

Review

A Comprehensive Review of Multi-Modal Data Fusion-Driven Systematic Knowledge Construction Technologies for HVDC Operation and Maintenance

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Abstract

Large-scale UHVDC and flexible DC projects accumulate scattered multi-modal O&M data across independent platforms, fragmenting domain knowledge and reducing the efficiency of intelligent fault diagnosis and disposal. Unstructured data typically account for more than 70% of converter-station O&M data volume, which intensifies fragmentation across SCADA, inspection media, fault recordings and documents. Distinct from prior HVDC intelligent O&M surveys, this review critically synthesizes the closed-loop knowledge construction chain via multi-modal data fusion—covering data governance, cross-modal semantic mapping, DIKW modeling, hybrid storage and knowledge graph development—and compares three fusion paradigms regarding latency, scalability and industrial deployment. It also addresses renewable-integrated O&M uncertainty, practical feature extraction, and why deep learning black-box behavior limits field practicality. Key gaps remain small-sample generalization, control-and-protection logic formalization, explainability and cross-system integration; future directions include few-shot cross-modal learning, LLM-driven knowledge evolution and digital twin coupling.

Keywords: multi-modal data fusion; HVDC operation and maintenance; knowledge system; knowledge graph; domain corpus; knowledge evolution



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1. Introduction

Against the backdrop of global carbon neutrality goals and large-scale construction of new power systems, high-voltage direct current (HVDC) and flexible direct current transmission technologies have become core carriers for long-distance, large-capacity renewable energy delivery and asynchronous grid interconnection [1,2]. In practice, many HVDC corridors are tightly coupled with wind and photovoltaic generation. Because wind speed and solar irradiance vary rapidly, the resulting power fluctuations, voltage/reactive excursions and frequent operating-point changes create distinctive O&M scenarios—such as renewable-induced commutation-failure risk periods, high-rate alarm floods and condition-based inspection under intermittent loading—that are not fully covered by conventional steady-state station-centric case studies. This review, therefore, treats renewable-integrated

uncertainty as a cross-cutting O&M context when discussing multi-modal data fusion and knowledge construction. Countries worldwide have successively built numerous ultra-high voltage direct current (UHVDC) and voltage source converter-based high voltage direct current (VSC-HVDC) converter stations, forming complex multi-station DC transmission networks with abundant power electronic equipment, converters, and auxiliary O&M devices [3,4]. The rapid expansion of DC power grids brings severe O&M pressure: converter stations generate multi-source heterogeneous data covering supervisory control and data acquisition (SCADA) time-series measurements, phasor measurement unit (PMU) synchronous phasors, fault recording waveforms, infrared inspection images, equipment ledgers, protection fixed-value files, operation regulations and fault disposal documents [5,6]. Field evidence indicates that unstructured data exceed 70% of converter-station data volume [7]; this scale underpins the data-governance priorities reviewed below. These multi-modal data are stored in isolated business platforms, leading to serious fragmentation of domain experience and professional knowledge. Frontline O&M staff cannot efficiently correlate cross-system data, fault root cause tracing relies heavily on manual experience, and standardized intelligent auxiliary decision support is difficult to realize, which greatly restricts the safety, efficiency and economy of DC station daily operation [8,9]. Therefore, excavating the deep value of multi-modal O&M data and constructing a complete, dynamically updatable HVDC domain knowledge system has become an urgent technical demand for the digital and intelligent transformation of DC transmission O&M.

Traditional DC intelligent O&M research mostly focuses on independent single-scene optimization. Early studies mainly adopted single-modal data analysis schemes: only SCADA signal threshold judgment for early warning, or merely using inspection images for surface defect identification [10,11]. With the development of artificial intelligence (AI), multi-modal data fusion technology has been gradually introduced into power system monitoring and diagnosis, realizing joint analysis of images, waveforms and text to improve the accuracy of anomaly identification [12,13]. Meanwhile, knowledge graph (KG) technology is widely applied to organize power equipment topology, fault modes and disposal rules, forming structured knowledge carriers for intelligent query and reasoning [14,15]. Existing review papers in related fields can be roughly divided into two categories: the first category mainly focuses on intelligent fault diagnosis algorithms for HVDC systems, emphasizing model accuracy under predefined benchmark datasets. Although these studies provide valuable algorithmic comparisons, they usually neglect the complete transformation process from heterogeneous operational data to reusable knowledge assets, thereby limiting their practical value for knowledge management [16]. The second category summarizes the development of power knowledge graphs. However, most existing reviews primarily discuss static ontology construction and graph modeling, while insufficient attention has been paid to cross-modal semantic alignment, dynamic knowledge evolution, and engineering deployment in large-scale converter stations. Consequently, current reviews fail to establish a complete technical framework covering data governance, semantic fusion, knowledge construction, storage, reasoning, and continuous evolution [17,18]. Prior HVDC intelligence surveys fall into two isolated branches with inherent structural limitations [15–18]. Fault diagnosis reviews overemphasize offline model accuracy benchmarking while neglecting the end-to-end pipeline converting raw heterogeneous data into reusable domain knowledge; knowledge graph summaries only elaborate on static ontology construction, without systematic integration of multi-modal governance and knowledge iteration [17,18]. More critically, nearly all existing work artificially decouples multi-modal fusion and knowledge engineering and ignores the coupling constraints between C&P hard logic and field O&M specifications, which leads to fragmented theoretical guidance for practical converter station deployment [19–24].

From the perspective of existing research gaps, current academic research lacks a comprehensive, end-to-end systematic review targeting the full-chain technology of HVDC O&M knowledge system construction driven by multi-modal data fusion. Most literature only discusses partial links such as data identification or single-scene knowledge reasoning, without unified sorting of heterogeneous data cleaning, three mainstream multi-modal fusion paradigms, hierarchical knowledge architecture design, hybrid multi-database storage, domain corpus construction and dynamic knowledge iteration mechanisms [25,26]. There is also a lack of comparative analysis on the adaptability of data-level, feature-level and decision-level fusion strategies under DC converter station complex working conditions, and few studies summarize the semantic fusion method of hard control and protection logic and soft operation and maintenance specifications, which cannot provide complete theoretical and technical references for the integrated construction of DC digital O&M platforms [27,28].

In view of the above research deficiencies, this paper takes multi-modal data fusion as the core driving technology and systematically combs the complete technical system of HVDC O&M knowledge construction. The main academic contributions of this review are reflected in four aspects: First, it classifies multi-source DC O&M data into structured, semi-structured and unstructured categories, summarizes three core data pain points including heterogeneity, low quality and semantic isolation, and elaborates standardized cross-modal data pretreatment pipelines [29,30]. Second, it comprehensively compares the principles, applicable scenarios, advantages and defects of data-level, feature-level and decision-level multi-modal fusion technologies, and innovatively expounds the bidirectional semantic association and consistency verification method of converter station C&P logic and O&M rules [31,32]. Third, it constructs a four-layer progressive data-information-knowledge-wisdom (DIKW) architecture, introduces the hybrid collaborative storage scheme of relational graph-vector-document databases, and summarizes the whole process of domain corpus, instruction set and multi-modal knowledge graph development [33,34]. Fourth, it puts forward the full-lifecycle dynamic evolution mechanism of O&M knowledge, including incremental extraction, quality evaluation and obsolete knowledge archiving, and summarizes current technical bottlenecks and future key research directions in a targeted manner [35,36]. This review can provide systematic theoretical support and implementation reference for the research and engineering application of intelligent DC O&M knowledge platforms [37,38].

To clarify how this comprehensive review proceeds and grows, Figure 1 presents a tree diagram of the paper structure.

This review follows the PRISMA 2020 guidelines to ensure methodological rigor and transparency. A systematic literature search was conducted across Web of Science Core Collection, Scopus, IEEE Xplore and ScienceDirect, covering English journal articles published from January 2018 to June 2026, with keywords targeting HVDC operation and maintenance, multi-modal data fusion and knowledge construction technologies. Predefined inclusion and exclusion criteria were applied: peer-reviewed full articles with HVDC O&M technical contributions or engineering validation were included, while conference abstracts and duplicates were excluded. Title/abstract screening was first performed independently by two authors to remove clearly irrelevant records, followed by full-text assessment of the remaining papers against the same inclusion/exclusion criteria; disagreements were resolved by discussion. All included papers underwent a multi-dimensional quality assessment to support subsequent critical comparative analysis and gap identification. The overall full-chain technical framework for HVDC O&M knowledge construction is illustrated in Figure 2.

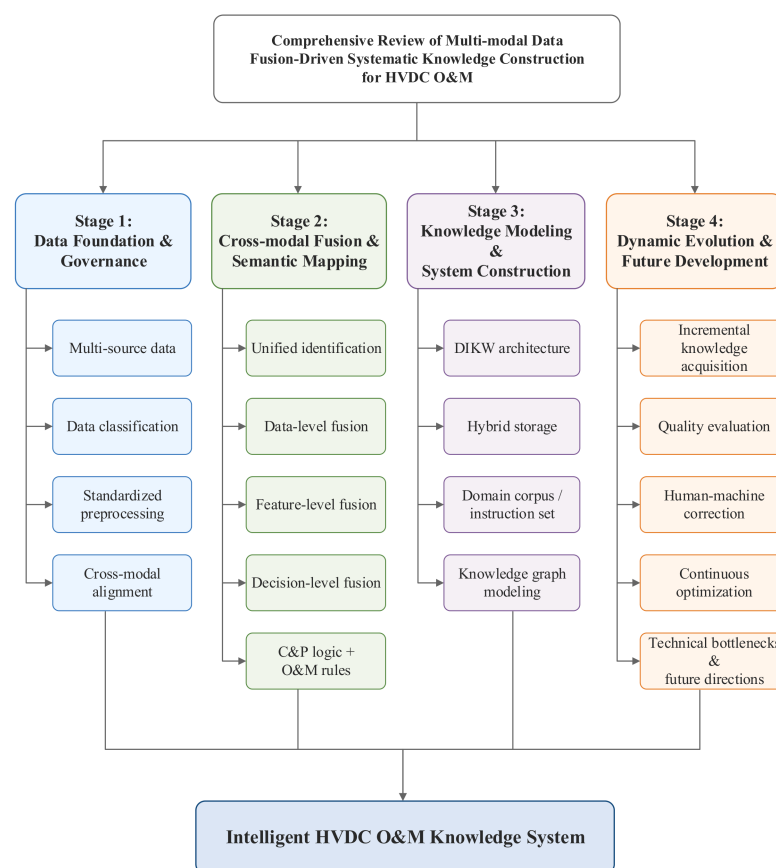


Figure 1. Tree diagram of the structure and expansion of this comprehensive review.

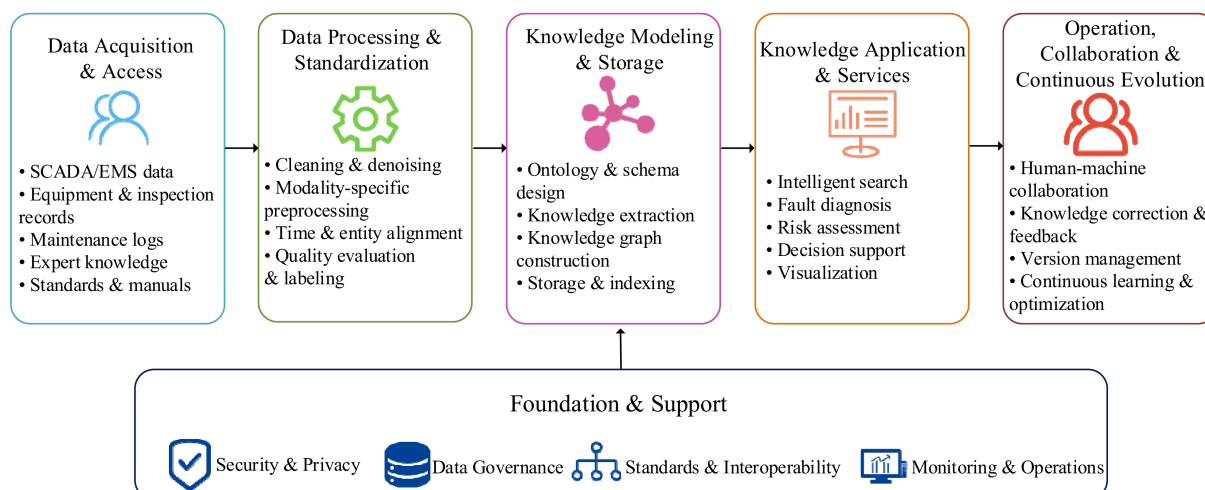


Figure 2. Full-chain technical overview diagram of systematic knowledge construction for HVDC operation and maintenance.

The remainder of this paper is organized as follows: Section 2 introduces the characteristics and governance technologies of multi-modal HVDC operation and maintenance data [39,40]. Section 3 reviews cross-modal semantic mapping and data fusion techniques [41,42]. Section 4 presents systematic knowledge construction and hybrid storage technologies [43,44]. Section 5 discusses dynamic knowledge evolution mechanisms [45], followed by a comparative analysis of recent reviews in Section 6, technical challenges and future directions in Section 7, and the conclusions in Section 8. The full-chain

technical overview diagram of systematic knowledge construction for HVDC operation and maintenance is shown in Figure 2.

2. Multi-Modal Data Foundation and Governance Technology for HVDC Operation and Maintenance

Multi-modal O&M data acts as the fundamental raw resource for constructing systematic HVDC knowledge systems. Massive monitoring, patrol and fault data generated by converter stations are scattered across isolated business platforms, with inconsistent formats, sampling frequencies and semantic standards [15,30]. Meanwhile, conventional fault diagnosis still depends strongly on expert experience and often lacks explicit logical relationships among multi-source fault evidence [7]. Without standardized classification, quality cleaning and cross-source association, raw heterogeneous data cannot be converted into computable standardized semantic units, which restricts the implementation of cross-modal fusion [13]. A unified metadata management system is the basic guarantee for realizing standardized management of multi-source heterogeneous data [46]. Although unified metadata management significantly improves data standardization, existing frameworks are mainly designed for general power systems rather than HVDC converter stations. They often ignore the temporal coupling among SCADA measurements, protection records, and inspection media, resulting in limited support for cross-modal semantic integration. This section systematically sorts the source classification, inherent bottlenecks and full-set pretreatment pipelines of HVDC multi-modal O&M data. A standardized multi-modal data governance workflow is constructed to provide unified, high-quality data support for subsequent semantic mapping and knowledge modeling. The overall technical flowchart of multi-modal data full-process governance is shown in Figure 3.

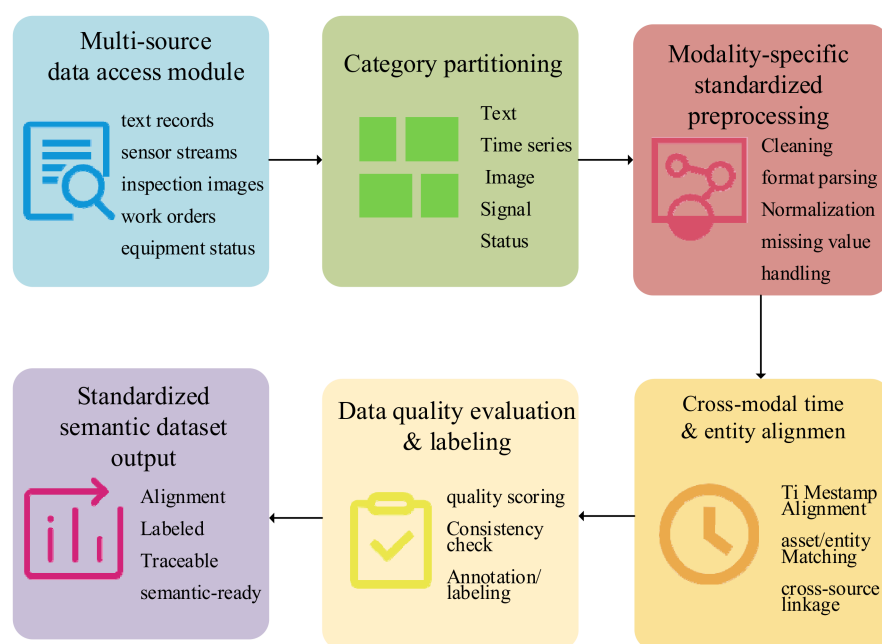


Figure 3. Full processing workflow of HVDC multi-modal operation and maintenance data.

2.1. Source and Classification of HVDC Multi-Modal O&M Data

Driven by different monitoring equipment, operation links and management systems, HVDC converter stations produce various multi-modal data with distinct structural characteristics. Based on storage format, organizational logic and business application scenarios, this paper divides all O&M data into three major categories—structured, semi-structured and unstructured—covering the full lifecycle data of equipment operation, online moni-

toring, manual inspection and fault disposal [2]. The mapping method of heterogeneous equipment data to knowledge graph ontology can effectively unify the definition of different types of data [47]. The detailed composition, storage form and application value of each data type are summarized in Table 1.

Table 1. Classification and application value of HVDC multi-modal operation and maintenance data.

Data Category	Typical Source	Typical Size	Sampling Frequency	Percentage	Engineering Value
Structured data [5,13]	SCADA, PMU	10 ⁶ records/day	1~5 s	15%	Real-time monitoring
Semi-structured data [6,21]	Alarm logs	10 ⁴ records/day	Event-driven	15%	Fault tracing
Unstructured data extraction of expert experience [11,23]	Images, Waveforms, Documents	>500 GB/day	Hourly/Event	70%	Knowledge extraction

2.1.1. Structured Data

Structured data is stored in relational databases with fixed field definitions, including SCADA bus voltage, converter valve current and other real-time telemetry indicators, complete equipment parameter ledgers, periodic maintenance records and full sets of converter protection fixed values [5]. Such data has unified dimensions and clear numerical correlations, which can be directly used for statistical analysis after simple normalization. However, different equipment manufacturers adopt inconsistent database field naming rules, leading to the same equipment attribute having divergent field labels across different monitoring platforms [45]. The unified metadata governance framework can eliminate the confusion of structured data fields from different manufacturers [46].

2.1.2. Semi-Structured Data

Semi-structured data mainly refers to various alarm messages and dispatch instruction streams generated by protection and station control systems, stored in XML and JSON formats following IEC 61850 communication standards [6]. These data carry hierarchical tag information but lack globally unique primary keys. Alarm timestamps, device IDs and fault description segments are randomly distributed within message contents, which cannot be directly associated with equipment records in structured ledgers; tag parsing and field extraction are required before subsequent data fusion [22].

2.1.3. Unstructured Data

Unstructured data accounts for more than 70% of the total data volume of converter stations [15], including three typical subtypes: visual patrol media, fault recording time-series waveforms and natural language documents/on-site voice. Infrared patrol images can reflect overheating defects of converter valves and cooling equipment; fault recording waveforms record transient voltage/current signals during commutation failures; operation regulations and accident reports contain massive qualitative disposal experience summarized by frontline experts [11]. This type of data lacks unified numerical dimensions and semantic labels, requiring noise reduction, feature extraction and semantic encoding to be converted into computable feature vectors for knowledge graph construction [26].

2.2. Core Characteristics and Governance Difficulties of Multi-Modal Data

HVDC multi-modal O&M data are generated by dozens of independent monitoring, protection and patrol subsystems and present three prominent inherent defects: cross-modal heterogeneity, widespread low-quality data and cross-system semantic isolation, which jointly form major obstacles to subsequent multi-modal fusion modeling [2,34].

2.2.1. Cross-Modal Heterogeneity

Heterogeneity exists in three dimensions: format inconsistency, mismatched sampling frequency and semantic dimension divergence [28]. Format-wise, structured tables, XML logs, images and waveforms adopt completely different storage carriers [10]; in terms of sampling rate, SCADA data updates every 1–5 s, PMU fault recording reaches millisecond sampling, while patrol images are collected hourly or daily, resulting in severe time granularity mismatch [5]; semantically, equipment such as converter valve has different coding labels in control systems, patrol platforms and protection logs, without unified mapping standards [44]. Such multi-dimensional heterogeneity makes raw data unable to be jointly modeled directly.

2.2.2. Widespread Low-Quality Data Caused by Field Interference

Long-term on-site electromagnetic interference and communication faults lead to universal data defects, including missing records, random noise and time desynchronization [33]. Communication interruptions cause incomplete telemetry data and truncated alarm logs; electromagnetic coupling superimposes high-frequency noise on fault waveforms and infrared pixel data; different subsystems deploy independent time synchronization modules, resulting in millisecond-level timestamp deviations for the same fault event [16]. If defective data are directly input into fusion models, feature distortion and incorrect equipment matching will occur, severely reducing the accuracy of fault knowledge extraction [29].

2.2.3. Core Characteristics and Governance Difficulties of Multi-Modal Data

Each converter station's control, protection and patrol departments build isolated data platforms based on their own business demands, without unified equipment and event identification standards [4]. Structured ledgers, alarm logs and patrol reports form independent "data silos" with disconnected semantic systems. For example, a commutation failure event only records numerical fluctuations in SCADA data, marks fault codes in protection logs and describes disposal schemes in maintenance documents, lacking automatic association channels among the three data types. Knowledge-graph-based fault diagnosis has therefore been investigated to strengthen interpretable reasoning over fault entities, relations and disposal knowledge [7]. Existing research mostly processes single-modal data separately and ignores cross-system semantic interworking barriers, which cannot support the construction of globally connected HVDC fault knowledge systems [17].

2.3. Core Characteristics and Governance Difficulties of Multi-Modal Data

Aiming at the three core bottlenecks of heterogeneous formats, low data quality and semantic isolation, this section establishes complete standardized pretreatment pipelines for structured and unstructured data, respectively, and further realizes unified cross-modal alignment from time and equipment entity dimensions, laying standardized data input for semantic mapping and multi-modal fusion in Section 3 [23,40].

2.3.1. Preprocessing Pipeline for Structured Data

Structured data preprocessing focuses on numerical consistency and time normalization, including four sequential technical steps: outlier elimination, data completion, feature normalization and unified time calibration [28].

- Outlier elimination: Combine the 3σ statistical criterion with equipment safe operating thresholds to identify abnormal telemetry points caused by sensor faults, filtering out extreme values beyond normal operation intervals [10];

- Missing data completion: Adopt linear interpolation for short-term continuous missing measurement values; fill long-period missing equipment parameters with standard ledger data of the same model [34];
- Feature normalization: Map voltage, current, temperature and all measurement indicators to [0, 1] via min-max scaling to eliminate magnitude interference during model training [29];
- Time synchronization: Convert all structured timestamps to a unified GPS time benchmark to eliminate second-level time deviations among different database records [13].

2.3.2. Preprocessing Pipeline for Unstructured Data

Unstructured data is divided into text, image and waveform branches for targeted cleaning and feature extraction [41]:

- Text & voice processing: Remove duplicate fault reports and redundant regulation paragraphs; construct a power professional glossary combined with a BiLSTM-CRF model for domain word segmentation and terminology normalization; convert patrol voice into standardized text via speech recognition and filter colloquial redundant expressions [17]. Duplicate reports are removed using document similarity thresholds above 95%. Documents are segmented into paragraphs containing 256–512 tokens before semantic encoding.
- Infrared patrol image processing: Apply median and bilateral filtering to eliminate shot noise; adopt threshold segmentation to extract the equipment region of interest (ROI), remove irrelevant background pixels and unify image resolution for visual feature extraction [15]. Median filtering using a 3×3 kernel is first applied to suppress impulse noise, followed by bilateral filtering ($\sigma_s = 5$ pixels, $\sigma_r = 25$ gray levels). Images are resized to 640×640 pixels before ROI extraction.
- Fault recording signals are sampled at 10–20 kHz. Daubechies-4 wavelet decomposition with three decomposition levels is adopted for denoising. Waveforms are segmented into 100 ms pre-fault and 500 ms post-fault windows before feature extraction [11].

2.4. Cross-Modal Unified Alignment Technology

After single-modality standardized preprocessing, cross-modal alignment is required to correlate multi-source data from time and entity dimensions, which is the prerequisite for cross-modal feature space mapping in Section 3 [42]. Three core alignment links are included:

- Timestamp cross-modal alignment: Take fault alarm trigger time as unified anchor, apply dynamic time warping (DTW) to match SCADA, waveform and patrol image time series, unify all data to a millisecond time benchmark and eliminate asynchronous sampling deviations [5].
- Equipment entity alignment: Construct a five-level global unified identification coding system extended from the IEC 61970 CIM standard; integrate attribute similarity, topological similarity and embedding vector similarity to calculate entity matching scores and resolve synonym/homonym confusion of cross-system equipment labels [44].
- Event trigger association: Take fault event chains as association clues, binding waveforms, images and text reports generated within the front and rear time windows of each fault trigger into complete multi-modal sample sets for subsequent fusion modeling [11,26].

A comparative analysis of mainstream multi-modal data pretreatment technologies in power O&M scenarios is summarized in Table 2.

Table 2. Comparative analysis of mainstream multi-modal data pretreatment technologies in power O&M scenarios.

Preprocessing Category	Method	Data	Advantages	Limitations
Structured cleaning	3σ + min–max	SCADA, ledgers	Fast, field-ready	Weak on long gaps [10]
Waveform denoising	Wavelet filter	Fault recordings	Cuts HF EM noise	Hard to tune by fault type [11]
Image pretreatment	Bilateral + ROI	Infrared patrol images	Keeps edges while denoising	Weak on dark/blurred images [15]
Text semantic normalization	BiLSTM-CRF	Reports, manuals	Strong domain terms	Needs good domain corpus [17]
Time alignment	DTW	Asynchronous series	Handles nonlinear lag	Costly on long sequences [5]
Entity matching	Multi-feature score	Cross-system ledgers	High match accuracy	Weight tuning is complex [44]

3. Cross-Modal Data Fusion and Semantic Mapping Technologies

Unified identification and semantic mapping serve as the fundamental prerequisite for cross-regional and cross-system operation and maintenance (O&M) data interoperability. Its core objective is to convert heterogeneous O&M data distributed across multiple nodes and systems into associable, computable standardized semantic units, providing underlying support for subsequent knowledge fusion and knowledge graph construction. Multi-modal fusion in power systems has evolved from single-modality analytics toward cross-modal joint modeling for fault diagnosis, defect recognition, and condition monitoring [48]. In transmission and converter-station O&M, early studies mainly exploited SCADA time series, protection events, or inspection images in isolation; recent work increasingly combines images, waveforms, logs, and documents through feature-level fusion and graph-based association [49,50]. For HVDC scenarios, however, existing reviews and applications remain biased toward AC substations or generic equipment graphs, with insufficient treatment of cross-regional data sharing, millisecond-level event chains, and C&P-specific rule systems [51,52]. The technical chain from multi-modal O&M data to semantic information is shown in Figure 4. Accordingly, this section focuses on identification, mapping, fusion paradigms, and domain rule integration as the technical bridge from heterogeneous O&M data to standardized semantic information.

3.1. Unified Identification and Semantic Mapping Technology for Multi-Modal HVDC O&M Data

The global unified identification system establishes a standardized coding framework for physical equipment and logical events in HVDC systems, with core features of global uniqueness, hierarchical resolvability and cross-system reference ability. Current engineering practices based on IEC 61970/61968 CIM and RDF face issues of insufficient granularity and coding inconsistencies for HVDC-specific equipment, which restricts cross-provincial and cross-bureau data sharing and collaborative analysis. Equipment identification adopts a five-level hierarchical coding structure to ensure intra-station uniqueness and mitigate synonym conflicts; however, it is sensitive to attribute changes and requires synchronous mapping maintenance after equipment retrofitting. For event identification, an event chain numbering mechanism is applied to adapt to the temporal and causal chain characteristics of faults and alarms, supporting subsequent temporal knowledge graph construction. Bidirectional mapping interfaces with CIM and enterprise coding standards shall be reserved at the ontology layer in the implementation phase. As the core link to eliminate data silos,

entity alignment is challenged by inconsistent ledger information and message format differences across protection and fault recording systems.

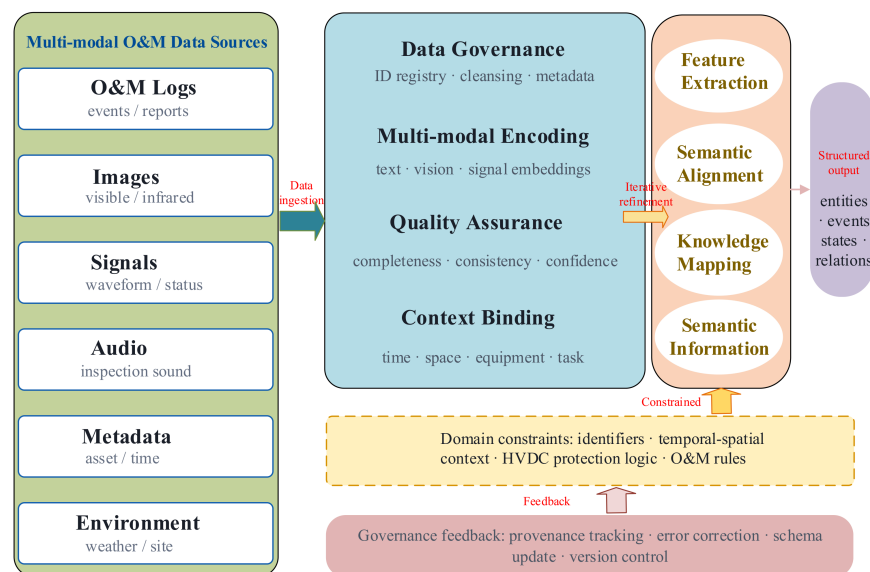


Figure 4. Technical chain from multi-modal O&M data to semantic information.

Unified identification in power utilities typically extends IEC 61970/61968 CIM and RDF-based resource modeling, supplemented by enterprise asset coding standards [53]. Entity alignment methods range from attribute similarity and graph matching to representation learning over knowledge embeddings [54,55]. Cross-modal mapping has progressed from early feature concatenation to shared encoders and contrastive learning (e.g., image-text and waveform-text alignment) [56,57]. Nevertheless, HVDC-specific challenges—including converter-level asset granularity, vendor-dependent C&P formats, and cross-regional identifier synchronization under offline or cross-network conditions—remain inadequately addressed in existing studies [58,59].

Equipment alignment integrates three types of features to calculate the comprehensive score, with the formula as follows:

$$\text{Sim}(e_1, e_2) = \alpha \cdot \text{Sim}_{\text{attr}} + \beta \cdot \text{Sim}_{\text{topo}} + \gamma \cdot \text{Sim}_{\text{emb}} \quad (1)$$

where Sim is the comprehensive entity alignment score; e is the entity object; Sim_{attr} is the attribute similarity; Sim_{topo} is the topological structure similarity; Sim_{emb} is the embedding vector similarity; and α , β , and γ are weight coefficients.

This weighted fusion formula assumes linear additivity of attribute, topological and embedding similarity features, with weight coefficients α , β , and γ manually or adaptively calibrated according to equipment granularity [44]. Practically, it solves cross-system equipment synonym matching in HVDC stations by multi-dimensional feature coupling. Its core limitation lies in ignoring nonlinear correlations between three similarity metrics, which reduces alignment accuracy under incomplete equipment ledger data. For this review, the formula is retained to quantitatively summarize mainstream entity alignment modeling logic, serving as a unified benchmark for comparing various equipment matching algorithms.

Among them, the attribute method relies on field matching accuracy, the graph matching method relies on topological structures such as primary wiring and protection zones, and the embedding method adapts to heterogeneous field scenarios through vector space mapping. Given the large quantity and non-standard naming of HVDC secondary equip-

ment, a single method has a high mismatch rate, and multi-feature fusion is required to improve alignment accuracy.

Event alignment adopts the joint constraint of time window, equipment ownership and action type, requiring millisecond-level time alignment based on unified GPS/PTP time synchronization while retaining both original and corrected timestamps. For cascading faults, the candidate range is first narrowed through equipment topology neighborhoods, and then chain matching is performed according to time sequence and protection logic order. For persistent alarms, repeated reports are merged and the first trigger and recovery times are retained. The disambiguation link handles homonym and synonym issues through terminology dictionaries and ontology constraints. Alignment results shall be attached with source system, confidence and evidence fields to provide a weighting basis for subsequent knowledge fusion.

Preprocessing is a prerequisite for reliable fusion and knowledge construction rather than a subsidiary step of data-level fusion. For HVDC O&M data, modality-specific pipelines should be standardized as follows: (i) text—deduplication, OCR correction, terminology normalization, and de-identification; (ii) images/infrared—denoising, registration, and region-of-interest extraction; (iii) waveforms/SCADA—filtering, resampling, anomaly clipping, and fault-window segmentation (e.g., pre-fault/post-fault intervals); (iv) alarms/work orders—deduplication, field normalization, and event-chain reconstruction. Cross-modal preprocessing further requires millisecond-level time synchronization (GPS/PTP), unified device/event identifiers, and explicit missing-value tagging. Existing power-data preprocessing frameworks are mostly designed for general grid analytics or single stations and lack HVDC-oriented protocols for commutation-failure waveforms, cross-regional data exchange, and security-grade desensitization [60,61]. The multi-modal preprocessing workflow for HVDC O&M data is shown in Figure 5. Therefore, establishing a preprocessing specification compatible with global identification and downstream graph construction is a necessary foundation for the mapping and fusion methods discussed above.

Cross-modal feature space mapping projects heterogeneous features such as text, images and waveforms into a unified semantic space to enable joint analysis of multi-modal information. It is divided into two technical routes: explicit mapping compresses features of each modality into the same latent space through shared encoders or multi-modal Transformers; implicit mapping relies on contrastive learning to pull semantically related modalities closer and push unrelated modalities apart through paired samples.

Current HVDC research mostly focuses on bimodal alignment of inspection images and defect texts, while joint mapping of fault recording waves and text reports still faces bottlenecks: fault recording is a continuous high-dimensional time series signal, while text is a discrete symbol sequence, with mismatched sampling semantics. Key waveform features require event segmentation before alignment with text fault information. When contrastive learning is applied to power multi-modal scenarios, domain positive samples shall be constructed based on work orders, fault recordings and alarms, and hard negative sample strategies of “same equipment with different faults” and “same fault with different equipment” shall be adopted, with reweighting to alleviate category imbalance. The contrastive learning loss function is as follows:

$$L = -\log \frac{\exp(\text{sim}(z_i, z_j) / \tau)}{\sum_k \exp(\text{sim}(z_i, z_k) / \tau)} \quad (2)$$

where L is the contrastive learning loss; z is the cross-modal vector; i and j are semantic paired sample indices; $\text{sim}(\cdot)$ is the similarity function; τ is the temperature coefficient; and k is the in-batch negative sample index.

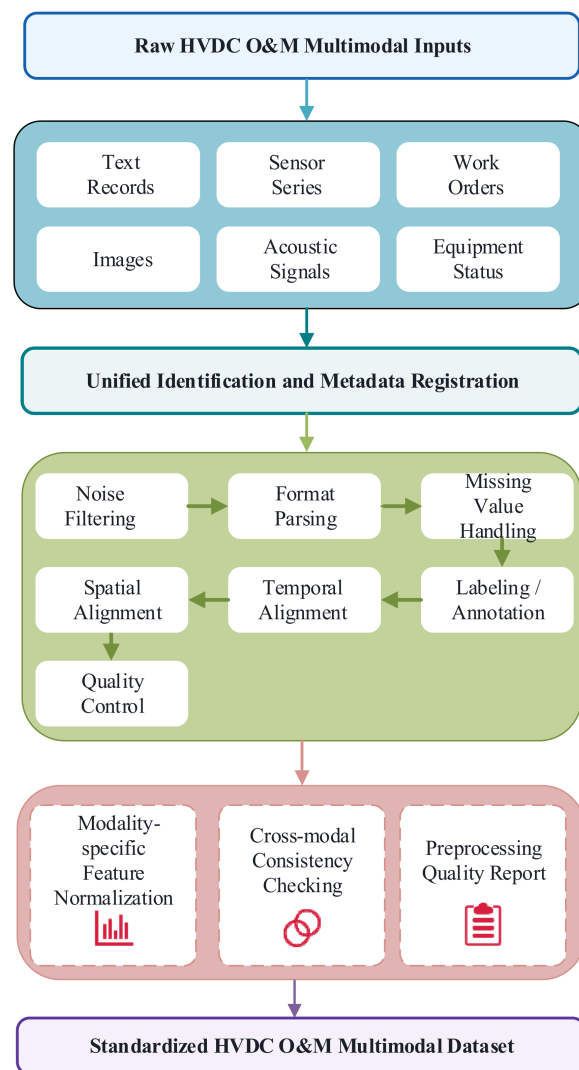


Figure 5. Multi-modal preprocessing workflow for HVDC O&M data.

The contrastive loss adopts the uniform Gaussian similarity distribution assumption controlled by the temperature hyperparameter τ . In HVDC multimodal alignment, it pulls fault waveform-text positive samples closer in shared semantic space while separating irrelevant modal pairs. Its limitation is heavy dependence on high-quality manually paired fault samples, which are scarce in real converter station datasets. This formula is included in the review to standardize the mathematical paradigm of cross-modal semantic mapping adopted by most vision-signal-power literature [56,57].

In engineering implementation, the cross-modal mapping module shall output interpretable intermediate representations such as defect categories, fault modes and key time periods, rather than only black-box vectors. For unified mapping of three or more modalities, the technical path of pairwise alignment and graph association is more feasible at this stage, realizing multi-modal information convergence at the knowledge graph layer through equipment IDs and event chains.

3.2. Technical Paradigms of Multi-Modal Data Fusion and HVDC Scenario Adaptation

According to the stage of fusion occurrence, multi-modal fusion can be divided into three paradigms: data-level, feature-level and decision-level fusion. HVDC business systems vary greatly in construction years and interface standards, so fusion selection must balance accuracy, latency, maintainability and compatibility with existing systems.

Beyond algorithmic feature fusion logic, the comparison of the three paradigms must incorporate four industrial-oriented evaluation metrics: computational complexity, cross-station scalability, anti-noise robustness under fault conditions, and on-site deployment compatibility with legacy HVDC SCADA/protection platforms [30,60]. Existing academic studies predominantly evaluate model offline diagnosis accuracy while neglecting real-time latency constraints, distributed expansion difficulty, noise anti-interference performance and transformation cost of practical converter station systems, which creates a critical gap between theoretical research and industrial application.

When HVDC systems evacuate intermittent renewables, O&M cases should explicitly include:

1. Ramping and curtailment events driven by wind/irradiance variability;
2. Transient stress on valves, AC filters and cooling systems during weak-grid or low-inertia intervals;
3. Correlated multi-modal evidence chains linking meteorological/power-forecast residuals, SCADA/PMU trends, fault recordings and inspection media.

Data-level fusion is useful for synchronized windowing of forecast–telemetry–waveform streams; feature-level fusion supports joint anomaly scoring under non-stationary loading; decision-level fusion is preferable when subsystems report asynchronous alarms during cloud-edge or wind-drop events. Ignoring these scenarios leads to knowledge graphs and diagnostic rules that overfit calm weather and under-represent high-volatility operating days.

3.2.1. Data-Level Fusion

Data-level fusion concatenates temporally aligned raw signals as model input, which preserves full primitive information with low deployment overhead [11]. Nevertheless, this paradigm demands consistent sampling dimensions; heterogeneous text-image data concatenation triggers dimensional explosion and severe noise amplification. For HVDC systems, it only applies to homologous time-series streams (multi-channel fault recordings, synchronized SCADA measurements). Pre-fault (100 ms) and post-fault (500 ms) signal segmentation is widely adopted to eliminate steady-state background interference.

3.2.2. Feature-Level Fusion

Feature-level fusion first extracts features independently by modality, then realizes feature interaction at the intermediate layer. It is the mainstream paradigm in current academic research and engineering trials. Different modalities adapt to differentiated feature extraction networks: CNN and ViT for spatial features of images; LSTM, TCN and 1D-CNN for temporal features of measurement data; domain fine-tuned pre-trained models for semantic features of text. For HVDC O&M implementation, the extracted features should be explicitly defined by modality so that fusion results can be reproduced and reused. SCADA and PMU streams typically yield statistical and temporal descriptors such as mean, variance, ramp rate, harmonic content and synchro phasor deviation. Fault recordings further provide time–frequency features from wavelet or fast Fourier transform coefficients, together with pre-fault and post-fault window signatures related to commutation failure. Infrared and visible inspection images contribute ROI thermal gradients, hotspot temperature rise and texture or shape descriptors of valves and cooling equipment. Text and alarm records contribute domain entities, fault-mode labels and disposal-action embeddings. Clarifying this modality-wise feature inventory strengthens downstream knowledge-graph construction and improves the feasibility of engineering deployment. Fusion mechanisms include feature concatenation, bilinear fusion, cross-modal attention, multi-modal Transformer and graph neural networks.

Cross-modal attention dynamically allocates modality weights according to task scenarios [48,49]. For example, in defect identification, text weight is automatically reduced when image features are clear, and text channel weight is increased when image quality is poor. Graph neural networks can mount multi-modal features to equipment nodes and propagate features through topological structures, especially suitable for association analysis of HVDC primary and secondary equipment [50,51]. The cross-modal attention calculation is as follows:

$$h_m = \sum_n \alpha_{mn} \cdot W_n h_n \quad (3)$$

where h is the modal feature vector; m and n are modality indices; W is the linear transformation matrix; and α is the cross-modal attention weight, obtained by normalizing compatibility scores via Softmax.

For knowledge system construction, the core pain point of feature-level fusion is that fusion results are difficult to precipitate and reuse, as most task models only output classification or scoring results. Therefore, a structured extraction head shall be added at the model output end to map fusion features into standardized knowledge units such as equipment, defects, fault modes and disposal suggestions, supporting subsequent knowledge graph storage.

Despite its superior representation capability, feature-level fusion generally requires large amounts of labeled multi-modal data and suffers from limited interpretability, which restricts its deployment in safety-critical HVDC operation and maintenance scenarios.

3.2.3. Decision-Level Fusion

Cross-paradigm benchmarking further exposes universal research gaps overlooked by single-task diagnostic literature. Data-level fusion retains complete raw signals yet fails to perform heterogeneous image–text joint analysis; feature fusion enables deep correlation mining but generates non-reusable black-box features; decision fusion adapts legacy platforms at the cost of truncated inter-modal causal clues. Few studies construct hybrid fusion frameworks balancing deep feature association and robust decision fallback for renewable-strapped HVDC grids. The adaptation comparison of three multi-modal fusion paradigms in HVDC O&M is summarized in Table 3.

Table 3. Adaptation comparison of three multi-modal fusion paradigms in HVDC O&M.

Fusion Paradigm	Representative Recent Studies	Datasets Used	Core AI Models	Core Advantages	Unaddressed Research Gaps	Key Limitations
Data-level fusion	[11,16]	Synchronous fault recording multi-channel time series	1D-CNN, TCN	Complete raw signal retention, low fusion latency	Only fit isomorphic data, dimensional explosion under multi-modality	Adaptation for asynchronous PMU-SCADA mixed streams
Feature-level fusion	[21,57]	Infrared inspection images + fault text + waveform	ViT, BiLSTM-CNN, Cross-Attention Transformer	Deep cross-modal correlation mining	Fusion features lack interpretability, hard to precipitate knowledge units	Few-shot cross-modal alignment under limited fault samples
Decision-level fusion	[7,27]	Multi-subsystem independent alarm outputs	D-S Evidence Theory, Fuzzy Weight Voting	Compatible with legacy O&M platforms, single-modal fault tolerance	Truncates fine-grained inter-modal causal links	Hybrid feature-decision fusion engineering validation

Current multi-modal fusion research lacks joint optimization targeting the four industrial metrics mentioned above. Most lightweight improvement efforts only reduce model parameter quantity at the cost of diagnostic robustness, while distributed scalable fusion architectures adapted to cross-regional HVDC networks remain underexplored. Few studies quantify the transformation cost and access difficulty of fusion algorithms on legacy converter station platforms, which restricts the engineering popularization of multi-modal intelligent O&M systems.

Although decision-level fusion offers high engineering robustness, the interaction among heterogeneous features is lost before decision aggregation, reducing its capability for deep knowledge mining.

3.3. Feature Fusion Mechanism of HVDC Control & Protection Logic and O&M Rules

Positioning. Sections 3.2.1–3.2.3 summarize general multi-modal fusion paradigms applicable to heterogeneous HVDC data. Section 3.3 addresses a domain-specific fusion problem: the integration of C&P logic and O&M rules. This rule-level fusion is not an alternative paradigm parallel to data/feature/decision fusion; rather, it represents deep semantic fusion of two core HVDC knowledge sources and constitutes a distinguishing feature of HVDC O&M knowledge systems relative to generic equipment knowledge graphs. C&P logic and O&M rules constitute the two main sources of HVDC O&M knowledge. The former is embedded in C&P systems as function blocks, logic diagrams, and setting tables, and acts as hard operational constraints; the latter resides in regulations, contingency plans, and work instructions, and serves as soft criteria for field execution. Long managed across separate departments, systems, and terminologies, the two knowledge streams often remain isolated. Without fusion, knowledge graphs risk structural gaps—equipment without associated rules, and rules without traceable control logic.

3.3.1. Knowledge-Based Transformation of Structured C&P Logic

HVDC C&P logic encompasses core functions including converter valve control, pole control, station control, protection criteria, and sequential control interlocking, and is presented in various technical forms such as function block diagrams, ladder diagrams, logic equations, setting lists, and manufacturer-specific configuration files. The goal of knowledge-based transformation is to convert logic embedded in control program systems into structured knowledge that supports query, inference, and mutual association within the knowledge base.

There are two transformation paths: first, rule engine-based transformation, which parses configuration files and converts conditional judgments and output actions into production rules, with low implementation cost and suitability for fast alarm explanation function mounting; second, formal modeling, which uses Petri nets, finite state machines and temporal logic to express cascading protection and sequential control, retaining temporal characteristics such as delay, blocking and reset, with strong expressive ability and suitability for complex logic simulation verification. The production rule expression is as follows:

$$R_k : \text{IF } C_k \text{ then } A_k \quad (4)$$

where R is the C&P rule; C is the condition set; A is the action set; and k is the rule index.

Differences in manufacturer configuration formats are the main obstacle to implementation. The same protection principle has significant differences in field names, hierarchical structures and expression methods in configurations from different manufacturers, and there is a lack of universal parsers. In engineering practice, adapters are usually established by manufacturers to convert private formats into unified intermediate representations before storage. Meanwhile, simple condition-action rules are insufficient to represent com-

plex cascading logic and cross-device collaboration mechanisms. Accordingly, relational attributes, including logic fragments, delay constraints and reset conditions, shall be predefined at the ontology layer to mitigate information loss during knowledge transformation.

3.3.2. Structured Extraction of Unstructured O&M Rules

O&M rules are scattered in documents such as operation regulations, fault disposal plans, maintenance processes and typical accident reports, with a colloquial language style and a large number of elliptical sentences, reference sentences and nested tables. Extraction technologies have evolved from regular matching and template matching to CRF, BiLSTM-CRF, and then to joint extraction based on domain pre-trained models.

General pre-trained models deliver limited recognition accuracy for HVDC professional terms, including commutation failure, pole balance transfer and valve cooling abnormality, and tend to omit nested rules and table-based rules in the extraction process. A practical and effective solution follows three sequential procedures: constructing a domain terminology dictionary and synonym lexicon, fine-tuning the pre-trained model with an HVDC-specific corpus, and conducting manual verification on high-value regulation documents [62].

The extracted rule elements shall cover at least six core components: applicable objects, trigger conditions, operation steps, constraint restrictions, risk prompts, and citation basis. Extraction results that retain only action phrases while omitting corresponding conditions and target objects cannot achieve effective alignment with C&P logic, nor can they provide valid support for subsequent decision-making. For table-formatted rules, the original layout structure shall be restored first, followed by rule fragment extraction conducted along row and column dimensions, so as to prevent table content from being misprocessed as ordinary text paragraphs.

3.3.3. Semantic Association and Consistency Verification of Two Types of Rules

Semantic association is designed to establish mapping relationships between C&P terminology and O&M terminology, enabling bidirectional correlation between protection actions and their corresponding disposal plans, operation ticket templates, and safety measure requirements. This process can be implemented through three technical approaches: ontology-based terminology mapping, vector similarity-based candidate matching, and co-occurrence statistics-based association discovery, with all derived association results subject to expert review and final confirmation. Notably, association construction is not a one-time task. Local re-association shall be triggered upon the release of new regulations, adjustment of protection settings, and completion of equipment retrofitting.

Consistency verification is designed to identify conflicts between O&M regulation requirements and C&P system constraints. Typical conflict instances include disconnector operations permitted by operational regulations that contradict hard blocking mechanisms in C&P systems, and disposal sequences specified in emergency plans that are misaligned with protection reset conditions. Most existing systems implement conflict detection relying on explicit rule sets, where the detection coverage is directly limited by the completeness of the underlying rule base. Nevertheless, complex scenarios involving temporal dependencies and multi-branch logic still necessitate manual review and validation.

From the perspective of knowledge system construction, the fusion of C&P and O&M rules should not be confined to superficial linkage between discrete entries. Instead, it should form a bidirectionally navigable knowledge architecture, through which disposal procedures are traceable from specific protection actions, and corresponding logical constraints and setting bases are retrievable from individual regulation clauses. This bidirectional fusion architecture constitutes a core distinguishing feature of HVDC O&M

knowledge compared with generic equipment knowledge graphs and also represents a prominent manifestation of the project's engineering value.

Existing studies on power knowledge construction mostly process control-protection logic and O&M operation rules in isolation, without critical discussion on their semantic mismatch defects. Hard C&P logic is expressed as formal conditional interlocking equations, while soft O&M specifications adopt unstructured natural language with elliptical descriptions; current term mapping methods only realize one-way entity matching, lacking bidirectional traceability between protection action triggers and corresponding on-site disposal procedures. In addition, most rule consistency verification algorithms rely on manually predefined conflict rule sets, which cannot automatically identify logical contradictions between equipment blocking interlocks and operation ticket permission clauses under complex transient fault chains, and no quantitative conflict credibility evaluation framework has been formed—these defects restrict the completeness and reliability of HVDC domain knowledge graphs in engineering practice.

4. Systematic Construction and Storage Technologies for HVDC O&M Knowledge

Multi-modal fusion technology addresses the fundamental challenge of transforming raw heterogeneous data into structured semantic information. By comparison, knowledge systematization further converts such semantic information into formalized structured knowledge endowed with four core capabilities: persistent storage, semantic retrieval, logical inference, and iterative evolution. This section elaborates on four core technical modules, namely architecture design, hybrid storage, corpus and instruction set construction, and knowledge graph development, and serves as the technical core section of the full paper. HVDC and power knowledge engineering has shifted from document management and isolated expert systems toward knowledge graphs, domain-adapted language models, and retrieval-augmented decision support [63,64]. Existing HVDC graph projects often target single tasks such as fault diagnosis, while corpus and instruction resources for converter stations remain scarce [62]. Following the architecture-first logic adopted in this review, Section 4.2 introduces hybrid storage and cross-database retrieval as the infrastructure layer because knowledge objects require persistent, secure, and cross-modal addressing before corpus, instruction, and graph construction can be operationalized at scale. Sections 4.3 and 4.4 then elaborate on the core knowledge carriers built upon this infrastructure. Existing HVDC knowledge graph studies mostly focus on entity organization and fault retrieval. However, the lack of continuous knowledge evolution, version management, and cross-regional synchronization mechanisms limits their applicability in large-scale engineering projects.

4.1. Hierarchical Architecture and Classification System of HVDC O&M Knowledge

4.1.1. Classification System of HVDC O&M Knowledge

Knowledge classification shall be oriented toward practical demands, including business retrieval, permission management, and lifecycle update maintenance, rather than being conducted as an end in itself. In alignment with HVDC O&M business workflows, O&M knowledge can be systematically categorized into four types:

1. Equipment foundation knowledge: It encompasses equipment ledgers, technical parameters, structural principles, manufacturer documentation, test records, and retrofitting histories, forming the entity-layer foundation of the entire knowledge system.
2. Operation rule knowledge: It covers C&P logic, operation regulations, dispatching rules, protection settings, and safety constraints, which define the operational boundary conditions of HVDC systems.

3. Fault disposal knowledge: It consists of fault phenomena, identification criteria, root causes, disposal procedures, typical cases, and risk prompts, and represents the most frequently accessed knowledge type for front-line O&M personnel.
4. O&M decision-making knowledge: It includes inspection strategies, maintenance plans, state evaluation schemes, risk assessment methodologies, and skill requirement specifications, focusing on the precipitation of management experience and decision support capabilities.

According to knowledge form, it can be divided into structured, semi-structured and unstructured categories, corresponding one-to-one with the data classification system in Section 2. Classification results directly determine storage selection and extraction strategies and shall be unified and standardized at the initial stage of platform construction to avoid version inconsistency caused by the independent definition of each subsystem.

4.1.2. Four-Layer Progressive Knowledge System Architecture

Built upon the classic data–information–knowledge–wisdom (DIKW) model and aligned with HVDC O&M business workflows, a four-layer progressive knowledge system architecture is established, consisting of the data layer, information layer, knowledge layer, and application layer.

1. Data layer: It is tasked with multi-source O&M data ingestion, raw data archiving, and foundational lifecycle management, serving as the underlying data source foundation of the entire system.
2. Information layer: It undertakes data cleaning, cross-source entity alignment, feature fusion, and quality labeling, delivering standardized and credible information units as intermediate outputs.
3. Knowledge layer: It focuses on the systematic precipitation and structured organization of domain corpus, instruction sets, knowledge graphs, and rule bases, producing reusable formalized knowledge objects.
4. Application layer: It delivers targeted knowledge services for practical O&M scenarios, including intelligent inspection, fault tracing, auxiliary decision-making, and personnel skill training.

At present, domestic HVDC O&M knowledge construction is generally fragmented, mostly adopting a siloed mode of single application with a single knowledge graph, which easily leads to repeated parameter maintenance and inconsistent versions. The four-layer architecture realizes traceable and reusable knowledge versions through clear boundaries and standardized interfaces, meeting the project goals of inheritability, replicability and exportability. The demarcation between the information layer and the knowledge layer is the core of the architecture: cleaned data belongs to information units and cannot be directly stored as knowledge.

4.2. Hybrid Storage and Cross-Database Retrieval Technology for Multi-Modal O&M Knowledge

4.2.1. Hybrid Storage Architecture for Multi-Modal Knowledge

HVDC O&M knowledge has the characteristics of strong association, rich documents, high vector retrieval demand and large-scale structured attributes. The cross-regional hybrid storage and synchronization architecture is shown in Figure 6. A single database cannot fully adapt to these demands, so a hybrid storage architecture is adopted to realize multi-database association mapping through global unified identification. Relational databases store transactional data such as ledgers and settings to ensure transaction consistency; graph databases store entity relationships such as topology, causal chains and rule associations to support multi-hop queries and path reasoning; vector databases store multi-modal embedding features to support semantic retrieval and large model retrieval

augmentation; document databases store unstructured documents such as regulations and reports to support full-text retrieval and flexible expansion.

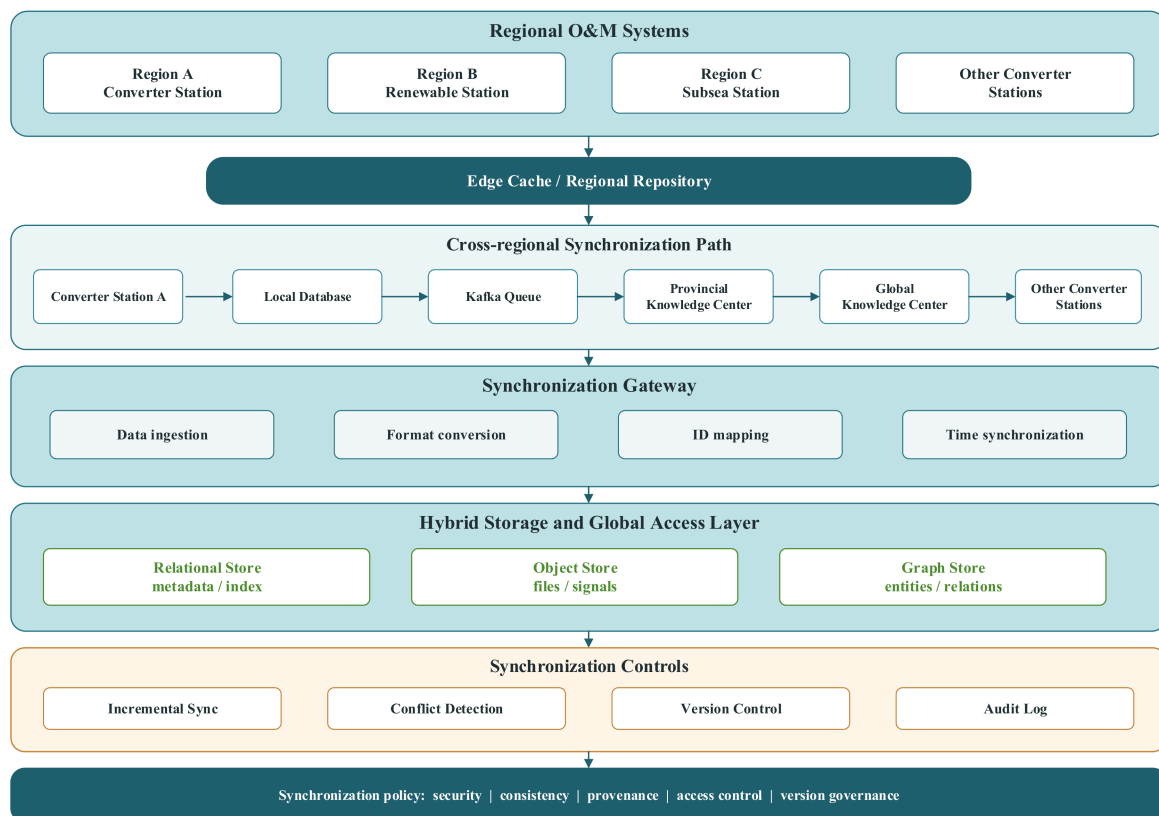


Figure 6. Cross-regional hybrid storage and synchronization architecture.

The four types of databases establish cross-database mapping through global unified identification. When each piece of knowledge is stored, its primary key, source, version, effective time and evidence location are recorded synchronously, with supporting mechanisms such as read-write separation, hot-cold stratification, permission control, audit and backup, complying with industry standards such as GB/T 42131.

$$M : \text{ID}(e) \mapsto (k_{\text{rel}}, k_{\text{graph}}, k_{\text{vec}}, k_{\text{doc}}) \quad (5)$$

where M is the cross-database mapping function; $\text{ID}(e)$ is the global entity identifier; and k_{rel} , k_{graph} , k_{vec} , and k_{doc} are locating keys in the relational, graph, vector, and document databases, respectively.

Cross-bureau and cross-station knowledge sharing requires a distributed storage architecture with explicit identifier mapping, version synchronization, and authority-aware access control. In practice, relational, graph, vector, and document repositories may be deployed across regional nodes while sharing a global logical ID namespace defined in Section 3. Data synchronization should support incremental updates, conflict detection, and rollback of obsolete regulations. Cross-domain security mechanisms—including graded classification, field-level desensitization, privacy-preserving sharing, and auditable cross-network exchange—are essential for applying federated or privacy-computing schemes without breaking semantic linkage [65,66]. Data ownership, effective-date management, and traceable evidence chains should be treated as first-class metadata for every knowledge object. The hybrid storage scheme for multi-modal knowledge is presented in Table 4.

Table 4. Hybrid storage scheme for multi-modal knowledge.

Storage Type	Typical Content	Main Capabilities	HVDC Scenario Notes
Relational database	Settings, ledgers, work order fields	Transaction consistency, conditional query	Suitable for static standardized data
Graph database	Equipment topology, causal chains, rule associations	Multi-hop association, path query	Ontology shall be mapped with CIM standards
Vector database	Text/image/waveform embedding features	Semantic similarity retrieval	Embedding models require domain fine-tuning
Document database	Regulations, reports, manuals	Full-text retrieval, flexible structure	Requires layout analysis and permission management

4.2.2. Multi-Modal Knowledge Indexing and Cross-Database Retrieval Technology

Traditional keyword retrieval has limitations such as insufficient synonym coverage, low accuracy of colloquial queries and difficulty in connecting cross-modal evidence. Semantic retrieval maps queries and knowledge into a unified semantic space through vector embedding, which can effectively alleviate the semantic gap.

$$\text{score}(q, d) = \cos[E(q), E(d)] \quad (6)$$

where score is the semantic relevance score; q is the query; d is the candidate knowledge document or snippet; $E(\cdot)$ is the embedding function; and $\cos(\cdot)$ denotes cosine similarity.

The core of multi-modal cross-database retrieval is to realize the association and connection of multi-source results [15,16]. The standard retrieval chain consists of query encoding, vector recall, global ID association, graph relationship expansion, and document evidence backfilling. By constructing a hierarchical index of converter station, voltage level, equipment type, fault type and knowledge type, the candidate set can be filtered step by step and latency can be reduced. For high-frequency query scenarios, topic caches and manually curated knowledge packages can be established to further improve response efficiency and result stability.

4.2.3. Cross-Regional Synchronization and Consistency Guarantee Strategy

In practical HVDC engineering projects, converter stations are geographically distributed across different provinces. Therefore, the hybrid knowledge storage architecture should support efficient cross-regional synchronization while ensuring data consistency and traceability.

Routine operational data are synchronized every 5–10 min using incremental replication, whereas critical fault events are transmitted immediately through message queue mechanisms such as Kafka to guarantee low-latency knowledge updates.

Strong consistency is maintained for protection settings, operation instructions and equipment ledgers through distributed transaction control, while eventual consistency is adopted for semantic knowledge objects, historical cases and document repositories to improve synchronization efficiency.

Every knowledge object is associated with a globally unique identifier, version number, timestamp, source station and evidence chain. Historical versions are retained to support rollback and auditing whenever conflicting updates occur.

When multiple regional stations upload inconsistent knowledge, the conflict is resolved according to source authority, update time, evidence completeness and expert verification. Unresolved conflicts are temporarily stored in a manual review queue before entering the global knowledge base.

4.3. Construction Methods of HVDC O&M Domain Corpus and Instruction Set

In this review, an HVDC knowledge package is defined as a scenario-oriented, structured knowledge unit designed for training, retrieval, and task execution in converter-station O&M. It packages a subgraph of the knowledge graph, standardized regulation fragments, C&P logic snippets, typical fault cases, and instruction templates under a unified theme. Knowledge packages can be partitioned by equipment type, fault pattern, voltage level, or business scenario, and should support version control, evidence tracing, and incremental updates. Corpus collections provide textual/multimodal raw material for packages; instruction sets provide task-formatted QA/operation pairs; knowledge graphs provide structured entity-relation backbones. This triad operationalizes the project requirement of knowledge-package-based corpus and instruction construction. The structure of an HVDC knowledge package and its relation to the corpus, instruction set, and knowledge graph is shown in Figure 7.

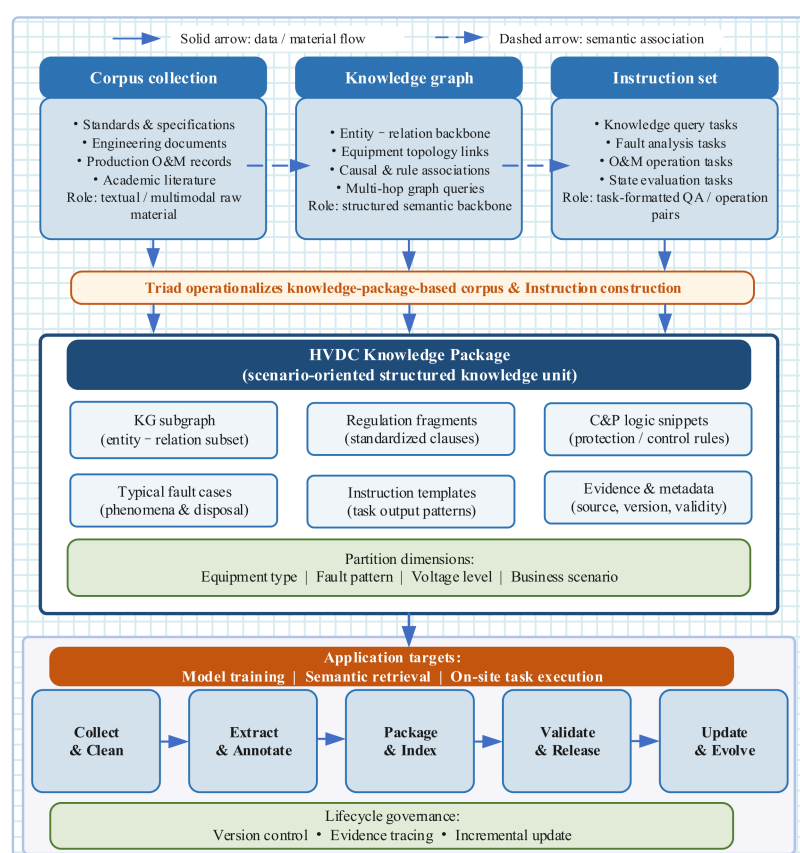


Figure 7. Structure of an HVDC knowledge package and its relation to the corpus, instruction set, and knowledge graph.

4.3.1. Construction of HVDC O&M Domain Corpus

The HVDC field has long faced the contradiction of a large stock of original data but few high-quality training corpora, mainly due to chaotic document formats, a high proportion of scanned copies, inconsistent terminology, long desensitization processes and numerous repeated alarms.

Corpus sources are divided into four categories: standards and specifications, engineering documents, production O&M and academic literature. Different categories adapt to differentiated cleaning strategies: standards focus on version management and clause number retention; production data focus on deduplication, desensitization and event chain reconstruction; engineering documents focus on layout analysis and chart extraction. Cor-

pus construction follows the process of collection, cleaning, standardization, annotation, quality inspection and release. It adopts a three-level quality inspection mechanism of machine initial annotation, manual fine annotation and expert review, and controls quality from three dimensions—professional accuracy, domain coverage and timeliness—to prevent invalid regulations from entering the training set [62].

4.3.2. Construction of HVDC O&M Instruction Set

The instruction set determines the task boundary and output style of domain large models. It must fit on-site demands, and the output should follow the specifications of step-by-step presentation, source attachment, and distinction between mandatory requirements and suggestions.

According to task types, instructions can be divided into four categories: knowledge query, fault analysis, O&M operation and state evaluation. Each category covers different difficulties and various question forms to prevent the model from only adapting to templated questions. There are three construction approaches: expert manual writing, template parameterized generation, and large model distillation amplification with expert screening. Instruction texts are close to on-site oral expressions and are linked with the knowledge package and knowledge graph: query instructions bind source nodes, analysis instructions require evidence chain output, and operation instructions clarify blocking constraints. At present, special instruction sets for HVDC control and protection and complex fault disposal are still scarce, which is the core direction of domain large model construction.

4.4. Multi-Modal Driven HVDC O&M Knowledge Graph Construction Technology

4.4.1. Ontology Design of HVDC O&M Knowledge Graph

As the schema layer of the graph, ontology defines the specifications and boundaries of entities, relationships and attributes. Core entities of the HVDC O&M graph cover primary/secondary equipment, faults and defects, rules and settings, O&M events, environment and personnel; core relationships include topology, causality, applicability, constraint, disposal and sequence.

Ontology design should avoid two extremes: being too narrow or too wide. A reliable scheme is to extend HVDC subclasses under the general framework of GB/T 42131 and retain bidirectional mapping interfaces with CIM/RDF and enterprise codes. For rule-based knowledge, attributes such as conditions, actions, versions and evidence are separately defined to support bidirectional connection between C&P logic and O&M regulations.

4.4.2. Multi-Modal Joint Knowledge Extraction Technology

Knowledge extraction is the process of identifying entities, relationships and attributes from multi-source data and forming knowledge structures. Entity-level alignment in joint extraction can reuse the multi-feature alignment framework in Section 3.1, while cross-modal evidence association can build upon the unified semantic space established in Section 2.1.3. Rule-related triples should be further linked to the C&P-O&M rule fusion mechanisms in Section 3.3, so that extracted knowledge remains consistent with both protection logic and operational procedures. Text extraction remains the main force, while images, waveforms and alarm sequences are supplementarily extracted through target detection, pattern recognition and sequence modeling respectively. The core value of multi-modal joint extraction lies in modal complementarity, which can make up for incomplete single-modal information. Technically, a multi-task learning framework is adopted, with multiple task heads set above the shared coding layer, and information complementarity is realized through cross-modal attention.

$$L_{\text{total}} = \lambda_1 L_{\text{NER}} + \lambda_2 L_{\text{RE}} + \lambda_3 L_{\text{modal}} \quad (7)$$

where L_{total} is the total loss; L_{NER} is the named entity recognition loss; L_{RE} is the relation extraction loss; L_{modal} is the cross-modal alignment loss; and λ_i are task weight coefficients.

This multi-task loss assumes independent gradient backpropagation among named entity recognition, relation extraction and cross-modal alignment subtasks, with hyperparameters λ_{1-3} balancing task weights [67]. Practically, it realizes joint multi-modal knowledge extraction from patrol images, fault waveforms and operation texts simultaneously. The main limitation is the fixed weight configuration, lacking dynamic adjustment for sparse fault text scenarios. The formula is justified for this review because it abstracts the universal multi-task training framework widely used in power knowledge graph construction.

The core constraint in HVDC scenarios is insufficient labeled samples, which can be alleviated through strategies such as rule-assisted annotation, distant supervision and active learning, with high-value historical cases as seed sets. All extraction results must retain evidence fields to ensure the auditability and error-correctability of the graph.

4.4.3. Multi-Source Knowledge Fusion and Completion

Multi-source knowledge inevitably has redundancy, conflicts and gaps. The fusion phase completes entity alignment and disambiguation, conflict resolution and knowledge completion in sequence.

Conflict resolution comprehensively determines triple credibility based on source authority, effective time and evidence completeness. Formal standards and effective regulations have higher weights than work orders and personal experience. Conflicts that cannot be automatically determined enter the manual arbitration queue.

$$\text{Conf}(h, r, t) = \frac{\sum_i w_i I_i(h, r, t)}{\sum_i w_i} \quad (8)$$

where Conf is the triple credibility score; h , r , and t denote the head entity, relation, and tail entity, respectively; I_i is the source-support indicator function; w_i is the source weight; and i is the source index.

The credibility calculation formula assumes that source weight w_i is assigned based on document authority. In HVDC knowledge fusion, it quantifies conflict resolution priority for contradictory triples from multi-source O&M documents. Its limitation is that static weight setting is unable to adapt to updated industry standards and new equipment specifications. As a core quantitative metric for knowledge quality evaluation, this formula is necessary for systematically comparing multi-source conflict elimination schemes in this review.

Knowledge completion adopts representation learning methods such as TransE and graph neural networks to mine implicit associations and fill missing edges. All completion results are marked as inferred and clearly distinguished from knowledge supported by original evidence.

$$h + r \approx t \quad (9)$$

where h , r , and t denote the vector representations of the head entity, relation, and tail entity, respectively; this is the translation assumption used for low-dimensional embedding learning and missing-relation completion.

4.4.4. O&M Knowledge Reasoning Technology

Reasoning capability determines the upgrading of the knowledge graph from queryable to usable. Current mainstream paths are divided into three categories: rule-based reasoning with strong interpretability and stable results, suitable for fixed regulations and known fault modes; representation learning reasoning that can discover implicit associations, suitable for relationship completion and similarity recommendation but with insuffi-

cient interpretability; and RAG + large model reasoning, adopting a retrieval-augmented generation architecture, balancing structured constraints and natural interaction, but whose effect is highly dependent on retrieval quality [64].

$$G_q = \text{TopK}[\text{sim}(q, G)], y = \text{LLM}(q, G_q) \quad (10)$$

where G is the knowledge collection; q is the query; G_q is the TopK retrieved knowledge subset; $\text{sim}(\cdot)$ is the relevance function; K is the number of recalled items; y is the model output; and $\text{LLM}(\cdot)$ is the large language model.

At present, on-site applications are still dominated by rule-based reasoning and keyword retrieval, with weak complex reasoning capability. The value release of the knowledge graph needs to be connected with storage, corpus, instruction set and the dynamic update mechanism in Section 5 to form a complete closed loop of construction, application, feedback and correction. Beyond corpus cleaning, the overall knowledge system requires systematic quality control. Core indicators include accuracy, coverage, consistency, interpretability, and usability. A hybrid evaluation combining automatic metrics, graph consistency checking, and expert review is recommended, especially for high-risk operation and fault-disposal knowledge. A comparison of O&M knowledge reasoning methods is summarized in Table 5.

Table 5. Comparison of O&M knowledge reasoning methods.

Reasoning Type	Representative Literature	Test Datasets	Core Model	Advantages	Limitations	Future Optimization Directions
Rule-based reasoning	[13,31]	Standard protection setting rule base	Logic production engine	Fully interpretable, stable output for known faults	Poor generalization for new atypical faults	Automatic rule update under equipment retrofit
Embedding-based reasoning	[54,68]	Multi-source HVDC equipment knowledge graph	TransE, GNN	Mine implicit fault causal relations	Black-box reasoning without audit traceability	Introduce physical constraint embedding for HVDC C&P logic
LLM-RAG reasoning	[64,69]	Fault case corpus + multi-modal embedding library	Domain fine-tuned LLM + vector retrieval	Support natural language O&M query	Diagnosis accuracy relies on corpus quality, prone to hallucination	Digital twin paired retrieval sample augmentation

Critical comparative analysis of three mainstream reasoning methods reveals clear trade-offs unaddressed by most HVDC intelligent O&M research. Rule-based reasoning delivers full interpretability and stable output for fixed fault modes, but its knowledge coverage is limited and cannot mine implicit causal associations in new atypical commutation failure events. Representation learning reasoning based on graph embedding can excavate hidden fault correlations, but the black-box vector operation process lacks traceable reasoning paths, failing to meet the audit and compliance requirements of safety-critical DC converter stations. RAG-LLM reasoning supports natural language interaction and colloquial fault queries, but its diagnostic accuracy heavily depends on the quality of multi-modal retrieval results. The existing domain corpus lacks high-quality fault waveform-text paired samples, leading to frequent model hallucinations in complex multi-source alarm

scenarios. At present, few studies construct hybrid reasoning frameworks that combine rule constraints, embedding associations and retrieval enhancement, which is a key bottleneck limiting the practical deployment of knowledge reasoning systems.

5. Evolution and Dynamic Updating Mechanism of the Knowledge System

5.1. Automatic Extraction and Ingestion of Incremental Knowledge

With the rapid expansion of HVDC systems, operational data streams from SCADA, protection devices, maintenance logs, and inspection sensors are continuously generated. Transforming these heterogeneous data streams into structured knowledge is the foundation of dynamic knowledge evolution [69–71]. The incremental knowledge acquisition and ingestion pipeline is shown in Figure 8.

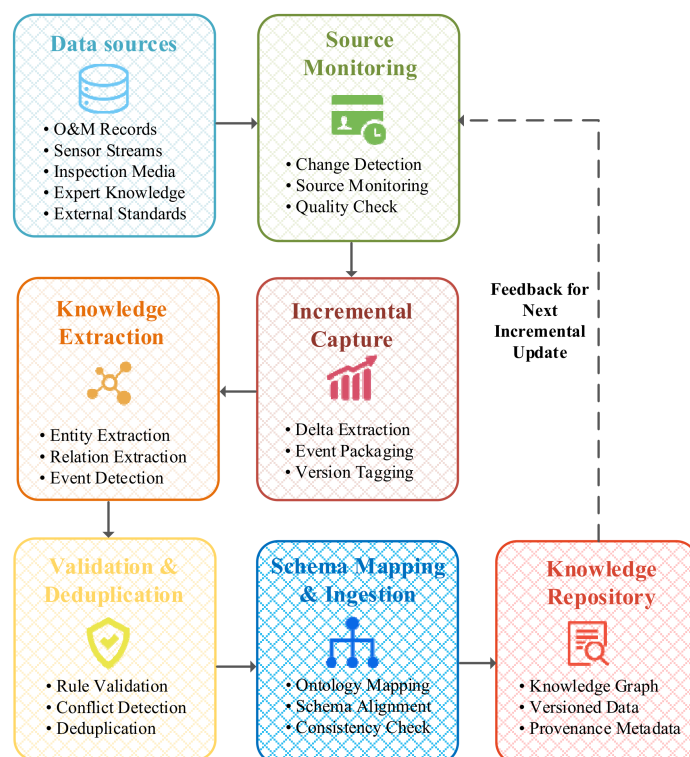


Figure 8. Incremental knowledge acquisition and ingestion pipeline.

5.1.1. Real-Time Knowledge Extraction from Streaming Data

Incremental knowledge extraction typically relies on streaming multi-modal processing pipelines. Structured telemetry data is processed through temporal anomaly detection and event segmentation, while unstructured data such as fault reports and inspection images require deep semantic encoding [72,73].

Recent studies have demonstrated that transformer-based temporal encoders and multimodal alignment networks significantly improve real-time event extraction performance in power systems. In HVDC scenarios, fault-related entities such as “converter valve overheating” or “DC line insulation degradation” can be dynamically extracted and linked to existing knowledge graphs [67].

5.1.2. Consistency Verification and Conflict Detection

Newly extracted knowledge often conflicts with existing rules due to sensor noise or incomplete labeling. Therefore, consistency verification is essential. Rule-based

reasoning combined with probabilistic graphical models is widely adopted to identify contradictions [74–77].

Graph neural networks (GNNs) have also been introduced to detect structural inconsistencies in knowledge graphs by measuring relational embedding deviations. These approaches ensure that newly added knowledge does not degrade system integrity [68,78].

5.2. Human-Machine Collaborative Knowledge Correction and Quality Control

Although automated pipelines provide scalability, human expertise remains indispensable in HVDC O&M due to the safety-critical nature of the system. Therefore, human-machine collaborative correction mechanisms are essential.

5.2.1. Multi-Dimensional Knowledge Quality Evaluation

Knowledge quality in HVDC systems is evaluated from multiple dimensions, including accuracy, completeness, timeliness, and consistency. A unified evaluation framework is necessary to assess the reliability of dynamically updated knowledge [79]. The key knowledge quality evaluation indicators are listed in Table 6.

Table 6. Knowledge quality evaluation indicators.

Dimension	Metric Description	Metric Description	Typical Range
Accuracy	Correctness of extracted entities	Expert validation/labeled benchmark	0–1
Completeness	Coverage of knowledge elements	Graph coverage ratio	0–100%
Consistency	Logical contradiction rate	Rule-based + embedding detection	0–1
Timeliness	Delay between event occurrence and update	Timestamp difference analysis	seconds–hours
Interpretability	Traceability of knowledge reasoning	Path-based explanation score	0–1

5.2.2. Human-in-the-Loop Correction Mechanism

Human experts play a corrective role by validating uncertain predictions and refining ambiguous relationships. Active learning strategies are commonly used to select high-uncertainty samples for expert annotation [80]. The human-machine collaborative knowledge correction framework is shown in Figure 9.

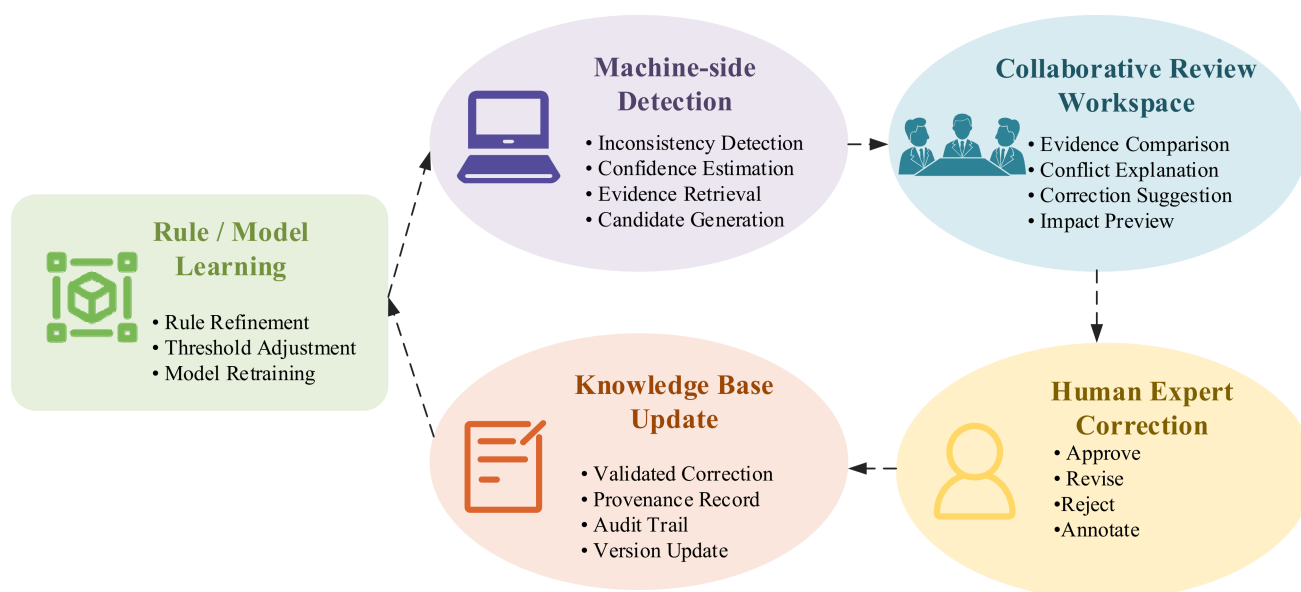


Figure 9. Human-machine collaborative knowledge correction framework.

A typical workflow includes:

- Model-driven knowledge extraction;
- Uncertainty estimation;
- Expert review interface;
- Feedback integration into model retraining.

This loop significantly improves long-term robustness, especially under low-sample fault scenarios.

5.3. Lifecycle Evolution of the Knowledge System

The knowledge system evolves throughout its lifecycle, transitioning from static rule representation to adaptive and self-evolving intelligence.

Operational feedback from maintenance outcomes, fault resolutions, and dispatch decisions is used to dynamically adjust knowledge confidence scores. Reinforcement learning-based weighting mechanisms have shown strong performance in similar industrial knowledge systems. Different operational scenarios (normal operation, fault state, recovery state) require different knowledge subsets. Context-aware retrieval mechanisms enable dynamic reorganization of knowledge subgraphs based on system states. Outdated knowledge rules, such as retired equipment operation constraints, must be systematically archived. Time-aware graph models and decay functions are used to gradually reduce the influence of obsolete knowledge [81]. A comparison of knowledge evolution strategies is summarized in Table 7.

Table 7. Comparison of knowledge evolution strategies.

Strategy Type	Mechanism	Advantages	Limitations
Rule-based update	Manual rule modification	High interpretability	Low scalability
Statistical update	Frequency-based adjustment	Simple implementation	Weak semantic understanding
Embedding evolution	Representation learning updates	Strong generalization	Requires large datasets
Reinforcement-based	Feedback-driven optimization	Adaptive and dynamic	Training instability risk

5.4. Discussion

Compared with traditional static knowledge bases, HVDC O&M knowledge systems require continuous adaptation due to rapid equipment evolution and increasing system complexity. Multi-modal data-driven dynamic knowledge construction enables:

- Real-time reflection of system state;
- Continuous improvement of diagnostic accuracy;
- Enhanced decision support under uncertainty.

However, key challenges remain, including semantic drift in long-term evolution, annotation bottlenecks, and balancing automation with expert control [82].

6. Comparative Analysis of Recent Related Review Articles

Three dominant categories of recent HVDC intelligent O&M surveys have been published in the past five years: fault diagnosis algorithm reviews [15], static power knowledge graph summaries [17], and general multimodal power perception overviews [14]. Their core coverage, omitted technical chains and research limitations are systematically compared in Table 8 to highlight the exclusive novelty of this work.

Table 8. Comparative overview of recent HVDC intelligent O&M review papers.

Dimension	Fault Diagnosis Review [15]	Power KG Review [17]	General Multimodal Power Survey [14]	This Work
Full-chain data-to-knowledge closed loop	✗ Only offline model comparison	✗ Static KG construction only	✗ General grid perception, no HVDC C&P rules	✓ Complete multimodal governance-fusion-knowledge-evolution chain
C&P logic + O&M rule bidirectional fusion	✗ Ignored control constraints	✗ No hard/soft rule semantic mapping	✗ Not oriented to DC converter stations	✓ Exclusive bidirectional semantic association & consistency verification
Industrial deployment metrics	✗ Only offline accuracy	✗ No engineering cost analysis	✗ Generic scene discussion	✓ Dedicated industrial-oriented comparative analysis for three fusion paradigms
Seven core open challenges	✗ Partial fault data discussion only	✗ Only KG reasoning gaps	✗ Partial AI algorithm limits	✓ Dedicated independent full coverage of all seven open research bottlenecks
Dynamic knowledge lifecycle evolution	✗ Static sample evaluation	✗ Static graph construction	✗ No incremental update mechanism	✓ Complete human-machine collaborative iteration & knowledge archiving framework

Existing surveys exhibit three universal defects: (1) They isolate multi-modal fusion and knowledge engineering as independent research lines, without constructing an end-to-end closed-loop pipeline from raw heterogeneous data to dynamically updatable knowledge; (2) They ignore the bidirectional semantic coupling between HVDC hard control-protection logic and soft on-site O&M specifications, a unique domain constraint exclusive to converter stations; (3) They lack systematic discussion of industrial metrics (computational complexity, cross-station scalability) and seven core open challenges (benchmark datasets, XAI, digital twin coupling, LLM adaptation, cybersecurity, interoperability, data quality) oriented toward practical deployment.

Distinct from prior descriptive summaries, this review innovatively integrates multi-modal fusion, hierarchical DIKW knowledge modeling, hybrid multi-database storage and full-lifecycle knowledge evolution into a unified framework, with targeted industrial feasibility analysis and complete sorting of unresolved research gaps.

7. Technical Challenges and Future Research Directions

7.1. Core Technical Challenges

7.1.1. Data-Level Challenges: Noise, Sparsity, and Heterogeneity

Existing multi-modal data preprocessing studies mostly target single-modal noise reduction or simple time alignment, without critical analysis of the coupling interference of data heterogeneity, sparse fault samples and asynchronous sampling frequency under renewable-access HVDC operating conditions. Most denoising algorithms are designed for single-type waveforms or images and cannot jointly suppress cross-modal composite noise

from SCADA telemetry, infrared patrol images and fault recording signals. Few research works construct multi-dimensional data quality evaluation systems covering completeness, synchronization and signal credibility, resulting in low robustness of subsequent fusion models under extreme fault working conditions.

HVDC systems operate under extreme environmental and operational conditions, leading to severe data incompleteness caused by sensor failures or communication delays, strong noise interference in waveforms and fault recordings, and highly heterogeneous modalities, including SCADA signals, protection logs, infrared images, and textual reports. These issues significantly reduce the robustness of multi-modal fusion models, especially under fault-critical conditions where data quality is most unstable.

Correlation coefficients can also be used to check these defects before fusion. Pearson/Spearman correlation (or cross-correlation for waveforms) helps identify noise-dominated channels, unstable associations under sparse fault samples, and weak or time-shifted links among heterogeneous modalities (e.g., SCADA vs. PMU). We, therefore, include correlation-based screening as part of the multi-modal data-quality assessment discussed in this review.

In addition, the sparsity of fault samples further aggravates the learning difficulty of data-driven models. Since HVDC fault events are relatively rare but highly diverse, most datasets exhibit strong class imbalance, which limits the generalization ability of deep learning models. This makes it difficult to construct stable feature distributions across different operating conditions [83].

Furthermore, differences in sampling frequency and system synchronization also introduce structural inconsistency across data sources. Without unified temporal alignment and standardized preprocessing, cross-modal fusion may suffer from feature misalignment, ultimately reducing the reliability of downstream knowledge construction.

7.1.2. Knowledge Construction Challenges: Semantic Gap and Conflict Resolution

Although knowledge graphs and rule-based systems have been widely adopted, key limitations remain, including the semantic gap between modalities (e.g., waveform vs. text fault reports), difficulty in encoding complex protection logic and control sequences, and a weak ability to automatically resolve conflicting knowledge from multiple sources. In particular, inconsistent maintenance records and real-time fault data often generate contradictory relationships in knowledge graphs, requiring advanced reasoning mechanisms such as probabilistic logic and graph neural consistency models [84].

Beyond these issues, HVDC systems introduce additional challenges due to the tight coupling between C&P logic and operational rules. The difference in expression form between “hard constraints” embedded in protection systems and “soft knowledge” recorded in operation manuals makes semantic unification highly difficult. This structural mismatch leads to incomplete or inconsistent knowledge representations in graph construction.

Moreover, existing conflict resolution methods are often rule-dependent and lack scalability when applied to large-scale multi-source environments. As a result, ensuring consistency while preserving heterogeneous knowledge diversity remains a key research challenge in HVDC knowledge engineering.

7.1.3. Engineering Deployment Challenges: System Integration and Real-Time Constraints

In practical HVDC operation environments, existing O&M systems such as EMS, SCADA, and dispatch platforms impose strict compatibility constraints. Knowledge systems must operate under real-time or near-real-time requirements while maintaining reasoning accuracy and traceability. Integration costs with legacy infrastructure are often extremely high.

At the same time, HVDC systems require strict latency control for fault diagnosis and decision support. However, most knowledge reasoning or graph-based inference models are computationally intensive, making it difficult to satisfy real-time deployment requirements in engineering scenarios.

Furthermore, heterogeneous system interfaces and non-unified communication protocols increase the difficulty of system integration. The coexistence of multi-vendor devices and multi-generation systems leads to fragmented architecture, which further complicates knowledge system deployment and cross-platform interoperability [83].

7.1.4. Safety and Interpretability Challenges

Most deep learning-based multi-modal fusion models proposed in existing literature only pursue offline fault diagnosis accuracy, while ignoring the interpretability requirements of power safety production. End-to-end black-box models cannot output explicit evidence chains composed of SCADA features, waveform segments and patrol image hotspots, which makes it impossible for operators to verify diagnostic results against protection fixed-value logic. Current explainable AI research for power systems stays at shallow feature visualization, lacking standardized interpretability evaluation indicators tailored to HVDC control-protection constraint scenarios, and the cybersecurity risks of distributed incremental knowledge updating pipelines have not been systematically quantified in prior surveys.

For safety-critical HVDC systems, additional concerns arise, including a lack of interpretability in deep multi-modal fusion models, difficulty in explaining knowledge-driven decisions to operators, and potential cybersecurity vulnerabilities in distributed knowledge updating pipelines. These issues limit the adoption of end-to-end AI-driven decision systems in real grid environments.

In particular, the black-box characteristics of deep learning models make it difficult for operators to trust diagnostic outputs, especially in high-risk fault scenarios. Without transparent reasoning paths, it is hard to verify whether the decision process aligns with actual protection logic.

The black-box nature of deep learning further reduces practicality in HVDC O&M because converter-station decisions are safety-critical, tightly constrained by control and protection logic, and subject to audit by dispatch and maintenance teams. End-to-end multi-modal models may output accurate fault labels yet cannot show which SCADA channels, waveform segments or inspection cues dominated the judgment, so operators cannot cross-check the result against protection setting sheets and interlocking rules. Under cascading alarms or renewable-induced operating-point changes, an opaque score is difficult to accept as an executable action, because a wrong trip recommendation or missed commutation-failure precursor can escalate into bipolar blocking and wide-area disturbance. Regulatory and enterprise compliance also require traceable evidence chains, whereas pure deep models store knowledge mainly in non-symbolic parameters that are hard to version, certify and transfer across stations. Therefore, deep fusion in HVDC should be paired with explainable interfaces, rule consistency checking and knowledge-graph evidence backfilling; otherwise, high offline accuracy still cannot translate into deployable on-site decision support.

Meanwhile, distributed knowledge updating mechanisms may introduce security risks such as data tampering, unauthorized access, or inconsistent version synchronization. These safety concerns are particularly critical in HVDC systems, where incorrect decisions may lead to large-scale power outages. The key technical bottlenecks and system-level constraints in HVDC knowledge systems are shown in Figure 10.

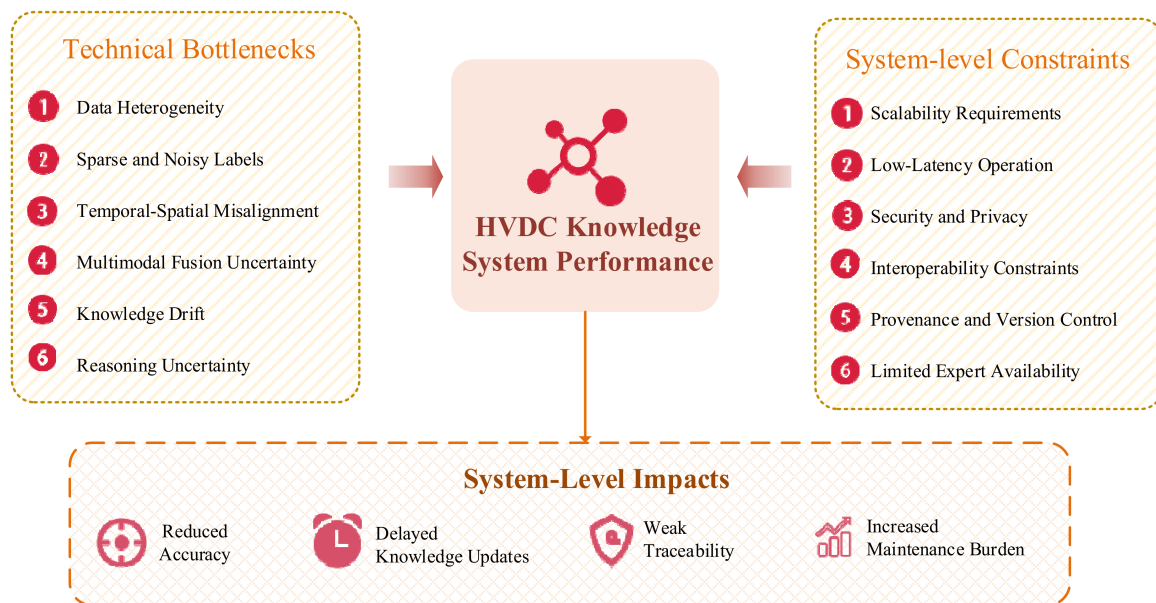


Figure 10. Key technical bottlenecks and system-level constraints in HVDC knowledge systems.

7.1.5. Dedicated Discussion of Core Open Challenges for Multi-Modal HVDC O&M

Seven interlocked open challenges restrict the large-scale industrialization of multi-modal knowledge systems, including data quality, unified benchmark datasets, cross-system interoperability, cybersecurity risks, explainable artificial intelligence (XAI), digital twin coupling and LLM domain adaptation, which are systematically discussed below with existing research limitations summarized [30,64,83]:

1. Data quality defects: Converter station data suffers from asynchronous sampling, electromagnetic noise and severe fault sample imbalance. Current single-modal cleaning algorithms fail cross-modal joint quality evaluation, lacking unified credibility quantification standards [83].
2. Lack of public benchmark datasets: Most existing experiments rely on private station offline data without standardized open multi-modal libraries integrating waveforms, infrared images and fault texts, leading to inconsistent horizontal comparisons of model performance [15].
3. Cross-platform interoperability barriers: Multi-vendor C&P devices adopt non-unified configuration formats and private communication protocols, and extended CIM ontology for HVDC equipment has not formed industry-wide unified specifications [45].
4. Distributed cybersecurity risks: Incremental knowledge synchronization, edge multi-modal data transmission and cross-station data sharing face threats such as tampering, unauthorized access and false data injection. Privacy-preserving fusion schemes remain immature [33,65].
5. Explainable AI bottlenecks: End-to-end multi-modal deep models act as black boxes without traceable fault evidence chains, failing to meet audit and safety verification requirements of high-voltage DC power grids [9].
6. Digital twin-knowledge graph decoupling: Current digital twin simulation platforms cannot realize closed-loop feedback iteration with multi-modal knowledge bases, lacking real-time mapping between the physical equipment state and domain reasoning rules [84].
7. HVDC-oriented LLM limitations: General large models produce professional hallucinations regarding control-protection logic. Dedicated instruction sets and fault paired corpora for converter stations are scarce, restricting reliable retrieval-augmented decision support [62,69].

7.2. Future Research Directions

Future research on HVDC O&M knowledge systems should primarily address the limitations of data scarcity, cross-modal misalignment, and insufficient reasoning robustness under real-world operational constraints. In particular, improving model generalization under limited fault samples remains a fundamental challenge. Although meta-learning and few-shot learning techniques have demonstrated promising results in related domains, their effectiveness in HVDC fault scenarios is still constrained by strong class imbalance and significant operating condition variability. To mitigate this issue, cross-modal contrastive learning that jointly exploits waveform, image, text, and SCADA data has emerged as a viable direction for enhancing shared semantic representation. Furthermore, transfer learning from simulation platforms or digital twin environments to real HVDC systems provides a practical pathway to reduce reliance on labeled fault data while improving model adaptability.

Recent advances in large language models (LLMs) have also introduced new opportunities for end-to-end knowledge construction in industrial domains. LLM-based frameworks enable unified processing of multiple subtasks, including entity extraction, relation identification, semantic normalization, and rule generation, thereby significantly improving the automation level of knowledge graph construction. However, despite these advantages, several critical challenges remain unresolved, including hallucination suppression, domain adaptation under strict operational constraints, and reliability assurance in safety-critical environments. In HVDC applications, these limitations are particularly significant due to the high requirement for correctness, traceability, and interpretability in operational decision-making.

From a system-level perspective, future research should further explore the deep integration of digital twin technology with knowledge-driven O&M frameworks [84]. Digital twins provide a physically grounded simulation environment that enables scenario reproduction, fault propagation analysis, and maintenance strategy evaluation. By coupling digital twin models with knowledge graphs and multi-modal learning systems, and by incorporating AI-enabled multi-agent decision-making for renewable-integrated smart-grid operation, it becomes possible to establish closed-loop mechanisms for knowledge validation and continuous refinement [85,86]. This integration not only enhances model robustness but also supports iterative improvement of knowledge quality through real-time feedback from operational data [87–89].

In addition, the standardization of HVDC knowledge representation remains a critical prerequisite for large-scale deployment. Current systems are still fragmented in ontology design, data interfaces, and rule representations across different vendors and platforms. Therefore, establishing unified semantic frameworks that cover equipment modeling, fault taxonomy, protection logic, and operational rules is essential for ensuring interoperability and long-term maintainability. In particular, cross-vendor knowledge alignment and consistent semantic interfaces will play a decisive role in enabling scalable and engineering-ready HVDC intelligent O&M systems.

7.3. Engineering Application Prospects

In practical scenarios, the proposed knowledge system can be applied to:

- Intelligent fault diagnosis and root cause analysis;
- Predictive maintenance and life-cycle assessment;
- Operator training and decision support systems;
- Real-time dispatch optimization in HVDC grids.

Beyond listing potential uses, the engineering deployment of multi-modal knowledge systems in HVDC O&M should be examined along the full closed loop from data intake to

operator action. In fault diagnosis, fused SCADA, fault recordings and inspection evidence can be mapped to graph entities and similar historical cases to support root-cause tracing under time pressure. In predictive maintenance, trend features from cooling, valve and filter-related measurements can be linked with work-order text to prioritize inspection and spare-part planning. In operator training and decision support, retrieved rules and past disposal paths can provide explainable recommendations that remain consistent with control and protection constraints. In dispatch-oriented assistance, near-real-time multi-modal cues can help operators interpret alarm floods during rapid operating-point changes and reduce purely experience-based responses.

A representative real-time example is a wind-integrated UHVDC sending-end event during a steep wind drop. Active- and reactive-power set points change within minutes, AC-side voltage dips trigger cascaded alarms, and subsequent infrared inspection may confirm thermal stress on cooling or filter equipment. A practical knowledge service should align the power-ramp window with SCADA/PMU segments and fault recordings, retrieve similar historical disposal knowledge, present ranked recommendations to operators, and write confirmed outcomes back into the knowledge graph. This example shows how the reviewed fusion and knowledge-construction chain can move from offline analysis to near-real-time O&M support.

With continued development, these systems will significantly enhance grid reliability and reduce operational costs.

8. Conclusions

Distinct from descriptive technical summaries and fragmented single-task HVDC surveys, this paper delivers a systematic critical evaluation of multi-modal governance, fusion paradigms and lifecycle knowledge evolution. By benchmarking the strengths and inherent limitations of mainstream technologies, this review explicitly sorts multi-layer unresolved research gaps from data processing to engineering deployment, providing condensed theoretical references for LLM and digital twin integrated intelligent O&M platforms. Critical challenges and future research directions are identified, with particular emphasis on the integration of large models, digital twins, and standardized knowledge frameworks as pivotal enablers of fully intelligent HVDC O&M systems. Overall, multi-modal data fusion constitutes the fundamental driver of knowledge systematization in HVDC environments, and this research field is expected to play a crucial role in the digital transformation of future power systems.

Unlike previous descriptive reviews that separately summarize fault diagnosis algorithms or static knowledge graph construction, this paper conducts a systematic critical comparison of mainstream multi-modal fusion, knowledge modeling and dynamic evolution technologies. It quantitatively analyzes the advantages, inherent defects and engineering adaptability of each technical route and clearly sorts out multi-layered research gaps from data, fusion, knowledge construction and system deployment dimensions. The critical evaluation of existing literature and targeted prospects for future research directions can provide differentiated technical references for follow-up few-shot cross-modal learning, LLM-knowledge graph coupling and digital twin collaborative O&M research in the HVDC field.

This paper's dedicated sorting of seven core open challenges also provides a standardized classification framework for follow-up research on HVDC multi-modal intelligent O&M [83].

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Z.G., investigation; X.Z., visualization; Y.H., validation; B.Y., writing. All authors have read and agreed to the published version of the manuscript.

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Nomenclature

1D-CNN	One-Dimensional Convolutional Neural Network
AI	Artificial Intelligence
BiLSTM-CRF	Bidirectional Long Short-Term Memory–Conditional Random Field
C&P	Control and Protection
CIM	Common Information Model
CNN	Convolutional Neural Network
CRF	Conditional Random Field
D-S	Dempster–Shafer Evidence Theory
DIKW	Data–Information–Knowledge–Wisdom
DTW	Dynamic Time Warping
EMS	Energy Management System
GNN	Graph Neural Network
GPS	Global Positioning System
HVDC	High-Voltage Direct Current
IEC	International Electrotechnical Commission
JSON	JavaScript Object Notation
KG	Knowledge Graph
LLM	Large Language Model
LSTM	Long Short-Term Memory
NER	Named Entity Recognition
O&M	Operation and Maintenance
OCR	Optical Character Recognition
PMU	Phasor Measurement Unit
PTP	Precision Time Protocol
QA	Question Answering
RAG	Retrieval-Augmented Generation
RDF	Resource Description Framework
ROI	Region of Interest
SCADA	Supervisory Control and Data Acquisition
TCN	Temporal Convolutional Network
TransE	Translating Embeddings
UHVDC	Ultra-High Voltage Direct Current

ViT	Vision Transformer
VSC-HVDC	Voltage Source Converter–Based High-Voltage Direct Current
XML	Extensible Markup Language

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