material .
  FILTER NOT EXISTS { ?anyProcess BPO:HasOutput ?
      material }
  OPTIONAL { ?material BPO:HasCO2Emissions ?
      materialCO2 }
  OPTIONAL {
    ?process BPO:HasInput ?material ;
             BPO:HasEnergyUse ?energy .
    OPTIONAL { ?energy BPO:HasCO2Emissions ?energyCO2
        }
  }
}
GROUP BY ?finalProduct
ORDER BY DESC(?totalCO2)
```

Results. The query results (Table 9) illustrate how BPO supports product-level environmental reporting by automatically aggregating emissions from both material and process sources. For instance, the final product *NMC Dried Electrode Sheet* exhibits a combined footprint of 32.537 kg CO_2 eq/kg, derived from 32.488 kg CO_2 eq/kg associated with input materials and 0.049 kg CO_2 eq/kWh generated through process energy consumption. This demonstrates how the ontology integrates life-cycle inventory data directly with process semantics, enabling consistent and queryable sustainability indicators within the manufacturing chain.

Table 9
Results of SPARQL query 5 applied to the production of an NMC electrode sheet.

Final product	Total materials CO_2 emissions ($kgCO_2eq/kg$)	Total processes CO_2 emissions ($kgCO_2eq/kWh$)	Total CO_2 emissions ($kgCO_2eq/kg$)
BPO:NMC_Dried ElectrodeSheet	32.488	0.049	32.537

5.3. Expert knowledge evaluation

Expert knowledge evaluation ensures that the ontology accurately represents domain-specific knowledge while aligning with the expectations of battery manufacturers, sustainability and environmental impact analysts, as well as researchers and professionals involved in the production and development of LIBs. For this purpose, a set of competency questions was derived from the ontology's objectives, focusing on critical aspects such as lifecycle modeling, environmental impact assessment and traceability. These questions were reviewed by experts in battery manufacturing and sustainability, who assessed whether the ontology's structure, classes, and relationships corresponded to their domain knowledge. An excerpt of the validation questionnaire is provided below.

Validation questionnaire for BPO

Section 1: Lifecycle modeling

1. Does the ontology accurately represent the stages of battery production, including electrode manufacturing, cell assembly, module and pack manufacturing? (Rating: 1 - Poor, 5 - Excellent) Comments:
2. Are the relationships between materials, intermediate products, and final products clearly defined and consistent with real-world production processes? (Yes/No) If no, please specify any gaps:
3. Does the ontology enable modeling of manufacturing workflows (e.g., process sequences like mixing, coating, drying)? (Yes/No) Suggestions for improvement:
4. Is the ontology capable of integrating inputs like energy consumption, material usage, and waste generation at each lifecycle stage? (Yes/No) Comments:

Section 2: Environmental impact assessment

1. Does the ontology correctly associate emission factors with energy sources, materials, and processes? (Yes/No) Please specify any inconsistencies:
2. Can the ontology effectively calculate the carbon footprint of intermediate and final products based on material and energy inputs? (Yes/No) Suggestions for better alignment with sustainability assessments:
3. Are SWRL rules or other logic-based methods adequately designed for environmental impact evaluation (e.g., CO2 emission calculations)? (Rating: 1 - Poor, 5 - Excellent)

The evaluation confirmed that the ontology effectively addresses key domain requirements, accurately modeling the relationships between materials, processes, and environmental impacts. Experts validated its capability to represent the lifecycle of a LIB, from electrode manufacturing to final pack assembly. However, they also provided detailed feedback to enhance its structure and functionality. One key suggestion was to expand the class hierarchy to include more specific processes for each general manufacturing process. For example, within the coating process, experts recommended incorporating sub-processes such as doctor-blade coating, slot-die coating, reverse rolling coating, and emerging new technologies used in coating applications. This level of granularity would enhance the ontology's capacity to model the diversity and specificity of industrial practices. Experts also recommended the inclusion of additional properties to capture machine-specific parameters, such as operating pressure, temperature, rotational speed, and coating thickness. Adding these properties would enable the ontology to model the precise operating conditions of manufacturing processes, facilitating a more detailed assessment of how these factors influence energy consumption, material quality, and environmental impacts. This enhancement would also support the evaluation of process optimization strategies and the adoption of advanced technologies in battery production. This feedback led to refinements in class hierarchies and property definitions, improving clarity and alignment with industry standards. The iterative expert review and refinement process ensured that the BPO ontology is both comprehensive and practical for its intended applications.

5.4. Criteria-based evaluation

The ontology was further evaluated against established quality criteria, including *accuracy, clarity, completeness, consistency, computational efficiency, adaptability, and conciseness*. Accuracy was assessed by comparing the ontology's definitions and relationships with validated sources in the battery production domain, including existing standards and expert knowledge. Key sources such as BatteryDesign.net, BattINFO, Wikidata, RWTH University guides, and input from battery professionals were used to ensure the definitions align with established terminology [23–25,52,82,83]. Clarity was ensured through the use of precise labels and detailed descriptions for each class and property, facilitating understanding and reuse by domain experts and developers. Completeness was demonstrated by the ontology's ability to comprehensively represent the entire battery production lifecycle, including materials, processes, emissions, and traceability, while aligning with recommended practices and multi-level production coverage as described in relevant domain literature and standards [51,62,84]

Consistency was validated through automated reasoning, which detected no contradictions or unsatisfiable axioms. The ontology demonstrated computational efficiency, with reasoning and querying tasks executed within reasonable time frames, averaging around a thousand milliseconds for typical dataset volumes. Adaptability was further demonstrated by aligning the ontology with other relevant ontologies, such as BattInfo, BVCO, and BONSAI, ensuring interoperability and flexibility. Its modular design enables it to serve as a basis or data model for emerging applications like the digital battery passport, while also accommodating future developments such as battery recycling and alternative energy storage technologies. Finally, conciseness was achieved by eliminating redundancies and ensuring that each class and property serves a distinct purpose. These results confirm that the BPO ontology meets or exceeds standards for high-quality ontology design while remaining adaptable to evolving industry requirements.

The evaluation of the ontology was performed using an *ontology pitfall scanner (OOPS!)*, which identified a set of common pitfalls impacting its overall quality. The results of this evaluation, presented in Fig. 10, highlight four key pitfalls: missing annotations (P08), inconsistent naming conventions (P22), untyped classes (P34), and missing license declarations (P41).

The *missing annotations* detected primarily refer to absent definitions for classes, properties, and entities within the ontology. While these definitions have been documented in a separate Excel sheet, integrating them directly into the ontology file would enhance its clarity and self-contained usability. Addressing this pitfall ensures that the ontology remains comprehensible without relying on external resources. Regarding the *naming conventions*, inconsistencies were detected specifically in the naming of individual instances. While this does not critically affect the ontology's functionality, standardizing the naming conventions for individuals in line with those used for classes and properties would improve readability, maintainability, and overall consistency.

Several key metrics were used to evaluate the proposed ontology, focusing on its structural quality, semantic richness, and usability. The evaluation followed the ontology module assessment framework proposed by Zubeida Casmod Khan [85], which provides quantitative indicators for measuring ontology completeness, cohesion, and structural balance. The results, summarized in Table 10, show that the ontology comprises 241 classes, 33 object properties, 14 data properties, and 17 individuals, demonstrating broad and detailed coverage of the battery production domain. The overall ontology size amounts to 305 entities, with 1113 axioms defined. According to Khan's evaluation framework, the appropriateness score of the ontology is 0.425, while its cohesion value is 0.06, indicating an adequate level of internal consistency and conceptual interconnectivity. Furthermore, the class hierarchy exhibits an average atomic size of 7.27, reflecting a well-balanced and cohesive structural organization.

6. Conclusion

The BPO presented in this work establishes a semantic foundation for representing LIB manufacturing, addressing the industry's growing demand for traceability, sustainability assessment, and regulatory compliance. By integrating essential concepts across production stages, material flows, energy consumption, and carbon emissions, BPO provides a standardized and interoperable framework for capturing and analyzing key data throughout the manufacturing chain. Its structured design aligns with emerging initiatives such as the European Digital Battery Passport, supporting comprehensive environmental impact assessments, detailed traceability, and improved data interoperability across stakeholders.

Compared with existing traceability solutions that couple physical identification with heterogeneous data stores, BPO provides a hierarchy-aware *computational knowledge model* that spans cell–module–pack, enables automated provenance reconstruction and constraint checking, and natively links traceability with sustainability indicators within a single semantic graph. This closes the gap between step-wise tracking and auditable, interoperable digital threads suitable for regulatory transparency. A feature-by-feature positioning is summarized in Table 2.

While BPO offers a comprehensive framework for the production phase, several limitations remain. First, its scope is confined to production; use-phase and end-of-life processes (second life, recycling, material recovery) are not yet modeled, preventing cradle-to-cradle analyses. Second, although semantic links to BONSAI, FOAF, and Schema.org

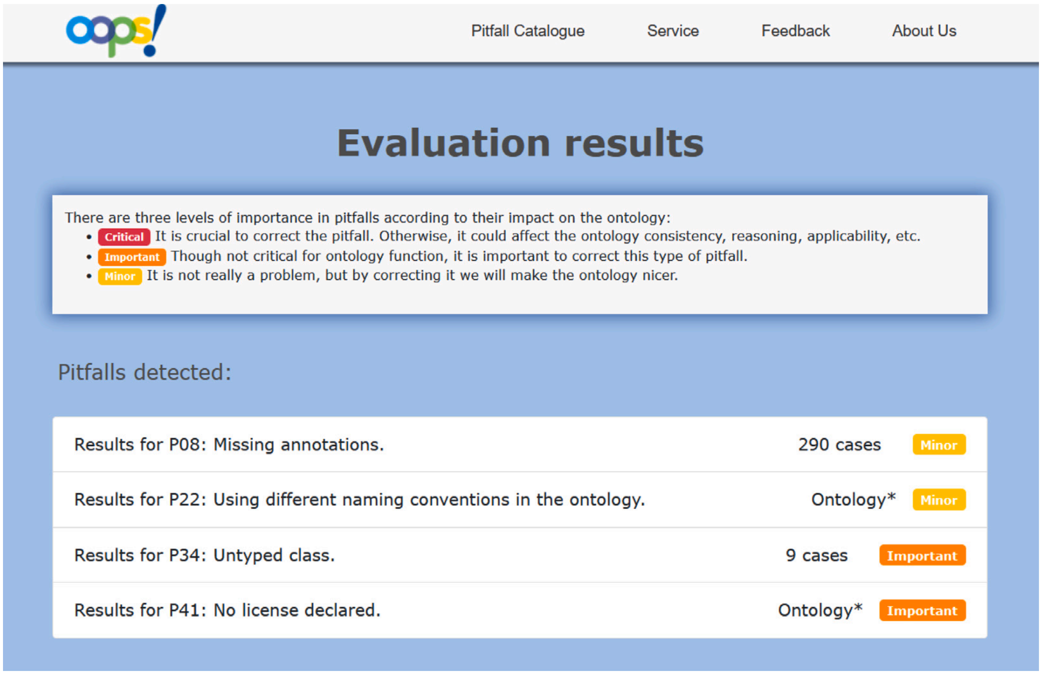


Fig. 10. OOPS! evaluation results.

Table 10
Evaluation metrics for the BPO ontology.

No. of classes	No. of op	No. of dp	No. of ind	Size	No. of axioms	App.	Atomic size
241	33	14	17	305	1113	0.425	7.27

are established, alignment with industrial standards (e.g., IEC 62660, ISO 14083, IEC 62890, OPC UA information models, and DBP data fields) is only partial and requires additional extensions and mapping patterns (identities, units, code lists). Third, validation has relied on lab-scale and case-based data; plant-scale deployment with heterogeneous MES/IoT sources, noisy and missing values has not yet been demonstrated, and both competency-question coverage and robustness to incomplete/erroneous links remain to be quantified. Fourth, operationalization aspects are not fully assessed: current pipelines assume curated mappings; the effort for ontology alignment, instance population, and SHACL authoring across sites has not been measured, and governance (versioning, change management) as well as the public release of artifacts (OWL, SHACL, SPARQL catalogs) are not yet formalized. Fifth, although modularization improves reasoning efficiency, no benchmark has been reported under high-volume, near-real-time streams (e.g., continuous genealogy completion and constraint checking); stream reasoning and CEP integration are left to future work. Finally, non-functional aspects such as security and access control, handling of uncertainty and provenance quality, and explicit data-quality constraints are currently out of scope.

We will extend BPO into a Battery Life Cycle Ontology (BLCO) to cover use-phase monitoring, second-life applications, and end-of-life recycling, providing a unified semantic framework for cradle-to-cradle modeling. We will also complete mappings to international standards and data-space models (e.g., IEC 62890, OPC UA, Catena-X, DBP), publish governed artifacts (OWL, SHACL, query catalog), and benchmark reasoning/streaming at plant scale with noisy data in pilot implementations interfacing MES, IoT infrastructures, and digital twins.

Through these developments, BPO lays the groundwork for a modular, interoperable, and lifecycle-aware semantic infrastructure that bridges data silos and enables intelligent, transparent, and sustainable battery production.

CRediT authorship contribution statement

Cyrine Soufi: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Ali Ayadi:** Writing – review & editing, Supervision, Conceptualization. **Tedjani Mesbahi:** Writing – review & editing, Supervision, Funding acquisition. **Ahmed Samet:** Writing – review & editing, Supervision. **Christophe Lallement:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Tedjani Mesbahi and Ahmed Samet reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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