Ontology-Driven Metrology Data Management for Wireless Charging, Battery Management and Predictive Maintenance in Electrical Vehicles

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***Abstract*— The growing adoption of electrical vehicles (EVs) requires efficient data management for charging, battery performance, and predictive maintenance. This paper introduces an ontology-driven framework to ensure interoperability across diverse data sources using semantic web technologies. AI-powered predictive analytics enhance battery health monitoring and maintenance, while cybersecurity measures protect metrology data. By unifying domain-specific and agnostic ontologies, the proposed system enables seamless integration of heterogeneous datasets, improving real-time decision-making. The research demonstrates how semantic technologies, AI diagnostics, and secure data architectures enable a scalable, intelligent metrology ecosystem, advancing sustainable mobility, safer charging, and battery management. Experimental evaluations show that our predictive models achieve a battery health estimation R^2 of 0.9913 (XGBoost) with 233.78 W power consumption, which is suitable for real-time edge deployment, while maintaining 97% accuracy in identifying low RUL symptoms through semantic-enhanced AI analytics. These results highlight the practicality and efficiency of the proposed framework in modern EV systems.**

Keywords—Ontology, Metrology, Electrical Vehicle, Battery Management Systems, Artificial Intelligence, Predictive Maintenance, Cybersecurity

I. Introduction

Ontology-based frameworks in metrology provide a structured and standardized approach to managing measurement data, ensuring interoperability, consistency, and semantic understanding across various industrial applications [1]. In automotive metrology, ontologies facilitate the integration of sensor data, calibration processes, and measurement uncertainty analysis, enabling efficient data exchange between quality control systems, manufacturing units, and digital twins. By leveraging semantic models, metrology data can be linked to AI-driven (Artificial Intelligence-driven) decision-making systems, improving predictive maintenance (PdM), process optimization, and compliance with industry standards. Ontologies also enhance traceability and data provenance, making it easier to track measurement variations, automate quality inspections, and apply machine learning algorithms for anomaly detection [2][3]. The adoption of ontology-driven metrology is becoming increasingly critical in Industry 4.0 and smart manufacturing, where real-time sensor fusion, digital twins, and AI-powered diagnostics require structured, meaningful, and reusable measurement knowledge [4].

Metrology for Electrical Vehicles (EVs) plays a crucial role in ensuring accuracy, reliability, and efficiency across various components, particularly in the Battery Management System (BMS), where precise measurement of voltage, temperature, and current is essential for optimal battery performance and longevity [5]. Advanced metrology techniques, integrated with AI, enable real-time data analysis and anomaly detection, facilitating PdM to prevent battery degradation and unexpected failures. AI-powered metrology frameworks process vast amounts of sensor data to optimize charging cycles, thermal management, and energy efficiency [6]. Furthermore, as EVs increasingly rely on connected infrastructure and over-the-air updates, metrology data security becomes a critical concern. Cybersecurity measures, such as blockchain for metrology data integrity and AI-driven threat detection, ensure that measurement data remains tamper-proof and resistant to cyber-attacks [7]. With the rise of Industry 4.0 and smart grids, metrology in EVs is evolving into an intelligent, autonomous system, integrating real-time analytics, machine learning, and secure cloud computing to enhance vehicle performance, safety, and sustainability.

Ontology-driven metrology offers advantages but faces challenges like data standardization, interoperability, and computational complexity, limiting real-time scalability. AI integration is hindered by data misalignment and lack of structured datasets, while cybersecurity risks arise from reliance on cloud and Internet of Things (IoT) platforms. Regulatory barriers further slow adoption, as International Organization for Standardization (ISO) and National Institute of Standards and Technology (NIST) standards lack ontology-based frameworks. Despite these challenges, ontology-driven metrology holds promise in improving PdM, AI-powered analytics, and secure data exchange, necessitating an integral approach and collaborative efforts between industries, academia, and regulatory bodies to drive standardization and large-scale implementation.

This paper aims to present how a domain ontology can be integrated with unified metrology in the EV domain for better data management incorporating innovations in AI, BMS, wireless charging and cybersecurity. This integral approach is presented experimentally on various implementations and use cases, including accurate and trustworthy data acquisition, measurements and the utilization of both rule-based and AI-powered data analyses, i.e., State-of-Charge (SoC), State-of-Health (SoH) and Remaining Useful Life (RUL) estimation to improve the overall EV performance. The presented ontology integration tactic can be applied to other ontologies that exist in the literature, showing how linked ontologies can be valorized in the targeted domains. The experiments focus on potential metrology benefits dealing with security and safety concerns in BMS and wireless charging. The organization of the paper is as follows. Section II presents the current state of the playground, Section III introduces the integrated semantic approach for PdM, Section IV presents the measurement strategy and practice, and finally, Section V concludes the paper.

II. Current State of Playground

Metrology in the automotive industry has a critical role, emphasizing the need for accurate and equitable measurements to ensure optimal quality assurance, structural integrity, and customer satisfaction. For instance, a recent work discusses how dimensional metrology impacts productivity, industrial automation, and socio-economic growth, with a focus on in-line and near-line measurement advancements [8]. Ontology-based metrology has gained momentum in recent years. For instance, a RESTful API-based ontology framework was designed to enhance measurement terminology interoperability across industries [9]. It addresses challenges arising from inconsistent terminologies used by National Measurement Institutes (NMIs), organizations, and stakeholders, which hinder cross-industry collaboration and data integration. By structuring discipline-specific glossaries into a machine-readable ontology, the EVs and EV Supply Equipment (EVSE) provide a centralized, accessible vocabulary service to standardize communication. A recent approach presents a domain-agnostic ontology for unified metrology data management to enhance reproducibility, traceability, and interoperability in measurement sciences [10]. This ontology serves as a sample model in our study, demonstrating its linkage with metrology ontologies.

A recent paper discussed the critical role of metrology charging infrastructure in ensuring the viability of electric mobility, with a focus on both urban and interurban charging challenges [6]. Another promising paper investigated the exposure to electromagnetic fields (EMF) from inductive power transfer (IPT) systems used for charging EVs [11]. The authors presented experimental measurements and numerical dosimetry to assess human exposure in both light vehicles and heavy electric buses. The MICEV (Metrology for Inductive Charging of Electric Vehicles) project focuses on improving measurement accuracy and safety assessment in wireless power transfer (WPT) systems for EVs [12]. The study addressed two key challenges: enhancing the traceability of power measurements in charging stations and evaluating human exposure to EMF. The findings indicated that EMF exposure from inductive charging remains within safety limits, but further improvements in standardization and measurement protocols were necessary. The placement of Battery EV charging infrastructure, identifying key influencing factors, metrics, and their impact on charger utilization, was examined in [13]. The study found that while average charger utilization remains similar across locations, charging behavior patterns vary significantly, emphasizing the need for demand-based site selection strategies to optimize charging station placement.

The growing power density of lithium batteries increases the need for high-gain measurement in battery management systems. This drives the development of advanced AI-based measurement and estimation algorithms. Voltage, current, and temperature each require unique measurement technologies [14]. High-bit-rate, ADCs (16+ bits) ensure efficient, high-resolution voltage measurement. A recent paper explored AI-driven methods for real-time learning and debugging SoH [15]. Electrochemical impedance spectroscopy (EIS) enhanced voltage accuracy, refining SoC and SoH estimates. Additionally, Coulomb Counting was proposed to track charge flow, improving battery state estimation[16][17]. Kelvin-coupled shunt resistors (milliohms) ensured precise, low-power current measurement by detecting voltage drops, also indicating charge/discharge direction. As emphasized in the literature accuracy depends on proper resistance calculation and calibration. Hall effect sensors offer reliable, isolated current detection. In another work, advanced AI-based filtering enhanced real-time monitoring accuracy [18]. Precise temperature measurement ensures efficient operation and longer battery life. High-precision thermistors offer a wide range and fast response, while digital sensors provide direct microcontroller data with built-in linearization. In large battery modules, fiber-optic sensors enable distributed temperature mapping for early detection of local overheating, preventing thermal anomalies [19].

AI-driven PDM enhances EV battery performance, reliability, and lifespan. Machine learning plays a key role in predicting RUL, ensuring operational standards and preventing failures [20]. From a metrology perspective, the accuracy of measurements and monitoring techniques plays a fundamental role in PDM for EV batteries. High-precision metrology tools, such as advanced impedance measurement techniques, are utilized to gain insight into battery degradation mechanisms and working conditions [21]. Combining measurements with AI, researchers develop robust health estimation models, improving predictive maintenance. Boosting Algorithms and Transfer Learning adapt battery performance data over time, ensuring accurate SoH estimation [22][23]. This synergy of precise metrology and advanced AI methodologies not only improves existing BMS but also contributes to the overall safety, operability, and longevity of EV batteries by anticipating potential failures and optimizing maintenance schedules.

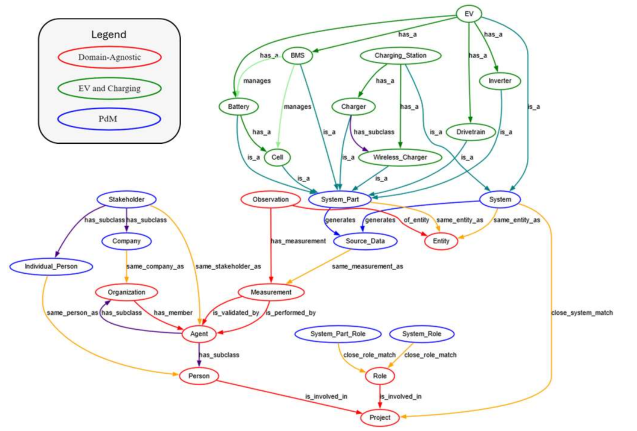


Fig. 1. High-Level integration of Unified Agnostic PdM Ontology

III. Semantic Approach

Ensuring semantic interoperability in PdM is crucial for integrating heterogeneous data sources, standardizing terminology, and facilitating automated reasoning. To achieve this, as depicted in Fig. 1, we have developed a Unified PdM Ontology by integrating Domain-Agnostic [10], EV and Charging, and PdM (Z-BRE4K [24]) ontologies. This unified framework establishes a structured representation of maintenance knowledge, enabling seamless data exchange across different domains.

A key aspect of this ontology is the use of semantic relationships such as is_a (owl:equivalentClass), same_X_as (owl:sameAs), and close_X_match (owl:closeMatch), which define hierarchical classifications, entity equivalences, and approximate correspondences. X denotes entities like Company, Stakeholder, Person etc. The is_a relation structures entities into taxonomies, allowing for generalization and specialization within the ontology. The main entities concerning the is_a relation are EV and Charging Station corresponding to pdm:System, and their components corresponding to pdm:System_Part (e.g., BMS, Drivetrain etc. is_a pdm:System_Part). As listed in Table I, the same_X_as relation ensures interoperability by linking conceptually identical entities across domains, while close_X_match captures near-equivalent but contextually distinct concepts. These relationships collectively enable a flexible yet rigorous integration of multiple ontological perspectives.

TABLE I. Unified PdM Ontology Integrating Predicates

Subject (PdM Ontology)	Predicate	Object (Domain Ontology)
Company	same_company_as	Organization
Stakeholder	same_stakeholder_as	Agent
Individual_Person	same_person_as	Person
Source_Data	same_measurement_as	Measurement
System_Part	same_entity_as	Entity
System	same_entity_as	Entity
System	close_system_match	Project
System_Part_Role	close_role_match	Role
System_Role	close_role_match	Role

By leveraging a structured semantic approach, we achieve seamless integration of diverse ontologies, ensuring consistent representation and interoperability in PdM. The use of is_a, same_X_as, and close_X_match relations enables hierarchical structuring, entity alignment, and approximate matching, facilitating automated reasoning and cross-domain knowledge sharing. Through this approach, the ontology serves as a foundation for harmonizing metrological data and enhancing predictive maintenance strategies. In further studies, the Unified Agnostic PdM Ontology can be enhanced by integrating Semantic Sensor Network Ontology (SSN) [25], also mentioned in [10], and ENISA Thread Taxonomy [26] to cover cyber threats.

IV. Integrated Measurement Strategy and Practice

The integrated architecture of the data acquisition system is illustrated in Fig. 2. Here, a wireless EV charging system is highlighted with its key components and their interactions. The charger side consists of a primary coil, a wireless transmitter power block, and a wireless transmitter main unit, which receives power from the power grid and transfers it wirelessly to the vehicle through inductive power transfer.

The onboard system features a secondary coil, a wireless receiver power block, and a wireless receiver main unit, which passes energy to the battery charger power block. The battery pack includes a Battery Control Unit (BCU), Cell Control Unit (CMU), lithium cells, and necessary safety components such as fuses, contactors, and isolation elements. A secure CAN gateway and a secure IoT gateway ensure communication with AI, cybersecurity, and cloud services for advanced monitoring and control, encountering both in-vehicle and out-vehicle data communication. Additionally, wireless control feedback ensures efficiency and safety in power transfer. The following subsections present how battery management, wireless charging, PdM and cybersecurity services are incorporated with the ontology-driven metrology management methodology.

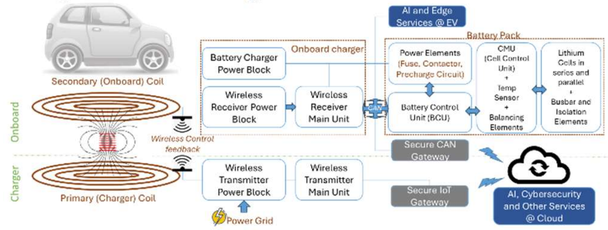


Fig. 2. High-level architecture.

A. Battery Management

Fig. 3 shows the building blocks of the developed BMS in a lithium-ion battery pack. This brings seamless collaboration of connected and edge services to strengthen local algorithms. The given approach has the capability of cell measurement of an individual cell of the battery pack and detection of any open wire (1). Detection and measurement features enhance functional safety by monitoring every individual cell's status point of view. This block's measurement results may improve by using RC filters for every cell, external and internal balance components, balance feedback, and short circuit protection of cells to any other cell.

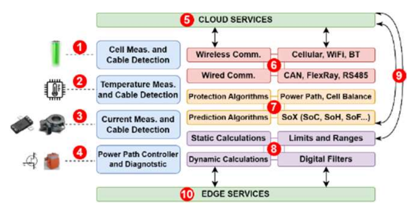


Fig. 3. Building blocks of the developed BMS

Temperature sensor measurement and sensor cable feedback (2) need to be handled in harmony with hardware and firmware features. Any type of temperature sensor (one wire digital, one wire analog, NTC, PTC …) has a crucial effect and direct impact on protection, prediction, and dynamic/static calculations. Any sensor malfunction or cable contact problem needs to be handled immediately and pass to other functions as a fault or warning signal. Current sensing should be handled by analog and digital sensors together to ensure safety level of the system. Current sensor selection needs to make by using system parameters (3) (short circuit, peak and continuous charge/discharge levels, desired sensitivity and accuracy). To minimize current sensing errors (Fig. 4), a hybrid approach using both analog and digital sensors on the same power path is common. Algorithms compare their outputs to correct readings or ignore faulty data. Additionally, redundant analog sensing with separate low- and high-current outputs enhances accuracy and ensures correct current levels and direction.

As a fuse nears end-of-life, it retains low resistance (1-10 ohms) but heats up under a high current, risking damage to nearby components. Similarly, high-power contactors may fail due to contact sticking or coil burning. To monitor health, auxiliary contact feedback is needed, requiring additional high-voltage measurement points in the BMS hardware(4).

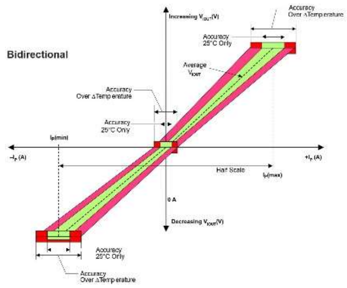


Fig. 4. Current sensor output voltage versus sampled current, total output error at 0 A and Half-Scale current.

An open gate to the outside of the battery pack as a communication line brings to BMS some advantages and disadvantages. A good BMS and battery pack need to have fast communication lines like CanBus, FlexRay and other industrial/automotive communication buses (6). This also means that communication lines need to protect against cybersecurity issues too. Most of the advantages come from cloud services (5) which can run new cell and battery models, and AI / ML algorithms to enhance the results of static and rule-based calculations on the BMS edge hardware (10). Some of the good examples are also explained in this paper.

Protection and prediction (7) algorithms are mandatory software parts of any type of BMS. Most algorithms rely on preset parameters set via communication lines, prioritizing battery operation. Hybrid SoX algorithms improve accuracy but face limitations under aging and predictive maintenance. Recalibrating SOC at full and empty states aids edge calculations, but system-wide calibration using historical data yields better results, requiring an adaptive approach. (9) to get and set system parameters, limits and ranges not only from static calculations (8) but also from cloud services and high-level algorithms to increase system robustness.

Practically, the lithium battery pack can be observed by using Togi Teknoloji's "Libat Connect" cloud platform. Measuring outputs of voltage, temperature, current and calculation-prediction results may help the user understand how a charging phase went until fully charged (Fig. 5). A cell balance progress started after certain thresholds on duty and result, only PCB (Fig. 6) started to increase because of heat on the cell balance resistors. So, users may understand that a successful balance progress started and ended properly when you look at the good measurement results and historical data on cloud infrastructure.

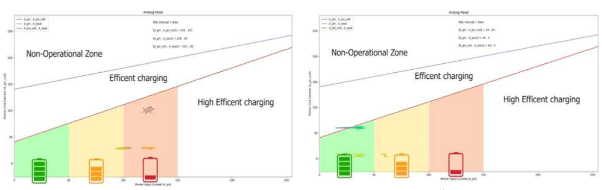
Fig. 5. A snapshot from start to end of charge phase of lithium battery pack, SoC, current and voltage realization.

Fig. 6. A snapshot from start to end of charge of lithium battery pack, temperature difference of cells and BMS board.

B. Wireless Charging

An IoT-enabled surface inductive charging system using conventional IGBTs is designed. The modular system supports 3.5 kW and 7.0 kW modules, scalable beyond 20 kW, with the current setup delivering 15 kW at 42V–55V operating at 20-50 kHz. IoT integration enables real-time bidirectional data transfer (Vehicle-to-Grid and Grid-to-Vehicle) via CAN bus (J1939 protocol) or wireless communication, ensuring comprehensive monitoring and analysis of key system metrics.

The data acquisition system can measure the parameters that define the key electrical, thermal, and system characteristics of the Wireless Power Transfer (WPT) system. They include electrical parameters such as input voltage (V_{pri}), input current (A_{pri}), receiver unit input/output voltages and currents (V_{sin}, A_{sin}, V_{sout}, A_{sout}), and efficiency (*Eff*) to monitor power flow and system performance. Thermal parameters include battery temperature (T_{batt}), ambient temperature (T_{amb}), and coil temperature (T_{coil}) to assess thermal stability. System identifiers, like IGBT-Type, Wireless Block ID (Wblock_ID), and coil distance (d), help in tracking hardware configurations. Operational data, such as plug-in time (t_{in}), plug-out time (t_{out}), and location (*loc*), provide insights into the system's real-time usage. Lastly, battery load parameters (**L**) monitor the charging state and energy storage characteristics. These parameters collectively ensure efficient, safe and monitored wireless EV charging.



(a) (b)

Fig. 7. Visualization of the battery charging process across different State of Charge (SoC) zones.

A 48 V lithium iron phosphate (LFP) battery with a maximum charging current of 30 A and a full-charge voltage of 54 V is selected for the tests. When the state of charge (SoC) is below 80%, the battery receives a constant charging current of 30 A at 48 V. As the SoC rises above 80%, the charging current gradually decreases from 30 A to 5 A. Fig. 7(a) illustrates this process, where the red zone represents the charging phase below 80% SoC, during which the battery is supplied with 30 A. As the SoC exceeds 80%, the charging status transitions into the orange zone, where the current begins to decline. When the supplied current reaches 5 A, the charging status enters the green zone, indicating that the battery has reached 100% SoC. As shown in Fig. 7(b), reaching the green zone signals the completion of the charging process, causing the operation to stop.

Efficiency increases with input power up to a certain level before stabilizing. Smaller coil distances (d=15mm and 30mm) yield higher efficiency, peaking around 86% and 84%, respectively. As distance increases (d=45mm and 60mm), efficiency decreases, with 60mm showing the lowest efficiency (~78%). This highlights the inverse relationship between coil distance and efficiency, emphasizing the importance of optimal coil alignment for better performance.

C. AI-Powered Predictive Maintenance

The complexity of EV battery systems demands AI-powered PDM solutions for predicting health degradation, failures, and efficiency. Gradient boosting (XGBoost) and Transformer-based models excel in analyzing multivariate sequential data and predicting SOH patterns and RUL with high accuracy, efficiency, and scalability.

XGBoost is a gradient-boosted decision tree (GBDT) model that has gained widespread adoption in predictive maintenance applications due to its ability to efficiently handle structured data, model non-linear relationships, and provide interpretable feature importance [27]. XGBoost's ensemble learning iteratively corrects errors, capturing complex battery degradation factors like charge cycles, voltage fluctuations, and temperature patterns. It is computationally efficient, handles missing data, and excels in real-time BMS for fast decision-making. Transformer-based models excel in battery health forecasting by using self-attention to capture short- and long-term dependencies in time-series data. Unlike RNNs/LSTMs, they effectively model degradation trends but require specialized preprocessing for numerical metrology data. Studies show that adding 1D-Convolutional layers before and an MLP layer after the Transformer enhances feature extraction and numerical stability, improving predictive accuracy. [28]. This hybrid approach allows the Transformer to better capture local dependencies within the data, thereby mitigating issues associated with raw real-valued inputs and optimizing predictive accuracy in battery health estimation tasks.

To evaluate the performance of these two approaches, both models were trained and tested on sequences in historical battery telemetry datasets, enriched with contextual features such as ambient temperature, cycle count, and charge/discharge profiles, assessing their predictive accuracy using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R^2 score, Pearson Correlation Coefficient (PCC), and Mean Directional Accuracy (MDA). The results, summarized in Table II, indicate that XGB outperforms the Transformer model in RMSE, MAE, R^2, and PCC, suggesting that it provides more precise estimations of battery health with lower prediction errors. However, the Transformer model excels in MDA, indicating its superior ability to predict the directionality of battery degradation trends, a crucial factor for proactive maintenance strategies.

TABLE II. PERFORMANCE OF AI ALGORITHMS

Model	RMSE	MAE	R^2	PCC	MDA
XGB	0.02	0.0154	0.9913	0.9956	0.9704
Transformer	0.0762	0.0622	0.8537	0.9766	0.9967

Beyond predictive accuracy, real-world deployment also requires an assessment of computational efficiency, particularly in terms of power consumption and memory footprint. Table III compares the hardware resource utilization of XGB and the Transformer model during training. The results demonstrate that while XGB is highly power-efficient, consuming only 233.78 W, the Transformer model requires approximately 34,569.08 W, which is nearly 147 times higher. Such a significant energy demand makes Transformers impractical for onboard, real-time inference in EVs, particularly in edge-computing environments with stringent power constraints. However, the Transformer model does exhibit a lower memory footprint compared to XGB, which suggests a more efficient use of storage, albeit at the cost of higher computation.

TABLE III. HARDWARE RESOURCE UTILIZATION

Model	Total Power (W)	Max Memory (MB)
XGB	233.78	1306
Transformer	34569.08	1136

These findings underscore the inherent trade-offs between accuracy, energy efficiency, and computational feasibility in AI-driven predictive maintenance systems for EVs. XGBoost remains the better choice for real-time deployment, particularly for BMS applications requiring low-latency decision-making with minimal energy consumption. In contrast, Transformer-based models offer richer temporal pattern recognition, making them more suitable for high-dimensional feature extraction in cloud-based battery analytics, where computational resources are less constrained.

D. Trustworthy Semantic Integration and Cybersecurity

To ensure trustworthy semantic integration, we employ a structured architecture that supports interoperability, consistency, and secure access to ontological data. At its core is the Virtuoso Triplestore, an RDF database enabling efficient SPARQL-based reasoning over distributed knowledge graphs. A REST API service facilitates external interaction with the data, while integration with Apache Jena ensures flexible RDF handling, ontology management, and reasoning. This setup allows seamless querying and manipulation of semantic data across systems. The SPARQL query presented in SPARQL Query 1 retrieves failure symptoms related to EV battery components with low RUL, links them to predictive maintenance actions and supports findings through associated measurements and validating agents. These queries complement AI models that achieve a 97.04% Mean Directional Accuracy, enabling explainable and traceable maintenance decisions.

SPARQL Query 1. Querying required actions for detected PdM Symptom, supported by Measurement data and its performer and/or validating Agent/Stakeholder

```
SELECT * WHERE {
  #Select failure symptoms and their associated parts
  ?failureSymptom
    pdm:Description_of_System_Part_Failure_Symptom
    ?failureDescription .
  ?failureSymptom pdm:inheres_in_System_Part
    ?systemPart .
  # Link to PdM Process Definition and its predictive actions
  ?failureSymptom pdm:requires_PdM_Process_Definition
    ?maintenanceProcess .
  ?maintenanceProcess
    pdm:predictive_actions_of_PdM_Process_Definition?
    predictiveActions .
  # Ensure the system part belongs to an EV
  ?system :is_a ev:EV .
  ?system pdm:has_Part ?systemPart .
  # Ensure the system part is a Battery
  ?systemPart :is_a ev:Battery
  # Filter for low RUL (e.g., "low" in the numerical thresholds)
  FILTER(CONTAINS(LCASE(?failureDescription),"low rul"))
  # Support the finding with measurement
  ?systemPart :same_entity_as ?entity .
  ?observation da:entity_of ?entity .
  ?observation da:has_measurement ?measurement .
  ?measurement da:has_value ?measurement_value .
  ?measurement da:has_unit ?measurement_unit .
  # The Agent/Stakeholder performing and/or validating the measurement
  ?measurement da:is_performed_by ?performing_agent .
  ?measurement da:is_validated_by ?validating_agent }
```

This architecture ensures semantic consistency while maintaining scalability and interoperability, allowing various stakeholders and services to interact with the knowledge base securely and efficiently. As semantic integration involves handling sensitive and interconnected data, cybersecurity is a critical component of the architecture. To ensure the integrity, confidentiality, and availability of semantic data, multiple security mechanisms are employed. The system ensures secure access control using OAuth 2.0 and OpenID Connect, allowing only authorized users to interact with the ontology. ERARGE's Secure IoT gateways, orchestrated by Hardware Security Module, namely PRIGM© Cyber Security Platform, as well as TLS encryption protect communications, preventing cyber threats. SPARQL query sanitization prevents injection attacks, while centralized logging and IDS enable real-time monitoring and anomaly detection. Data integrity is maintained through provenance tracking and cryptographic hashing, ensuring authenticity and preventing tampering. By integrating these cybersecurity measures, we ensure that the semantic integration framework remains resilient against potential threats while maintaining its interoperability and accessibility.

V. Conclusion

The described ontology-driven metrology approach offers a transformative solution for wireless charging, battery management, and PdM in EVs, enhancing interoperability, AI-powered diagnostics, and cybersecurity. Integrating semantic web technologies, AI models, and secure data frameworks enables accurate, standardized, and intelligent data management across EV infrastructure. Despite challenges such as data standardization, computational complexity, and regulatory barriers, the synergy of ontology, AI analytics, BMS, and PdM supports a scalable and secure metrology ecosystem. Experimental implementations—including battery diagnostics, adaptive charging, and semantic threat detection—demonstrate its practical viability. These results confirm that semantic integration enhances system transparency, predictive accuracy, and safety in data-intensive EV environments. Future progress will require collaboration between industry, academia, and regulators to drive standardization and extend the framework with additional ontologies and advanced AI for intelligent, cyber-secure mobility systems.

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