Engineering Informatics and Intelligent Systems 1 (2026)
journal homepage: http://eiis.informaticsfoundry.org/

Research Article

Multimodal Knowledge Fusion and Ontological Reasoning for Distributed Energy Resources in Power Systems: A Semantic-Driven Framework

Zhenting Gao*, Yongfang Liu, Xuemei Zhang, Ziyang Song, Peifan Zhai, Siying Chen

State Grid Shanghai Electric Power Design Co. Ltd, Shanghai, China

* Correspondence: gaozt@sh.sgcc.com.cn

ABSTRACT Distributed Energy Resources (DERs) generate heterogeneous operational information spanning sensor measurements, equipment topology, engineering documents, and maintenance requirements. Although existing power-system monitoring and data-fusion methods can process individual data sources effectively, their outputs are often represented and analyzed independently, limiting the ability to relate numerical anomalies to their physical and operational context. This paper proposes a semantic-driven multimodal knowledge fusion framework that integrates heterogeneous DER information through a unified ontological representation. The framework comprises four layers: Data, Ontology, Information, and Knowledge. A top-level DER ontology aligned with the Basic Formal Ontology (BFO) provides a common semantic structure for representing facilities, equipment, processes, events, operational states, technical requirements, regulations, and organizations. Modality-specific information extraction methods transform textual documents, engineering information, and multivariate sensor streams into structured entities and events, which are subsequently reconciled through entity matching and multi-view entity alignment and integrated into a Knowledge Graph. The framework is demonstrated using a fault-diagnosis case study involving a 1 MW photovoltaic sub-array. By combining CIM-derived equipment topology, an operational threshold extracted from an OEM manual, and real-time SCADA sensor events, the Knowledge Graph associates simultaneous power-loss symptoms across ten PV strings with their common upstream inverter. Cross-modal reasoning further identifies an inverter temperature exceeding the derating threshold, tracing the observed alarm pattern to inverter thermal derating and producing a targeted cooling-fan inspection recommendation. The results demonstrate how ontology-mediated knowledge fusion can transform fragmented multimodal observations into an explicit and traceable diagnostic reasoning chain, providing a foundation for explainable fault diagnosis and knowledge-driven maintenance in heterogeneous DER environments.

Keywords: Knowledge Graph, Basic Formal Ontology, Cross-modal Reasoning, Fault Diagnosis, Semantic-Driven Framework

1. Introduction

The increasing penetration of Distributed Energy Resources (DERs), including photovoltaic (PV) systems, wind generation, and energy storage, is reshaping power systems from predominantly centralized architectures toward more distributed and actively managed networks. While DERs provide important opportunities for renewable-energy integration and operational flexibility, their distributed deployment, heterogeneous technologies, intermittent behavior, and evolving network configurations also introduce substantial challenges for system monitoring, control, and fault diagnosis [1–3]. At the operational level, DER ecosystems consequently generate and depend on increasingly heterogeneous information, ranging from continuous sensor measurements and network topology to equipment records, technical documents, and engineering diagrams.

Conventional Supervisory Control and Data Acquisition (SCADA) systems and energy management platforms remain primarily organized around structured numerical measurements, such as voltage, current, power, and temperature. These measurements are indispensable for operational monitoring, but numerical observations alone may not provide sufficient context for interpreting complex equipment conditions. A detected anomaly can, for example, depend on the connectivity and physical configuration of the affected equipment, its operating history, and maintenance or operational requirements documented outside the sensor stream. Existing studies have therefore increasingly explored the integration of sensor observations with process information, textual records, topology, and other forms of domain knowledge [4–6]. Without an explicit mechanism for relating these heterogeneous sources, operators may still need to manually associate numerical warnings with physical configurations and supporting technical information during diagnosis.

Recent advances in artificial intelligence, knowledge graphs, and heterogeneous data fusion provide promising mechanisms for addressing this fragmentation. In power systems, multi-source fusion has been investigated for applications including equipment-quality analysis, distribution-network awareness, load forecasting, voltage control, and fault diagnosis [1–4]. Ontology- and knowledge-graph-based models have likewise been developed for power-asset management, household energy management, grid dispatching, and PV power stations [5, 7–9]. The potential of ontology-centered semantic integration has also been demonstrated outside the power-system domain. For operational fire-safety compliance, Chen et al. [10] developed a three-layer knowledge-driven architecture in which heterogeneous perception outputs are normalized and integrated through an ontology-based semantic layer before being used for rule-based reasoning. However, the reviewed literature remains fragmented across particular applications, data modalities, and domain-specific models. Many fusion approaches operate primarily on already structured numerical or relational inputs, while automated extraction from unstructured text and engineering imagery is often treated as a separate problem [6, 11]. Existing ontology models are also commonly developed for a specific system or application domain rather than as an upper-level semantic structure spanning heterogeneous DER facilities, equipment, processes, events, and operational knowledge.

Motivated by these limitations and opportunities, this study proposes a semantic-driven framework for multimodal knowledge modeling and information fusion in DER management. Rather than treating sensor analysis, information extraction, and knowledge representation as independent tasks, the framework establishes explicit semantic relationships among physical entities, operational processes, observed events, and supporting domain information. The framework is organized into four functional layers: Data, Ontology, Information, and Knowledge. Together, these layers provide a structured pathway from heterogeneous raw data to machine-interpretable knowledge and cross-modal reasoning.

The main contributions of this paper are summarized as follows:

- **A BFO-Aligned Top-Level DER Ontology:** We construct a cross-domain DER ontology aligned with the Basic Formal Ontology (BFO) [12]. By organizing DER concepts under upper-level categories such as *Continuants* (e.g., facilities and equipment) and *Occurrents* (e.g., processes and events), the ontology provides a consistent semantic foundation for integrating concepts across heterogeneous DER applications.
- **An Ontology-Guided Multimodal Information Extraction Pipeline:** We implement an Information Layer that transforms heterogeneous raw data into ontology-grounded structured information using modality-specific methods. The layer combines BERT-BiGRU-CRF-based entity extraction and relation parsing for unstructured text, CNN- and OCR-based processing for engineering diagrams, and graph-based learning for multivariate time-series sensor data.
- **A Semantic-Driven Knowledge Fusion Mechanism:** We develop a Knowledge Layer that combines ontology grounding, cross-source entity matching and alignment, and graph-based relation consolidation. This separates semantic typing from identity resolution and enables sensor observations, textual rules, and structural information referring to the same physical system to be represented within a common Knowledge Graph for traceable cross-modal reasoning.

The remainder of this paper is organized as follows. Section 2 reviews related work on data and knowledge fusion, knowledge modeling, and heterogeneous information extraction. Section 3 presents the proposed four-layer framework. Section 4 presents an experimental case study demonstrating cross-modal fault root-cause reasoning. Section 5 discusses the implications and limitations of the framework, and Section 6 concludes the paper.

2. Related Work

2.1. Existing Data and Knowledge Fusion Systems in Power Systems

Data and knowledge fusion techniques have been increasingly explored as a means of managing the complexity of modern power systems. Combining multiple information sources can provide additional context for applications such as fault diagnosis, load forecasting, equipment assessment, and grid control. Representative approaches are summarized in Table 1. Nevertheless, the literature also shows substantial variation in both the types of information being integrated and the level at which fusion is performed.

For example, Han et al. [4] proposed a knowledge-data fusion model for power-equipment quality analysis by combining general information, quality data, and process-flow information. Liu et al. [1] developed a knowledge-fusion-based voltage-control strategy for distribution networks, using incremental learning to improve the adaptability of deep reinforcement learning agents under changing network topologies. Other studies have focused on spatial-temporal or relational dependencies. Luo et al. [2], for instance, investigated heterogeneous data fusion for distribution-network awareness, while Wu et al. [3] incorporated spatial-temporal graph modeling and expert knowledge for multivariate load forecasting.

Despite these advances, most approaches address a relatively constrained fusion problem. Zhang et al. [13], for example, proposed a hierarchical cognition and fuzzy decision framework for multi-fault diagnosis based primarily on sensor and fault-pattern information. Similarly, Wang et al. [16] combines electrical signal and switching information through compressed sensing and Dempster–Shafer evidence theory for fault location, but remains focused on structured power-system measurements. At the other end of the modality spectrum, Xin et al. [6] focuses on extracting equipment-fault knowledge from textual records. These studies are effective within their respective tasks, but they do not provide a common mechanism for simultaneously integrating numerical measurements, engineering imagery, textual information, and structural relationships.

A related limitation concerns the boundary between information extraction and information fusion. Several fusion models operate on data that have already been represented as numeri-

Table 1
Summary of Data and Knowledge Fusion Methods in Power Systems

Literature	Area	Technical Approach	Data Types
Liu et al. [1]	Voltage control in DERs	Incremental learning, multi-agent deep reinforcement learning	Dynamic sensor data, topology data
Luo et al. [2]	Distribution network awareness	Graph attention coding, heterogeneous data fusion	Static sensor data, dynamic time-series data
Wu et al. [3]	Multivariate load forecasting in IES	Multi-task spatial-temporal graph convolutional network	Time-series data, building usage data, expert knowledge
Zhang et al. [13]	Multi-fault diagnosis in ICS	Hierarchical cognition, fuzzy decision framework	Sensor data, fault pattern data
Han et al. [4]	Power equipment quality analysis	Neural network with multi-source data fusion	Process flow data, sensor data, textual records
Wang et al. [14]	Knowledge fusion in ontology mapping	Self-organizing map (SOM), unsupervised learning	Heterogeneous knowledge graph data
Wang et al. [15]	Battery anomaly detection	Encoder-decoder with expert knowledge integration	Multi-source sensor data, expert filters
Wang et al. [16]	Fault location in power grids	Compressed sensing, DS evidence theory	Electrical signal data, switching data
Jie et al. [17]	PV station identification	Convolutional neural network with edge detection	High-resolution image data
Yang et al. [5]	Power asset management	Knowledge graph	Sensor data, textual documents
Yang et al. [8]	Grid dispatching	Knowledge graph attention network (KGAT)	Structural, relational, and attribute data
Xin et al. [6]	Equipment fault diagnosis in thermal plants	BERT-WWM, RoBERTa-BiLSTM for knowledge extraction	Text records

cal features, graph structures, or other structured inputs [2, 3]. The problem of converting raw and unstructured sources into semantically consistent information is therefore frequently addressed separately. This separation becomes particularly important in DER applications, where relevant information may originate from live sensor streams, network models, equipment documentation, maintenance records, and engineering drawings.

Consequently, the research gap is not an absence of fusion methods for DERs or power systems, but the limited availability of an end-to-end framework that connects heterogeneous information extraction, semantic normalization, and knowledge-level fusion. Addressing this gap requires a framework in which different data modalities can first be transformed into structured information and subsequently related through a shared semantic model rather than being fused only at the feature or decision level.

2.2. Knowledge Models in Power Systems

Ontology-based modeling and Knowledge Graphs provide a complementary approach to heterogeneous data integration by explicitly representing entities, relationships, and domain semantics. Within power systems, these techniques have been applied to a range of smart-grid, energy-management, and asset-management problems.

Dogdu et al. [18] emphasize the integration of operational technologies (OT) with information and communication technologies (ICT) in smart grids and highlight the role of ontologies in providing a common information model for decision-support applications. Similarly, López et al. [19] present an OWL-based ontology developed within the ENERsip project to support energy efficiency in nearly Zero-Energy Neighborhoods (nZEN). The ontology formalizes domain vocabulary and relationships, illustrating how semantic models can provide common representations across heterogeneous energy-management information.

At a more decentralized scale, Wu et al. [7] propose an ontology-modeling approach for household energy-management systems that integrates device-level energy information with external contextual sources such as weather data. Ontology-based representations have also been developed for larger facilities. Tomasevic et al. [20], for example, propose an ontology-based facility data model for energy management in complex infrastructure such as airports, demonstrating how semantic representations can help integrate heterogeneous datasets and communication protocols.

Knowledge graphs extend this principle by representing interconnected entities and their attributes in graph-based structures that support querying and reasoning. Tang et al. [21] investigate automated ontology construction and graph-database-based data management for power systems, emphasizing scalability for large knowledge structures. In renewable-energy applications, Wang et al. [9] develop an ontology-based framework for PV power stations that integrates information across design, construction, and operational stages. Knowledge-graph approaches have likewise been explored for power-asset management and grid dispatching [5, 8].

Most of these models are domain ontologies developed around a particular application or asset category. A complementary strategy is to organize domain concepts beneath a reusable upper ontology. Basic Formal Ontology (BFO), for example, distinguishes entities at the upper level into categories including continuants and occurrents and is designed to provide a common architectural basis for domain ontologies [12]. Such an upper-level structure is particularly relevant when concepts from multiple technical domains must coexist within a single semantic framework.

Nevertheless, the reviewed power-system knowledge models remain predominantly application-specific, including household energy management, facility energy management, PV stations, power assets, and dispatching [5, 7–9, 20]. They do not collectively provide an upper-level semantic model spanning heterogeneous DER facilities, equipment, processes, operational events, and supporting domain knowledge. This motivates the development of a DER-specific framework that combines an extensible top-level ontology with automated multimodal information extraction and knowledge fusion.

2.3. Automated Information Extraction Methods from Heterogeneous Data

DER management involves heterogeneous information sources that differ substantially in structure and representation. Relevant inputs can include multivariate time-series sensor measurements, unstructured technical and maintenance documents, and visual or spatial information contained in engineering drawings and other imagery. Before these sources can be integrated at the knowledge level, modality-specific methods are therefore required to transform raw data into structured and semantically meaningful information. This section reviews representative approaches for the three principal data types considered in this study.

2.3.1. Time-Series Data from Sensors

Automated information extraction from time-series measurements has advanced substantially through deep learning and graph-based methods. Temporal models can identify patterns that are difficult to capture using static threshold rules, while graph representations additionally allow relationships among multiple measurements or system components to be modeled.

For example, Pan et al. [22] propose a Bi-LSTM model for anomaly detection in satellite telemetry data. The model exploits temporal dependencies between measurements and incorporates dynamic thresholding to identify deviations between predicted and observed telemetry. Although the application is outside the power domain, the underlying temporal anomaly-detection problem is relevant to monitoring dynamic DER sensor streams.

Graph-based methods provide an additional mechanism for representing relationships among multiple measurements or components. Yu et al. [23] present a GNN with dynamic graph embedding for fault diagnosis in rolling bearings, combining CNN-based feature extraction with graph learning under variable operating conditions. Within power systems, Nguyen et al. [24] and Hu et al. [25] apply graph-based models to fault diagnosis, location, and classification in distribution networks by exploiting spatial-temporal relationships among electrical measurements. These studies demonstrate the potential of temporal and graph-based learning for converting multivariate sensor measurements into higher-level diagnostic information.

2.3.2. Textual Data Extraction

A substantial portion of operational knowledge is contained in unstructured text, including project documents, equipment records, maintenance reports, technical manuals, and fault logs. Transformer-based natural language processing methods have substantially improved the extraction of structured entities and relationships from such sources.

Ma et al. [11] introduce an ontology-based BERT approach for automated information extraction from geological-hazard reports, combining BERT, BiGRU, and CRF components for entity and relationship extraction. Importantly, the information-extraction process is guided by explicitly defined domain entities and ontology concepts, illustrating how unstructured text can be mapped into a predefined semantic representation.

Within the power domain, Xin et al. [6] propose a BERT-WWM-based approach for extracting equipment-fault knowledge from multiple types of textual records. Extracted entities and relationships are subsequently represented within a knowledge graph. Such methods are particularly relevant to DER management because they provide a mechanism for transforming maintenance records, technical descriptions, and other textual sources into structured information that can subsequently be connected with sensor- and asset-level knowledge.

2.3.3. Image and Engineering Diagram Data

Visual information provides another important source of engineering knowledge. Depending on the application, image-based extraction may involve object recognition, condition classification, text recognition, or recovery of spatial and topological relationships from technical drawings. Deep-learning methods have been applied to engineering drawings and equipment-condition analysis [26, 27], while combinations of computer vision and optical character recognition (OCR) have been used to recover structured information from floorplans and technical drawings [28, 29].

These approaches are relevant to DER applications in which equipment layouts, wiring relationships, component identifiers, or other structural information may exist primarily in graphical engineering documents rather than in machine-readable databases. Converting such visual sources into structured entities and relationships is therefore an important prerequisite for integrating them with sensor and textual information at the knowledge level.

2.3.4. Summary

As summarized in Table 2, mature methods now exist for extracting higher-level information from individual heterogeneous data modalities. Temporal and graph-based learning can derive diagnostic information from sensor measurements; transformer-based NLP can identify entities and relationships in unstructured text; and computer-vision and OCR techniques

Table 2
Automated Information Extraction Methods from Heterogeneous Data

Data Type	Processing Method	Literature
Sensor Data	Bi-LSTM for anomaly detection	Pan et al. [22]
	GNN with dynamic graph embedding	Yu et al. [23]
	Temporal recurrent GNN for fault diagnostics	Nguyen et al. [24]
	Deep graph learning for fault location and classification	Hu et al. [25]
Textual Data	Unsupervised ontology population for knowledge extraction	Chasseray et al. [30]
	BERT-BiGRU-CRF for entity recognition	Qin et al. [31]
	Ontology-based BERT for entity and relation extraction	Ma et al. [11]
	BERT-WWM for fault knowledge extraction	Xin et al. [6]
Image Data	Deep learning for mechanical engineering drawings	Xu et al. [26]
	CNN for gearbox fault diagnosis	Jing et al. [27]
	CNN for floorplan recognition	Lv et al. [28]

can recover information from images and engineering drawings.

The remaining challenge is therefore not simply the extraction of information from each modality in isolation, but the semantic integration of their outputs. Sensor-derived anomalies, entities extracted from documents, and components identified from engineering diagrams may describe the same physical asset or operational event using different representations. Without a common semantic layer, these outputs remain disconnected. A comprehensive DER framework must therefore connect modality-specific information extraction with ontology-based normalization and knowledge fusion, enabling heterogeneous evidence to be represented and reasoned over within a unified knowledge structure.

3. Proposed Framework

The proposed framework integrates heterogeneous DER information through four functional layers: Data, Ontology, Information, and Knowledge, as illustrated in Figure 1. The Data Layer ingests and organizes heterogeneous operational sources, including sensor measurements, technical documents, and engineering representations. The Ontology Layer defines the shared semantic structure through which physical entities, operational processes, events, requirements, and other DER concepts can be consistently represented. The Information Layer transforms modality-specific raw inputs into structured entities, attributes, relations, and observations. Finally, the Knowledge Layer grounds these outputs to the ontology, resolves cross-source entity identity, consolidates their relationships, and materializes the resulting representation as a Knowledge Graph. This separation allows information extraction and semantic integration to remain modular while providing a common basis for cross-modal querying and reasoning.

3.1. Data Layer

DER environments generate information with substantially different levels of structure. Structured data include multivariate time-series sensor measurements, asset identifiers, equipment registers, and machine-readable topology records. Semi-structured data include tagged event logs, XML or JSON exports, configuration files, and other sources with partially defined schemas. Unstructured sources include OEM manuals, maintenance reports, regulatory documents, engineering drawings, and schematics. Together, these sources describe complementary aspects of the same operational system: sensor streams capture dynamic behaviour, topology and asset records describe physical connectivity, and textual or graphical documents provide engineering and operational context.

Preprocessing is performed according to the characteristics of each modality before information extraction. For numerical sensor streams, this includes quality control, outlier screening, temporal synchronization, and treatment of missing observations. Statistical or machine-learning-based anomaly detection methods may be used to distinguish measurement errors from operational deviations, while missing values can be handled through interpolation, regression-based methods, or more advanced imputation approaches such as GAIN [32], depending on the temporal structure and missingness mechanism. Where dimensionality reduction is required for downstream analysis, methods such as PCA can be applied while retaining the variables needed for semantic interpretation. Textual and graphical sources undergo their respective parsing, normalization, and image-preprocessing procedures in the Information Layer.

Following preprocessing, data are stored in formats appropriate to their access patterns while preserving identifiers required for subsequent semantic integration. Structured operational records can be maintained in relational systems, high-frequency measurements in time-series databases such as InfluxDB [33], and documents or engineering files in document-

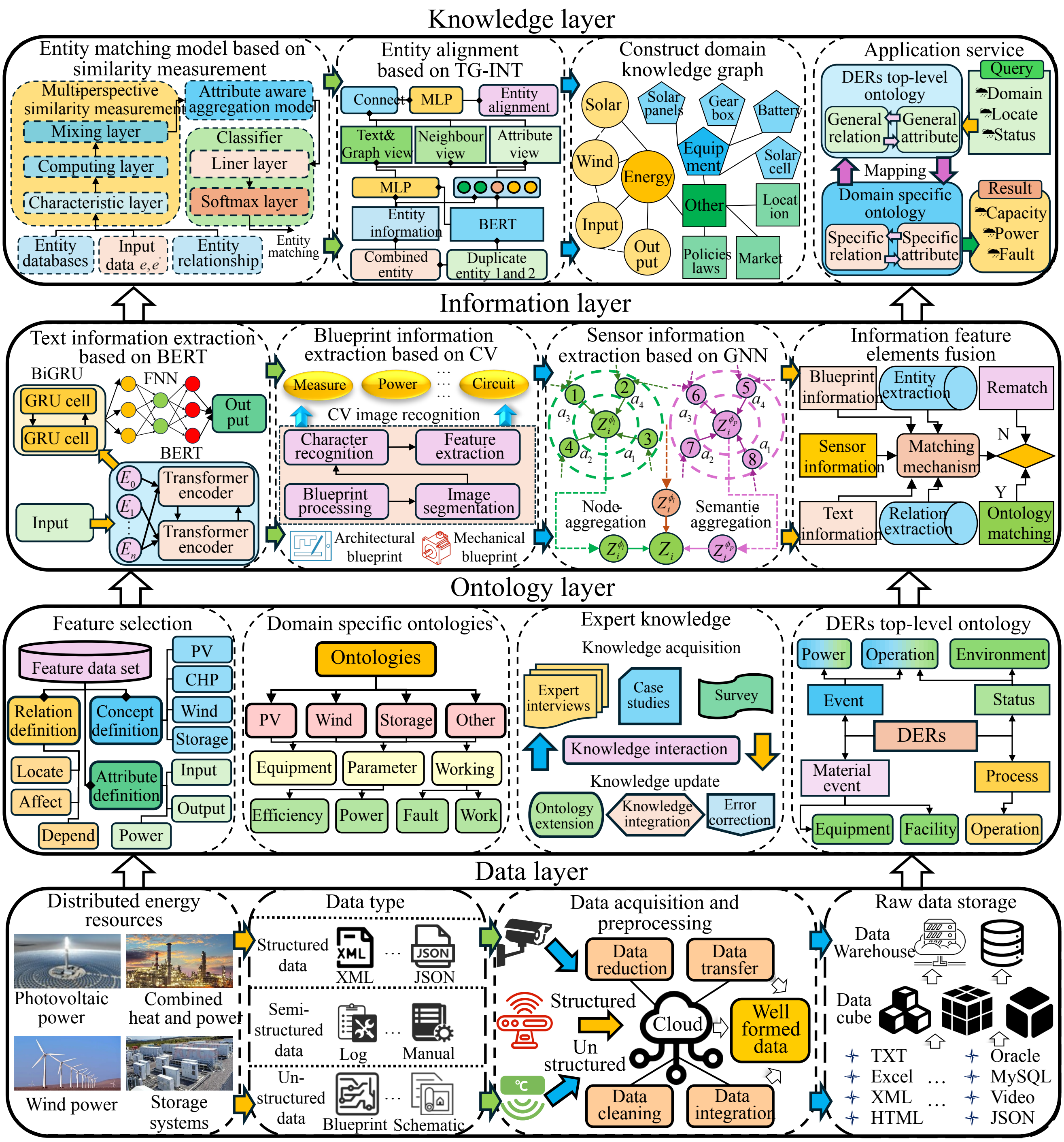


Fig. 1. Data and Knowledge Fusion Framework for DERs Management

oriented or object-based storage. A key requirement at this stage is the preservation of provenance, timestamps, asset identifiers, and source metadata, because these provide the contextual evidence required to ground extracted information to ontology entities in the subsequent layers.

3.2. Ontology Layer

The ontology layer serves as the foundational framework for integrating and standardizing knowledge across diverse domains within DERs management. This layer leverages the preprocessed data, existing domain ontologies, and insights derived from expert interviews to construct a comprehensive top-level ontology that encapsulates the core concepts and relationships necessary for effective DER management. The primary function of the ontology layer is to provide a unified, structured representation of knowledge that facilitates interoperability and integration across various DER systems, thereby enabling more holistic and informed decision-making.

As depicted in Figure 2, the DER top-level ontology development began by analyzing existing domain-specific ontologies, which typically focus on particular aspects of energy systems, such as PV plant operations or power plant equipment manage-

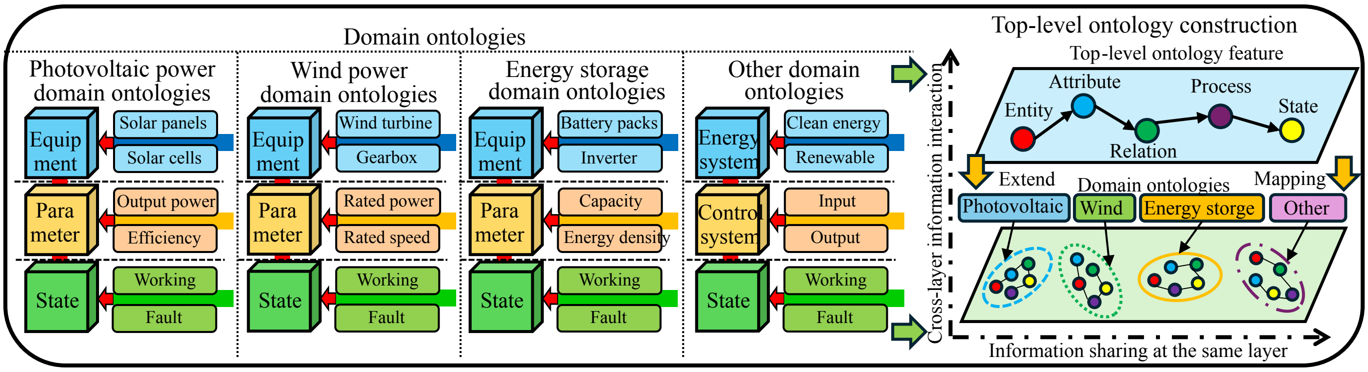


Fig. 2. Development of Top-level DER ontology model from domain ontologies

ment. Although these domain ontologies are well-developed in their respective fields, they often lack the ability to address the broader integration of DERs with the grid. To overcome this limitation, our approach involved extracting key concepts and relationships from these existing ontologies, focusing on the types, properties, and interrelations that are common across different domains. This analysis allowed us to identify the core concepts and shared characteristics that are critical to a comprehensive understanding of DERs.

Based on these shared characteristics, we enriched the existing domain ontologies by defining hierarchical structures and relationship types specific to DER management. This process involved establishing a clear hierarchy of concepts, from broad categories such as facilities and equipment down to specific instances and rules that govern their interactions. By comparing the common features across different domain ontologies, we abstracted general concepts and relationships that could serve as the foundation for a cross-domain top-level ontology. The principles guiding our construction included modularity, reusability, and alignment with a recognized foundational ontology to ensure both flexibility and interoperability.

To ensure a robust and extensible structure, we aligned our top-level ontology with the Basic Formal Ontology (BFO). BFO is a widely adopted foundational ontology that provides a high-level framework for organizing the entities and processes within various domains. It distinguishes between two primary categories of entities: Continuants, which are entities that persist through time while possibly undergoing changes, and Occurrents, which are entities that unfold over time, such as events or processes. This alignment allows us to leverage BFO's well-defined conceptual structures to support the complex and dynamic nature of DER management.

$$C_{\text{DER}} = \{K_P, K_E, K_S, K_F, K_Q, K_T, K_R, K_O\}, \qquad (1)$$

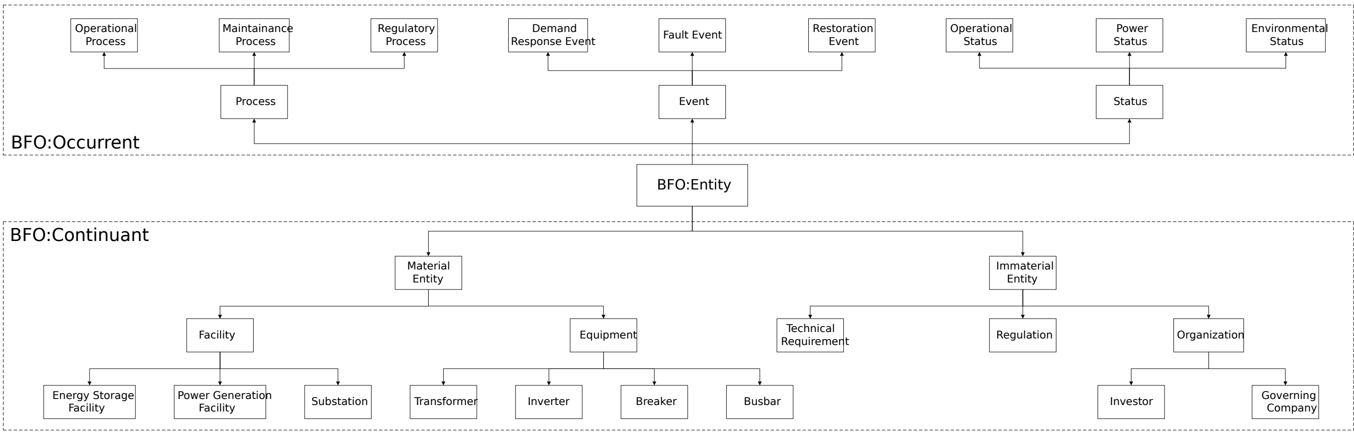
Figure 3a illustrates the top-level ontology we developed for DER management, based on BFO. At the DER application level, the ontology is organized around eight core concept families: Process (K_P), Event (K_E), Status (K_S), Facility (K_F), Equipment (K_Q), Technical Requirement (K_T), Regulation (K_R), and Organization (K_O). Each of these elements represents a critical aspect of DERs, encapsulating the essential knowledge required for effective management.

At the application level, K_P (Process) represents operational processes such as power generation and maintenance, while K_E (Event) represents temporally bounded operational or fault occurrences. These concepts are aligned with the occurrent branch of BFO; depending on their temporal extent, individual event classes may be represented as processes or process boundaries. K_F (Facility) and K_Q (Equipment) represent physical DER entities such as generation facilities, storage systems, transformers, inverters, and breakers, and are aligned with material entities on the continuant branch.

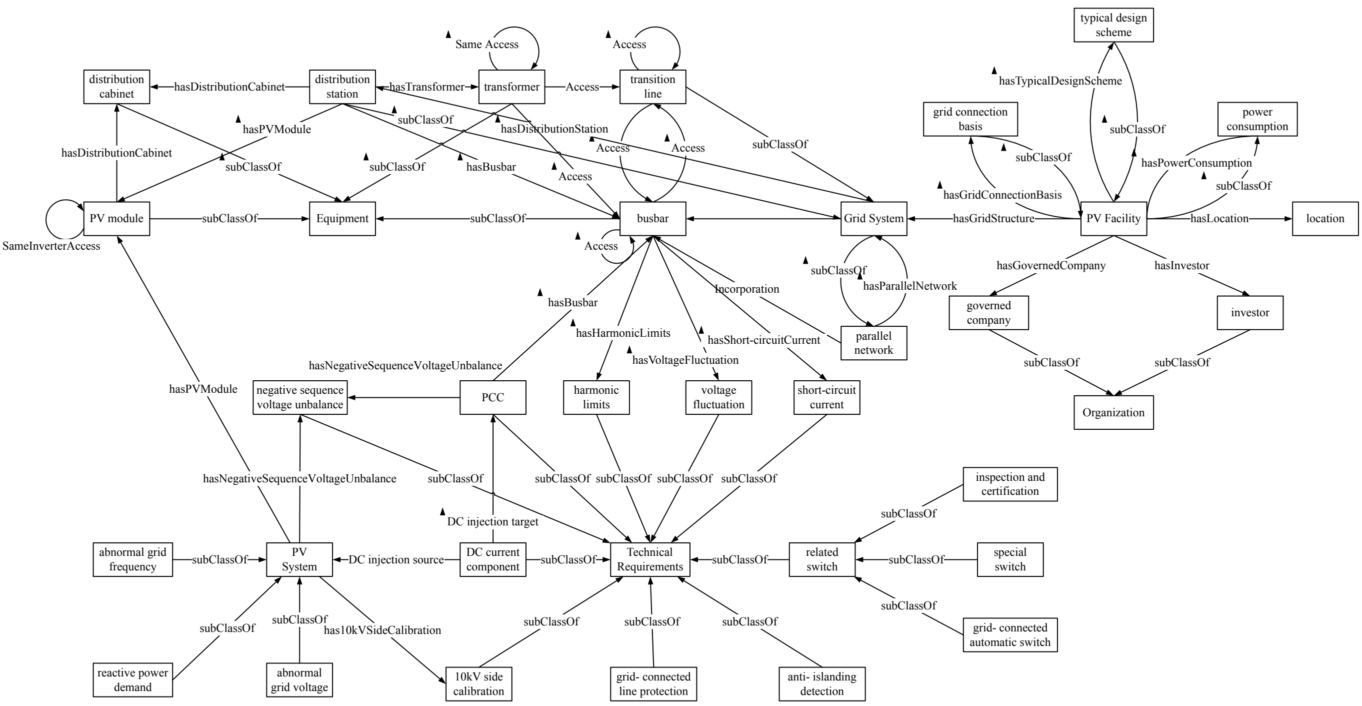
The remaining concept families capture contextual information associated with these physical entities and processes without forcing every DER-level class into a direct BFO subclass. K_S (Status) represents time-indexed information about the condition or operating state of an entity and is linked to the relevant equipment, process, or event. K_T (Technical Requirement) and K_R (Regulation) represent information-bearing specifications that prescribe constraints or expected behaviour. K_O (Organization) represents the social entities responsible for ownership, operation, regulation, or maintenance of DER assets. These classes are connected to the BFO-aligned physical and process entities through explicit semantic relations.

This modelling strategy uses BFO as an upper-level reference rather than treating all DER concepts as immediate children of BFO classes. The distinction is important because the eight concept families serve application-level knowledge requirements, whereas BFO provides the more general ontological categories required to maintain semantic consistency across domains.

Alignment with BFO provides a common upper-level reference for organizing DER concepts and can facilitate interoperability with other BFO-aligned ontologies. Such interoperability is not assumed to arise automatically from the use of BFO alone; it additionally depends on explicit mappings between domain-level classes and on consistent relation semantics. The role of BFO in the proposed framework is therefore to provide a stable ontological architecture within which DER-specific concepts can be defined and related.



(a) BFO-aligned top-level ontology for DER management, defining the core semantic categories and relationships shared across heterogeneous DER domains.



(b) PV station domain ontology as a domain-specific specialization of the top-level DER ontology, illustrating the mapping of PV facilities, equipment, processes, and associated concepts to the common semantic structure.

Fig. 3. Hierarchical ontology architecture for DER knowledge modeling. The BFO-aligned top-level ontology provides a shared semantic foundation across DER domains, while domain-specific ontologies extend this structure with application-level concepts and relationships.

Figure 3 demonstrates how this top-level ontology integrates with domain-specific ontologies, such as the one developed by Wang et al. [9] for PV plant management. The alignment of core concepts like equipment and facilities with our defined continuants and occurrents ensures that the specific details of PV plant management can be effectively mapped onto our broader ontology framework. This not only facilitates the integration of knowledge across different DER domains but also supports the development of a unified knowledge base that can drive more effective and coordinated management strategies across the entire spectrum of DERs.

In summary, the ontology layer is the cornerstone of our knowledge modeling and fusion framework, providing the structure and semantics necessary to integrate diverse sources of knowledge into a cohesive system. By aligning with BFO and abstracting general concepts from domain-specific ontologies, our top-level ontology enables comprehensive and interoperable management of DERs, addressing the gaps identified in existing research and paving the way for more holistic energy management solutions.

3.3. Information Layer

The Information Layer plays a critical role in transforming raw, heterogeneous data collected from DERs into structured, meaningful information that can be further processed and integrated into the overarching knowledge management system. This layer is essential for bridging the gap between data collection and knowledge generation, enabling the extraction of relevant features from diverse data sources, such as textual documents, images, and sensor data. By employing a variety of advanced information extraction techniques, the Information Layer ensures that the disparate forms of data are systematically processed and prepared for subsequent integration within the ontology framework.

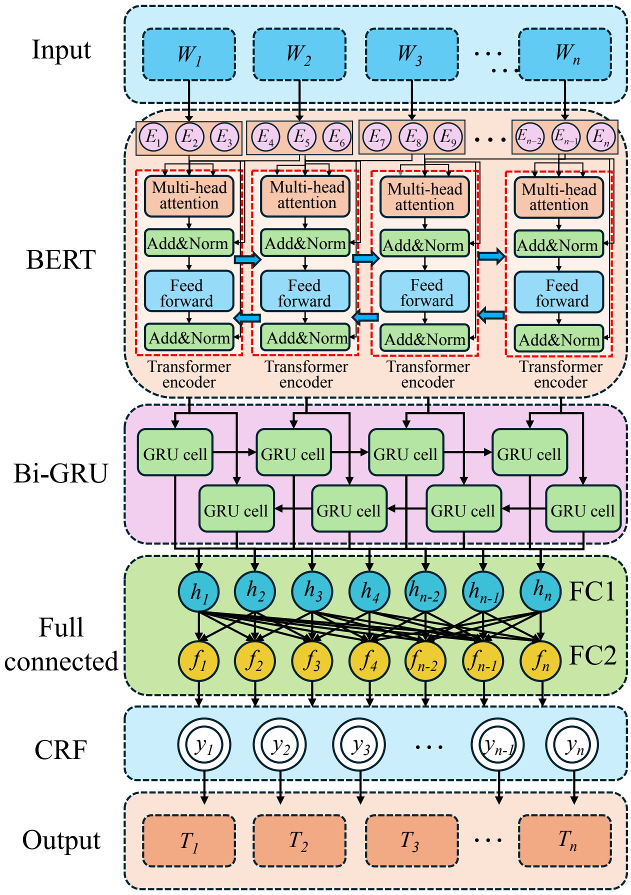


Fig. 4. BERT-BiGRU-CRF model structure

For textual sources such as DER project documents, technical manuals, and regulatory records, we employ a BERT-BiGRU-CRF-based pipeline following the general approach of Ma et al. [11]. BERT provides contextual token representations, while the bidirectional GRU captures sequential dependencies in both directions. The CRF layer performs sequence-level decoding to produce consistent entity labels. Relations among the extracted entities are subsequently identified through relation or dependency parsing and mapped to the corresponding ontology concepts. This separation between entity recognition and relation extraction provides structured outputs that can be grounded to the DER ontology before knowledge fusion.

For image data, particularly those related to DER facilities and equipment blueprints, we implement advanced Computer Vision techniques to extract information. In this project, we utilize a CNN combined with OCR methods to process and interpret the visual data. The CNN architecture is adept at handling the spatial hierarchies in image data, which allows us to effectively segment blueprints into distinct regions corresponding to different informational modules. This segmentation process is preceded by essential image preprocessing steps, including noise reduction and image enhancement, to improve the clarity and accuracy of the extracted information. Once segmented, each region of the blueprint is subjected to OCR, which converts the visual text into machine-readable text. From this extracted textual data, key information such as component specifications, labels, and annotations are identified and isolated for further processing.

Sensor data provide the dynamic observations required for equipment monitoring and fault analysis. We adopt a graph-based learning approach following Nguyen et al. [24] to model dependencies within multivariate time-series measurements. In the resulting graph representation, nodes correspond to sensor channels, monitored variables, or associated equipment, while edges encode physical or statistically inferred dependencies. The graph model extracts temporal and relational patterns and produces structured anomaly or fault indicators that can subsequently be represented as ontology-linked observations or events. In this study, these model outputs are used as inputs to the semantic fusion framework; the principal focus is therefore on their integration and reasoning role rather than on proposing a new GNN architecture.

Outputs from the modality-specific extraction pipelines are first grounded to the ontology by assigning semantic types and relations to the extracted entities, observations, and events. At this stage, source identifiers, timestamps, equipment references, and contextual attributes are retained as provenance for subsequent integration. Records that may refer to the same real-world entity are then passed to the Knowledge Layer, where cross-source identity resolution and entity alignment are performed. This separation distinguishes semantic grounding from entity identity resolution and provides a consistent interface between information extraction and knowledge fusion.

By efficiently extracting and processing relevant features from heterogeneous data sources, the Information Layer lays the groundwork for the subsequent stages of knowledge fusion and management. This layer ensures that all relevant information is captured, structured, and ready for integration, enabling the development of a robust, unified knowledge base that supports advanced DER management and decision-making processes.

3.4. Knowledge Layer

The Knowledge Layer materializes the ontology-grounded outputs of the Information Layer as an integrated Knowledge Graph. Semantic integration at this stage involves three related but distinct operations: grounding information to the ontology-defined schema, resolving cross-source references to the same real-world entities, and consolidating the resulting entities and relationships into a coherent graph representation. Entity Matching (EM) and Entity Alignment (EA) therefore address the identity-resolution component of knowledge fusion rather than constituting the semantic fusion process in isolation.

EM is the first critical step within the Knowledge Layer. It involves the identification and linking of records or data points that refer to the same real-world entity across multiple, heterogeneous data sources. Given the diversity of sources—from textual documents and sensor outputs to blueprints and regulatory filings—entities related to the same physical or conceptual object often appear under different names, identifiers, or formats. The EM process employs advanced Similarity Measurement techniques, such as the Attribute-Aware and Multi-Perspective Similarity Measurement method [34], to evaluate the similarity of entity attributes. For instance, textual descriptions are compared using natural language processing techniques, while numerical attributes might be assessed using statistical measures. This careful analysis ensures that even subtle variations in data representation do not hinder the accurate identification of identical entities.

Following the initial matching, the Knowledge Layer proceeds to the more complex task of EA. While EM is concerned with identifying potential matches, EA focuses on integrating these matched entities into the Knowledge Graph in a way that preserves data integrity and enhances semantic richness. EA addresses challenges such as entity deduplication, conflict resolution, and the consolidation of attributes and relationships into a unified entity representation. Utilizing a multi-view interactive alignment framework like TG-INT [35], EA not only aligns entities based on their attributes but also considers the broader relational structures and contextual dependencies within the dataset. This approach ensures that the aligned entities are not merely duplicates of one another but are integrated with full recognition of their roles within the DER ecosystem.

The integrated representation can be persisted in a graph database such as Neo4j, in which entities are represented as nodes and semantic or physical relationships as edges. This representation supports graph traversal, structured querying, provenance inspection, and rule-based reasoning over interconnected DER information. In the present implementation, Neo4j provides the execution environment for the cross-modal graph queries demonstrated in Section 4.

The Knowledge Graph serves as a powerful tool in DER management, providing a unified, enriched view of all relevant data. It enables stakeholders to access and analyze information across different domains seamlessly, whether for operational monitoring, strategic planning, or regulatory compliance. For instance, an operator can query the Knowledge Graph to track the operational status of equipment across various facilities, identify potential vulnerabilities, or ensure that all regulatory requirements are met. Additionally, by integrating real-time data streams, the Knowledge Graph can support predictive maintenance, optimize energy distribution, and enhance the overall resilience of the energy grid.

4. Case Study and Framework Demonstration

To demonstrate the end-to-end operation and cross-modal reasoning capability of the proposed framework, we construct a case study based on a realistic fault scenario in a decentralized photovoltaic system. The purpose of the case study is to verify whether heterogeneous evidence from equipment topology, textual operational rules, and time-series sensor observations can be integrated within a common semantic representation and used to produce a traceable root-cause reasoning chain.

4.1. Scenario Description and System Setup

The experimental scenario simulates a 1MW sub-array within a utility-scale distributed photovoltaic (PV) station located in Shanghai, China. To accurately reflect the high dimensionality and complexity of modern grid topologies, the physical infrastructure is modeled hierarchically. The testbed comprises one central step-up transformer ($Trans_{01}$), which aggregates power from 10 string inverters (100kW capacity each, labeled INV_{01} to INV_{10}). Each inverter fundamentally governs 10 discrete PV strings.

For this case study, the baseline physical topology is imported from an existing State Grid digital-twin Common Information Model (CIM) database [36] rather than reconstructed from CAD drawings. This reflects a realistic situation in which machine-readable asset and connectivity information is already available and allows the case study to focus specifically on semantic integration and reasoning. It also demonstrates representation-level compatibility with standardized power-system information models. The engineering-diagram extraction branch remains part of the general framework but is therefore not exercised in this particular case study.

The injected fault scenario represents a cascading symptom pattern in which a single upstream equipment condition produces multiple downstream operational alarms. At approximately 12:00 PM, under high solar irradiance, the cooling fan of inverter INV_{01} begins to degrade, resulting in a progressive increase in internal inverter temperature. By 12:35 PM, the temperature exceeds the 65°C protection threshold specified in the OEM manual. The inverter protection logic consequently enters a derating mode, reducing its power output. This upstream condition manifests operationally as a near-simultaneous active-power reduction across the 10 PV strings connected to INV_{01}.

4.2. Automated Multimodal Information Extraction

The Information Layer is tasked with simultaneously processing the raw, heterogeneous data streams to populate the semantic components defined by our top-level Basic Formal Ontology (BFO).

First, the OEM rule is processed by the textual information-extraction pipeline. As illustrated in Fig. 5, the pipeline identifies the relevant equipment entity (*inverter* $\rightarrow K_Q$), the monitored attribute (*internal temperature*), the threshold (*65°C*), and the consequent operational action (*derate*). These extracted elements are mapped to the ontology and represented as a structured operational rule associated with the corresponding inverter entity. The resulting representation converts the human-readable OEM requirement into machine-interpretable information that can subsequently participate in graph reasoning.

Concurrently, the temporal anomaly detection module evaluates the continuous time-series data streamed from SCADA sensors. Fig. 6 visualizes the physical manifestation of the cascading fault. While normal operational fluctuations (noise) are filtered out, the algorithm captures the specific timestamp (12:35 PM) where the internal temperature of INV_{01} struc-

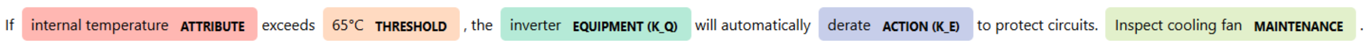


Fig. 5. Automated entity and rule extraction from the unstructured OEM maintenance manual using the NLP pipeline. The algorithm identifies bounding boxes for equipment (K_Q), critical thresholds, and consequent actions (K_E), successfully mapping human-readable text into ontological components.

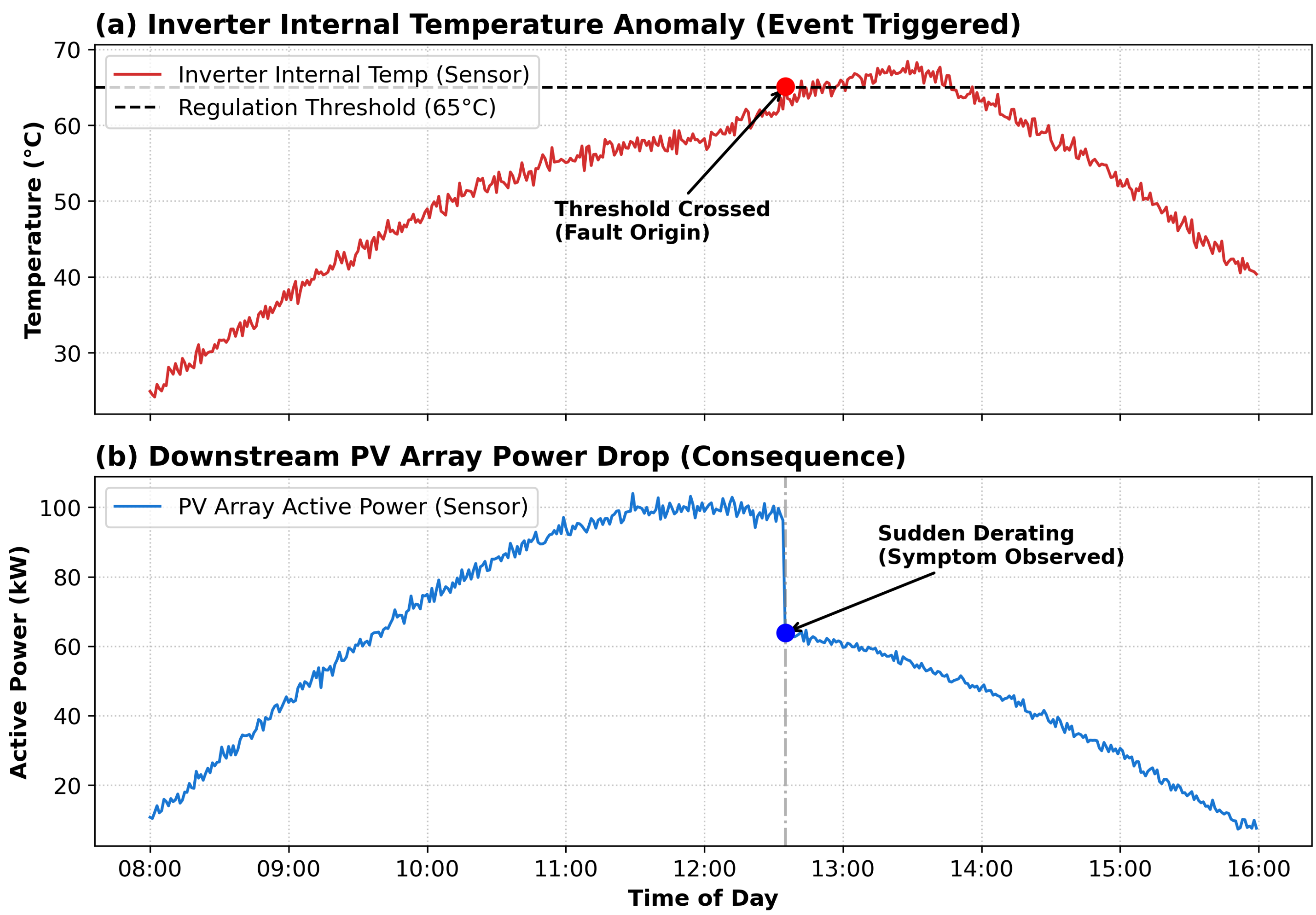


Fig. 6. Sensor modality analysis and feature extraction: (a) The origin of the fault where the inverter's internal temperature progressively climbs and crosses the 65°C threshold; (b) The subsequent downstream observable symptom, demonstrating a sudden active power drop in the connected PV strings.

turally deviates and crosses the 65°C threshold (Fig. 6a). Almost instantaneously, this is followed by a severe active power drop anomaly (Fig. 6b). These multimodal anomalies are not treated as mere numerical out-of-bounds alerts, but are dynamically extracted and instantiated as specific Event nodes (K_E) within the semantic space.

4.3. Knowledge Fusion and Graph Construction

The core contribution of this framework lies in the Knowledge Layer, where extracted features across disjointed modalities are fused using multi-view entity alignment (e.g., TG-INT). The physical *Equipment* nodes imported from the CIM topology, the *Regulation* rules parsed from the NLP pipeline, and the real-time *Event* nodes from the sensor streams are semantically interwoven.

Fig. 7 displays a localized, high-density visualization of the resulting Knowledge Graph rendered in Neo4j. The graph exhibits a multi-dimensional semantic network: the central string inverter node (INV_{01}) is distinctly populated with its mapped textual rule nodes and is structurally surrounded by its interconnected downstream PV string nodes. Crucially, the newly instantiated real-time anomaly events (highlighted in red) are accurately anchored to their respective physical entities. This dense semantic mapping proves that the system can accommodate large-scale, high-concurrency DER environments while maintaining precise ontological relationships.

4.4. Cross-modal Reasoning and Root Cause Diagnostics

The diagnostic superiority of the semantic-driven framework is explicitly verified during the root cause analysis phase. In

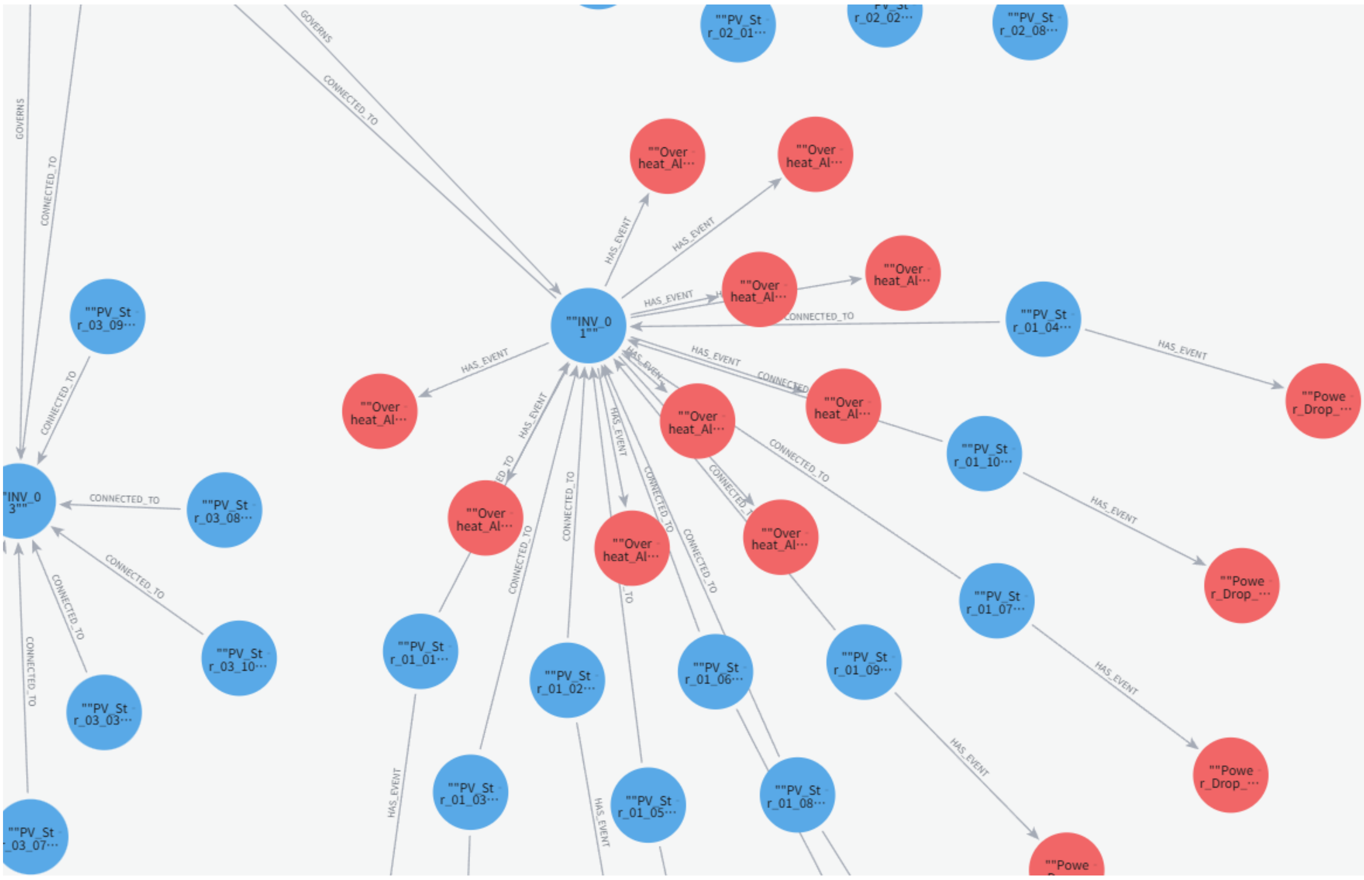


Fig. 7. A localized visualization of the multi-layered Knowledge Graph generated in the Neo4j database. The topology demonstrates the dense semantic integration of physical equipment nodes, textual operational rules, and real-time anomaly events converging around the target inverter (INV_{01}).

a conventional, unimodal SCADA system, operators face a severe "alarm storm." Triggered by the events shown in Fig. 6b, the control room would be inundated with simultaneous warnings indicating low power output from the 10 discrete PV strings. Driven purely by these numerical symptoms, operators routinely misdiagnose the issue as localized array shading or component failure, deploying maintenance crews to the roof—a futile effort since the root cause resides upstream in the inverter chassis.

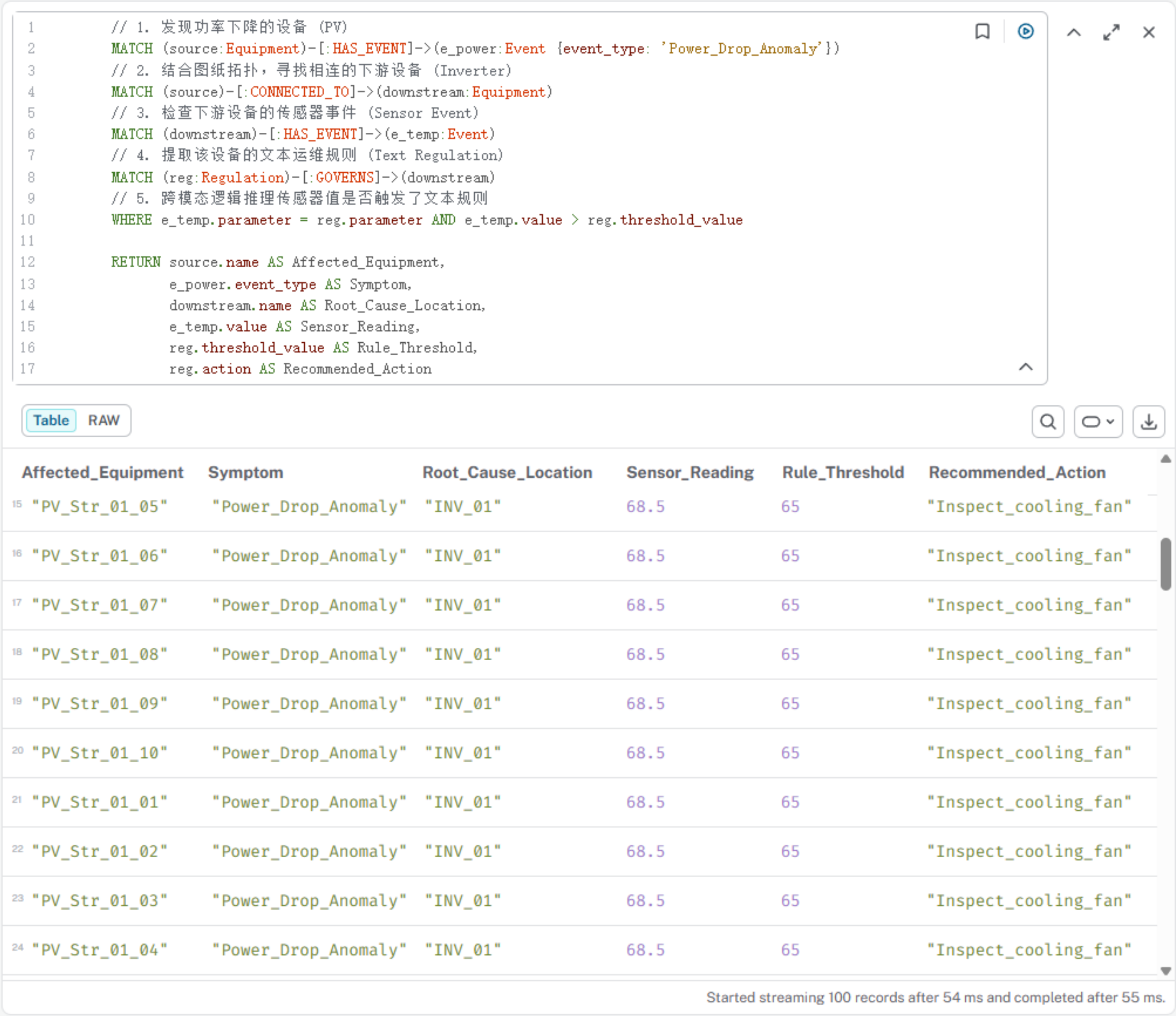
Conversely, our proposed framework autonomously executes a semantic reasoning chain via Cypher querying, bypassing the superficial alarm storm. Upon detecting the power drop events, the graph reasoning engine traces the physical topology upstream from the 10 symptomatic PV strings, aggregating at their common parent node, INV_{01}. It subsequently cross-references the real-time sensor events tied to INV_{01} against the textual $Regulation$ nodes bound to it.

As depicted in the final diagnostic output (Fig. 8), the reasoning engine successfully bridges the semantic gap. It mathematically confirms that the sensor reading (68.5°C) logically violates the textual regulation threshold (65°C). The system autonomously concludes that the inverter's thermal derating—triggered by the breached OEM rule—is the definitive root cause. Ultimately, it distills the chaotic telemetry into a single, precise maintenance recommendation ("Inspect cooling fan"), proving the framework's capability to transform reactive numerical monitoring into intelligent, semantic-driven predictive maintenance.

5. Discussion

The case study provides functional evidence for the central premise of the proposed framework: heterogeneous DER observations become more informative when they can be interpreted within a shared semantic context. In the demonstrated PV scenario, the framework connects sensor observations, equipment topology, and an operational rule that would otherwise reside in separate information sources.

Conventional SCADA systems are highly effective for acquiring numerical measurements and generating threshold-based alarms, but the contextual information required to interpret these alarms may reside in separate topology models, engineering documents, or maintenance rules. The contribution of the proposed architecture is to make these relationships explicit. The Information Layer produces structured observations from modality-specific data, while the Ontology and Knowledge layers associate those observations with equipment entities, physical relationships, and applicable operational rules. Consequently, an anomaly can be represented not only as a numerical deviation but also as a time-stamped event associated with a specific asset and interpreted within its operational context.



```
// 1. 发现功率下降的设备 (PV)
MATCH (source:Equipment)-[:HAS_EVENT]->(e_power:Event {event_type: 'Power_Drop_Anomaly'})
// 2. 结合图纸拓扑，寻找相连的下游设备 (Inverter)
MATCH (source)-[:CONNECTED_TO]->(downstream:Equipment)
// 3. 检查下游设备的传感器事件 (Sensor Event)
MATCH (downstream)-[:HAS_EVENT]->(e_temp:Event)
// 4. 提取该设备的文本运维规则 (Text Regulation)
MATCH (reg:Regulation)-[:GOVERNS]->(downstream)
// 5. 跨模态逻辑推理传感器值是否触发了文本规则
WHERE e_temp.parameter = reg.parameter AND e_temp.value > reg.threshold_value

RETURN source.name AS Affected_Equipment,
       e_power.event_type AS Symptom,
       downstream.name AS Root_Cause_Location,
       e_temp.value AS Sensor_Reading,
       reg.threshold_value AS Rule_Threshold,
       reg.action AS Recommended_Action
```

Table RAW

	Affected_Equipment	Symptom	Root_Cause_Location	Sensor_Reading	Rule_Threshold	Recommended_Action
15	"PV_Str_01_05"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
16	"PV_Str_01_06"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
17	"PV_Str_01_07"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
18	"PV_Str_01_08"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
19	"PV_Str_01_09"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
20	"PV_Str_01_10"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
21	"PV_Str_01_01"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
22	"PV_Str_01_02"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
23	"PV_Str_01_03"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"
24	"PV_Str_01_04"	"Power_Drop_Anomaly"	"INV_01"	68.5	65	"Inspect_cooling_fan"

Started streaming 100 records after 54 ms and completed after 55 ms.

Fig. 8. The automated cross-modal reasoning output, demonstrating the framework's ability to trace upstream power drop symptoms to a downstream thermal fault governed by textual operational thresholds.

A further benefit of the proposed architecture is the traceability of the final reasoning stage. Although some upstream information-extraction components are learned models and are therefore not intrinsically interpretable, the diagnostic inference itself is represented through explicit graph relations and rule evaluations. In the case study, the resulting explanation exposes the physical path connecting the symptomatic strings to the inverter, the OEM-derived threshold that is evaluated, and the sensor observation that satisfies the triggering condition. The framework therefore provides structural explainability for the knowledge-fusion and reasoning process, while the interpretability and uncertainty of the individual learned extraction modules remain separate considerations.

The case study also illustrates the potential value of semantic aggregation when one upstream condition generates multiple downstream alarms. Rather than treating the 10 PV-string power reductions as independent fault indications, the graph structure identifies their shared upstream inverter and evaluates additional evidence associated with that entity. This can reduce diagnostic ambiguity and support more targeted maintenance investigation. However, operational benefits such as reductions in truck rolls, Mean Time To Repair (MTTR), or maintenance cost would require evaluation under field deployment conditions and are not quantified in the present study.

Several limitations define the scope of the present study. First, the case study evaluates a single injected fault scenario within a PV subsystem and is intended primarily to demonstrate end-to-end semantic integration and reasoning; broader generalization across DER technologies, operating conditions, and fault classes remains to be established. Second, the study focuses on the integrated framework rather than independently benchmarking the accuracy and uncertainty of every upstream information-extraction and entity-alignment module. Errors introduced by these components may propagate into the Knowledge Graph and should therefore be quantified in future evaluations. Third, the present ontology demonstrates the proposed upper-level organization and domain mapping, but broader validation through additional DER domains, competency questions, and formal consistency testing would further establish its coverage and interoperability. Finally, dynamic updating of textual rules and the computational performance of continuous graph reasoning have not yet been evaluated at city- or regional-grid scale.

Future work will extend both the semantic model and its empirical evaluation. Additional DER technologies and fault scenarios will be used to assess ontology coverage and diagnostic generalization, together with quantitative evaluation of information-extraction, entity-alignment, and end-to-end reasoning performance. LLM-assisted information extraction will also be investigated for complex maintenance and operational documents, with provenance tracking and human verification retained for safety-critical rule updates. In parallel, incremental Knowledge Graph updating and temporal graph representations will be explored to reduce reasoning overhead and support larger, continuously evolving DER networks.

6. Conclusion

This paper presented a semantic-driven multimodal knowledge fusion framework for integrating heterogeneous information in DER management. The four-layer architecture separates data organization, ontology-based semantic modeling, modality-specific information extraction, and knowledge-level integration. A BFO-aligned DER ontology provides the upper-level semantic structure, while entity matching and alignment resolve cross-source identity and a Knowledge Graph materializes the resulting entities, observations, rules, and physical relationships for graph-based reasoning.

The framework was demonstrated through an injected thermal-derating scenario in a 1MW PV subsystem. By integrating CIM-derived equipment topology, an operational threshold extracted from an OEM manual, and time-series SCADA observations, the Knowledge Graph related simultaneous power reductions across 10 PV strings to their common upstream inverter. The reasoning workflow then identified that the observed inverter temperature exceeded the OEM derating threshold and returned the corresponding cooling-fan inspection action. The case study therefore demonstrates the principal capability targeted by the framework: transforming heterogeneous, independently represented observations into an explicit and traceable cross-modal diagnostic reasoning chain.

The present study establishes a proof-of-concept foundation rather than a comprehensive performance benchmark. Future work will extend the ontology and evaluation to additional DER technologies and fault conditions, quantify uncertainty and error propagation across the information-extraction and alignment stages, and evaluate the computational scalability of dynamic Knowledge Graph reasoning. These developments will support the broader use of ontology-mediated information fusion for explainable fault diagnosis and knowledge-driven maintenance in increasingly heterogeneous DER environments.

Acknowledgements

This research was funded by State Grid Shanghai Economic Research Institute (SGTYHT/23-JS-004).

Author Contributions

Zhenting Gao: Conceptualization, Methodology, Supervision, Resources, Project administration, Formal analysis, Writing – original draft. **Yongfang Liu**: Methodology, Software, Validation, Formal analysis, Investigation, Writing – review & editing. **Xuemei Zhang**: Methodology, Software, Validation, Investigation, Visualization, Writing – review & editing. **Ziyang Song**: Software, Formal analysis, Data curation, Validation, Visualization. **Peifan Zhai**: Data curation, Investigation, Resources, Validation. **Siying Chen**: Data curation, Investigation, Visualization.

Data Availability Statement

Data will be made available on request.

Conflict of Interest

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

References

[1] Liu, M.; Chen, D.; Li, X.; Su, H.; Zhou, X. Voltage Control Strategy for Distribution Network Based on Incremental Learning and Knowledge Fusion. In Proceedings of the 2024 12th International Conference on Smart Grid (icSmartGrid), 2024, pp. 589–596. https://doi.org/10.1109/icSmartGrid61824.2024.10578128.

[2] Luo, C.; Feng, Y.; Wu, K.; Zhou, J.; Wu, S.; Guo, X. Research on Multi-source Data Fusion Standardization and User Electricity Knowledge Map Construction Technology of Distribution Network. In Proceedings of the 2023 IEEE 6th International Electrical and Energy Conference (CIEEC), 2023, pp. 209–214. https://doi.org/10.1109/CIEEC58067.2023.10166241.

[3] Wu, L.; Zhao, Y.; Qin, W.; et al. Knowledge-Data Fusion Model for Multivariate Load Short-Term Forecasting of Integrated Energy System. *Journal of Shanghai Jiaotong University (Science)* **2024**. https://doi.org/10.1007/s12204-024-2740-1.

[4] Han, X.; Jiang, J.; Zhang, C.; Wen, Z.; Chen, G.; Liu, Y. Research on quality problems management of electric power equipment based on knowledge–data fusion method. *IET Generation, Transmission & Distribution* **2020**, *14*, 745–751. https://doi.org/10.1049/iet-gtd.2019.0832.

[5] Yang, Y.; Chen, Z.; Yan, J.; Xiong, Z.; Zhang, J.; Tu, Y.; Yuan, H. Multi-source Heterogeneous Information

Fusion of Power Assets Based on Knowledge Graph. In Proceedings of the 2019 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 2019, pp. 213–218. https://doi.org/10.1109/SOLI48380.2019.8955005.

[6] Xin, Y.; Chen, L.; Yang, Y. Online Knowledge Fusion Method for Fault Diagnosis of Power Plant Equipment. In Proceedings of the 2023 IEEE 11th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), 2023, Vol. 11, pp. 1236–1240. https://doi.org/10.1109/ITAIC58329.2023.10408849.

[7] Wu, J.; Orlandi, F.; AlSkaif, T.; O'Sullivan, D.; Dev, S. Ontology Modeling for Decentralized Household Energy Systems. In Proceedings of the 2021 International Conference on Smart Energy Systems and Technologies (SEST), 2021, pp. 1–6. https://doi.org/10.1109/SEST50973.2021.9543327.

[8] Yang, L.; Lv, C.; Wang, X.; Qiao, J.; Ding, W.; Zhang, J.; Wang, F.Y. Collective Entity Alignment for Knowledge Fusion of Power Grid Dispatching Knowledge Graphs. *IEEE/CAA Journal of Automatica Sinica* **2022**, *9*, 1990–2004. https://doi.org/10.1109/JAS.2022.105947.

[9] Wang, S.; Pang, A.; Tian, D.; Zhang, J. Ontology Development and Knowledge Modelling for Photovoltaic Power Stations. In Proceedings of the 2024 5th International Conference on Computer Engineering and Application (ICCEA). IEEE, 2024, pp. 1824–1831.

[10] Chen, D.; Chen, L.; Yang, Y.; Lu, Q.; Hancock, C.; Lock, R.; Sølvsten, S. A knowledge-driven approach for automated fire safety compliance checking in operational buildings. *Knowledge-Based Systems* **2026**, *336*, 115156. https://doi.org/10.1016/j.knosys.2025.115156.

[11] Ma, K.; Tian, M.; Tan, Y.; et al. Ontology-Based BERT Model for Automated Information Extraction from Geological Hazard Reports. *Journal of Earth Sciences* **2023**, *34*, 1390–1405. https://doi.org/10.1007/s12583-022-1724-z.

[12] Arp, R.; Smith, B.; Spear, A.D. *Building Ontologies with Basic Formal Ontology*; The MIT Press, 2015. https://doi.org/10.7551/mitpress/9780262527811.001.0001.

[13] Zhang, T.; Tao, L.; Wang, X.; Zhang, C.; Li, S.; Hao, J.; Lu, C.; Suo, M. Hierarchical cognize framework for the multi-fault diagnosis of the interconnected system based on domain knowledge and data fusion. *Expert Systems with Applications* **2022**, *193*, 116503. https://doi.org/10.1016/j.eswa.2022.116503.

[14] Wang, X.; Zhao, L.; Zhang, S.; Wang, Y.; Qin, D.; Sun, W. Self-Organizing-Map-based Knowledge Fusion Method for Heterogeneous Ontologies in Power Grid Networks. In Proceedings of the 2020 5th International Conference on Mechanical, Control and Computer Engineering (ICMCCE), 2020, pp. 321–325. https://doi.org/10.1109/ICMCCE51767.2020.00078.

[15] Wang, Y.; Bai, X.; Liu, C.; Tan, J. A Multi-Source Data Feature Fusion and Expert Knowledge Integration Approach on Lithium-Ion Battery Anomaly Detection. *Journal of Electrochemical Energy Conversion and Storage* **2021**, *19*, 021003. https://doi.org/10.1115/1.4051716.

[16] Wang, H.; Huang, C.; Yu, H.; Zhang, J.; Wei, F. Method for fault location in a low-resistance grounded distribution network based on multi-source information fusion. *International Journal of Electrical Power & Energy Systems* **2021**, *125*, 106384. https://doi.org/10.1016/j.ijepes.2020.106384.

[17] Jie, Y.; Ji, X.; Yue, A.; Chen, J.; Deng, Y.; Chen, J.; Zhang, Y. Combined Multi-Layer Feature Fusion and Edge Detection Method for Distributed Photovoltaic Power Station Identification. *Energies* **2020**, *13*. https://doi.org/10.3390/en13246742.

[18] Dogdu, E.; Murat Ozbayoglu, A.; Benli, O.; Akinc, H.E.; Erol, E.; Atasoy, T.; Gurec, O.; Ercin, O. Ontology-centric data modelling and decision support in smart grid applications: A distribution service operator perspective. In Proceedings of the 2014 IEEE International Conference on Intelligent Energy and Power Systems (IEPS), 2014, pp. 198–204. https://doi.org/10.1109/IEPS.2014.6874179.

[19] López, G.; Custodio, V.; Moreno, J.; Sikora, M.; Moura, P.; Fernández, N. Modeling Smart Grid neighborhoods with the ENERsip ontology. *Computers in Industry* **2015**, *70*, 168–182. https://doi.org/10.1016/j.compind.2015.01.008.

[20] Tomasevic, N.M.; Batic, M.C.; Blanes, L.M.; Keane, M.M.; Vranes, S. Ontology-based facility data model for energy management. *Advanced Engineering Informatics* **2015**, *29*, 971–984. Collective Intelligence Modeling, Analysis, and Synthesis for Innovative Engineering Decision Making Special Issue of the 1st International Conference on Civil and Building Engineering Informatics, https://doi.org/10.1016/j.aei.2015.09.003.

[21] Tang, Y.; Wu, X.; Zhou, C.; Zhu, G.; Song, J.; Liu, G.; Li, Z. Automatic schema construction of electrical graph data platform based on multi-source relational data models. *Data & Knowledge Engineering* **2023**, *145*, 102129. https://doi.org/10.1016/j.datak.2022.102129.

[22] Pan, D.; Song, Z.; Nie, L.; Wang, B. Satellite Telemetry Data Anomaly Detection Using Bi-LSTM Prediction Based Model. In Proceedings of the 2020 IEEE

International Instrumentation and Measurement Technology Conference (I2MTC), 2020, pp. 1–6. https://doi.org/10.1109/I2MTC43012.2020.9129010.

[23] Yu, Z.; Zhang, C.; Deng, C. An improved GNN using dynamic graph embedding mechanism: A novel end-to-end framework for rolling bearing fault diagnosis under variable working conditions. *Mechanical Systems and Signal Processing* **2023**, *200*, 110534. https://doi.org/10.1016/j.ymssp.2023.110534.

[24] Nguyen, B.L.H.; Vu, T.V.; Nguyen, T.T.; Panwar, M.; Hovsapian, R. Spatial-Temporal Recurrent Graph Neural Networks for Fault Diagnostics in Power Distribution Systems. *IEEE Access* **2023**, *11*, 46039–46050. https://doi.org/10.1109/ACCESS.2023.3273292.

[25] Hu, J.; Hu, W.; Chen, J.; Cao, D.; Zhang, Z.; Liu, Z.; Chen, Z.; Blaabjerg, F. Fault Location and Classification for Distribution Systems Based on Deep Graph Learning Methods. *Journal of Modern Power Systems and Clean Energy* **2023**, *11*, 35–51. https://doi.org/10.35833/MPCE.2022.000204.

[26] Xu, Y.; Zhang, C.; Xu, Z.; Kong, C.; Tang, D.; Deng, X.; Li, T.; Jin, J. Tolerance Information Extraction for Mechanical Engineering Drawings – A Digital Image Processing and Deep Learning-based Model. *CIRP Journal of Manufacturing Science and Technology* **2024**, *50*, 55–64. https://doi.org/10.1016/j.cirpj.2024.01.013.

[27] Jing, L.; Zhao, M.; Li, P.; Xu, X. A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox. *Measurement* **2017**, *111*, 1–10. https://doi.org/10.1016/j.measurement.2017.07.017.

[28] Lv, X.; Zhao, S.; Yu, X.; Zhao, B. Residential Floor Plan Recognition and Reconstruction. In Proceedings of the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2021, pp. 16717–16726.

[29] Chen, D.; Chen, L.; Zhang, Y.; Lin, S.; Ye, M.; Sølvsten, S. Automated fire risk assessment and mitigation in building blueprints using computer vision and deep generative models. *Advanced Engineering Informatics* **2024**, *62*, 102614. https://doi.org/10.1016/j.aei.2024.102614.

[30] Chasseray, Y.; Barthe-Delanoë, A.M.; Négny, S.; Le Lann, J.M. Knowledge extraction from textual data and performance evaluation in an unsupervised context. *Information Sciences* **2023**, *629*, 324–343. https://doi.org/10.1016/j.ins.2023.01.150.

[31] Qin, Q.; Zhao, S.; Liu, C. A BERT-BiGRU-CRF Model for Entity Recognition of Chinese Electronic Medical Records. *Complexity* **2021**, *2021*, 6631837. https://doi.org/10.1155/2021/6631837.

[32] Yoon, J.; Jordon, J.; Schaar, M. Gain: Missing data imputation using generative adversarial nets. In Proceedings of the International conference on machine learning. PMLR, 2018, pp. 5689–5698.

[33] InfluxData. InfluxDB, 2024. https://www.influxdata.com/products/influxdb/, Accessed: 2024-09-05.

[34] Xing, X.; Wang, N. Entity Matching Based on Attribute-Aware and Multi-Perspective Similarity Measurement. *Journal of Information Science & Engineering* **2023**, *39*.

[35] Jiang, J.; Li, M. Entity Alignment Based on Multi-view Interaction Model in Vulnerability Knowledge Graphs. In *Web and Big Data*; Song, X.; Feng, R.; Chen, Y.; Li, J.; Min, G., Eds.; Springer: Singapore, 2024; Vol. 14332, *Lecture Notes in Computer Science*. https://doi.org/10.1007/978-981-97-2390-4_34.

[36] Li, F.; Bai, W.; Liu, S.; Zhang, Y.; Guo, M. Grid resource data differentiation standard based on CIM model. *Scientific Reports* **2025**. https://doi.org/10.1038/s41598-025-03420-x.