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Knowledge Graph Construction, Management, and Application in Wireless Networks

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Abstract: Wireless networks generate large volumes of heterogeneous data from network elements, user equipment, and management systems, posing significant challenges for effective network monitoring, fault management, and resource optimization. Traditional rule-based or data-driven approaches often lack unified knowledge representation and reasoning capability, limiting their scalability and interpretability. To address these challenges, this paper proposes a knowledge-graph-based framework for wireless network knowledge construction, management, and application. The proposed framework integrates multi-source network data through ontology-driven modeling and rule-based semantic mapping, enabling structured representation of network entities, events, and their relationships. An event-driven incremental update mechanism is introduced to efficiently maintain the knowledge graph in dynamic network environments without full reconstruction. Furthermore, a lightweight reasoning mechanism is employed to infer implicit network states and support intelligent network management decisions. The framework is designed to balance expressiveness and computational efficiency, making it suitable for large-scale wireless networks. To quantitatively evaluate the effectiveness of the proposed approach, extensive experiments are conducted under different network scales. The experimental results demonstrate that the proposed framework consistently outperforms traditional rule-based methods in terms of fault localization accuracy and resource utilization efficiency, while exhibiting lower query latency and better scalability as the network size increases. The results indicate that the proposed knowledge-graph-based framework provides an effective and scalable solution for intelligent wireless network management, with potential applicability to fault detection, resource optimization, and network security analysis.

Keywords: Knowledge Graph; Wireless Networks; Construction; Management; Application

1. Introduction

With the wide deployment of 5G technology, the rapid progress toward 6G [1], and the increasing scale of Internet-of-Things applications, wireless networks are evolving toward higher data rates, larger connectivity, and lower latency. However, this rapid development also brings several critical challenges that hinder efficient network operation and maintenance. In particular, wireless networks are becoming more difficult to monitor, optimize, and secure due to growing data diversity, complex device interactions, and highly dynamic network environments. The introduction of knowledge graph techniques offers new perspectives for addressing these issues.

The low efficiency of troubleshooting in wireless networks has become a prominent challenge. Wireless infrastructures include a wide range of devices such as base stations, routers, switches, and optical links, all of which continuously generate alarm logs, performance records, and configuration data. Because these data are heteroge-

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neous, fragmented, and distributed across multiple subsystems, traditional manual troubleshooting methods are often slow, labor-intensive, and prone to oversight. For example, in a 5G deployment in one city, users reported sudden signal degradation in several areas. Manual inspection revealed a damaged optical cable caused by nearby construction, an issue that could have been identified earlier if the semantic associations among base stations, optical links, and historical fault records had been automatically analyzed [2]. By integrating entities such as devices, transmission media, and fault events as well as their relationships, knowledge graphs can rapidly correlate related components and support fast root-cause localization.

Resource optimization in wireless networks is another major challenge. Due to diverse user behaviors, complex topologies, and highly dynamic traffic patterns—especially in scenarios such as vehicular networks—traditional resource allocation strategies struggle to deliver real-time and fine-grained optimization. For instance, in the Internet of Vehicles, the fast movement of vehicles causes frequent handovers, and different services require varying levels of bandwidth and latency. Static allocation strategies often result in overloaded resources in certain areas and underutilized resources elsewhere [3]. This is similar to the scenarios in the transportation field where traffic flow changes need to be dynamically predicted. The TreeCN [4] model processes traffic time series data through a tree convolutional network, effectively capturing the patterns in dynamic changes. Meanwhile, other advanced traffic prediction models [5] also provide valuable references for the logic of resource optimization. For instance, in research focused on mining trajectory features, the accuracy of travel time prediction has been enhanced, which can inspire the integration of user motion trajectory data in wireless networks for more precise resource pre-allocation. Inspired by approaches in transportation flow prediction, where models such as tree-structured convolutional networks effectively capture dynamic patterns, knowledge graphs can integrate information such as user mobility, service requirements, and radio conditions to support more intelligent resource scheduling.

Security protection is also facing increasing pressure. As attack methods evolve, traditional rule-based detection systems have difficulty identifying new or concealed threats such as identity forgery and abnormal signaling patterns. Attack behaviors are often subtle and distributed, requiring multi-dimensional, cross-domain contextual analysis that conventional systems are unable to provide. Insights from other domains—such as multi-source fusion used in predicting urban health risks—demonstrate the value of integrating heterogeneous data for risk assessment. By incorporating user behavior, device logs, known vulnerabilities, and external threat intelligence into a unified semantic network, knowledge graphs can infer potential attack paths and provide earlier and more accurate security warnings.

Security protection is also facing increasing pressure. As attack methods evolve, traditional rule-based detection systems have difficulty identifying new or concealed threats such as identity forgery and abnormal signaling patterns. Attack behaviors are often subtle and distributed, requiring multi-dimensional, cross-domain contextual analysis that conventional systems are unable to provide [6]. Insights from other domains—such as multi-source fusion used in predicting urban health risks [7]—demonstrate the value of integrating heterogeneous data for risk assessment. By integrating internal network data such as user behavior, device logs, and attack characteristics, as well as external related data such as regional network attack trends, device vulnerability databases, and network threat intelligence, knowledge graphs can form a more comprehensive security correlation network, enabling early detection of potential cross-regional and cross-type attack risks and further enhancing the proactive defense capabilities of wireless networks. By incorporating user behavior, device logs, known vulnerabilities, and external threat intelligence into a unified semantic network, knowledge graphs can infer potential attack paths and provide earlier and more accurate security warnings.

Overall, the convergence between knowledge graph technologies and wireless network needs is driven by three key factors: (1) the ability to model complex, multi-level entities and relationships; (2) the suitability of knowledge graphs for dynamic, incremental reasoning; and (3) their effectiveness in integrating heterogeneous, cross-domain information. These capabilities make knowledge graphs particularly valuable for enhancing wireless network operation and maintenance, supporting tasks such as fault analysis, resource optimization, and security threat detection.

To provide an intuitive visual synopsis of the limitations inherent to the aforementioned existing approaches, **Figure 1** delineates the core deficiencies of conventional wireless network operation and maintenance paradigms alongside the targeted solutions proposed in this study. Traditional operation and maintenance schemes predominantly rely on manual expertise or static pre-defined rules, which inherently fail to accommodate the dynamic topology and intricate operational characteristics of modern wireless networks. Accordingly, there exists an urgent imperative to develop a knowledge-driven intelligent operation and maintenance framework, where the construction and practical deployment of domain-specific wireless network knowledge graphs serve as the pivotal enabler for addressing the aforementioned challenges. Extensive experiments are conducted to quantitatively evaluate the proposed framework in terms of fault localization accuracy, resource utilization efficiency, and scalability under different network scales.

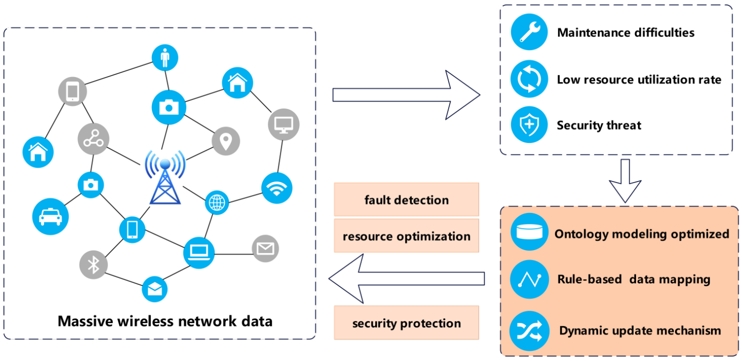

Figure 1. Core Deficiencies and Corresponding Solutions.

2. Related Work

The concept of the knowledge graph was first formally introduced by Google in 2012 with the goal of enhancing search engine performance by structuring scattered online information into entity–relation networks [8]. Since then, knowledge graph technologies have significantly advanced, driven largely by progress in natural language processing, deep learning, and large-scale data management [9]. The optimization strategies explored in cross-domain spatiotemporal graph modeling—such as tree-structured spatial–temporal models for traffic prediction [10]—further demonstrate the effectiveness of organizing fragmented information through structured graph representations, which is consistent with the fundamental objective of knowledge graphs.

Research on domain-specific knowledge graphs has also expanded steadily, supported by general-purpose projects such as Freebase and Wikidata, which provide foundational resources for vertical applications [11,12]. In fields such as healthcare, knowledge graphs constructed from medical literature, electronic records, and drug databases support disease diagnosis and treatment recommendation; SNOMED CT, developed by Stanford University, is one of the most influential ontology systems in clinical decision support [13]. In finance, knowledge graphs help model corporate ownership structures and transaction behaviors to enable risk warning and fraud detection [14]. In intelligent manufacturing, knowledge graphs integrating equipment parameters and fault records support predictive maintenance and production optimization [15].

In the transportation domain, spatiotemporal data fusion and graph-based modeling have demonstrated strong potential. For example, the ST-TDCN model improves traffic velocity prediction by optimizing tree-structured spatiotemporal features [16]. Other studies—such as the classification of urban functional regions using empty-vehicle transmission data [17] and trajectory-based pedestrian movement prediction in complex intersections [18]—illustrate how multi-source data fusion and interactive entity modeling can enhance intelligent decision-making. These methods offer insights that can be extended to wireless network scenarios, such as classifying coverage areas or modeling user mobility for resource optimization. Recent works including spatiotemporal tensor autoregression for shared mobility demand prediction [19], second-order continuous GNN-based traffic flow forecasting [20], and meta-analysis for traffic safety prediction [21] further highlight the value of advanced spatiotemporal modeling in dynamic environment analysis, which can inspire wireless network optimization strategies.

Knowledge graph techniques have also been explored in emerging communication domains. For instance, in low Earth orbit (LEO) satellite communication, researchers have applied knowledge graphs to spectrum-sensing data to improve semantic integration and representation [22]. These studies collectively demonstrate the increasing relevance of knowledge graphs in next-generation communication systems, where large-scale heterogeneous data must be fused to support intelligent network management.

Overall, the compatibility between knowledge graphs and wireless networks is reflected in three aspects. First, wireless networks involve numerous entities such as base stations, user terminals, and core network devices with hierarchical, causal, and interactive relationships that naturally align with the triplet representation of knowledge graphs. Second, the dynamic characteristics of wireless networks—including changes in topology, user behavior, and service demand—require models capable of incremental updates and real-time reasoning, both of which are strengths of knowledge graphs. Third, the need for cross-domain knowledge integration in wireless networks, involving protocols, parameters, and user behaviors, matches the semantic unification capabilities of knowledge graphs, which help break data silos and enhance intelligent decision-making.

3. Construction of Wireless Network Knowledge Graph

As a large-scale system composed of diverse entities, complex relationships, and continuously evolving data, wireless networks generate extensive information during operation, including device parameters, alarm logs, user behaviors, and security events. These data often exhibit fragmentation and multi-source heterogeneity [23]. Traditional data management approaches struggle to capture the deep semantic associations among such heterogeneous information, leading to delayed fault detection, inefficient resource utilization, and difficulty in identifying security threats in a timely manner. Knowledge graphs, as structured knowledge representations capable of modeling multi-level relationships between entities, are well suited to address these challenges.

On the one hand, knowledge graphs can systematically integrate key associations in wireless networks through the triplet structure of "entity–relationship–entity," such as the communication links between base stations and users, or the causal dependencies between faults and equipment. This structured representation enables the transformation of massive raw network data into machine-interpretable semantic knowledge. On the other hand, knowledge graphs support incremental updates and logical reasoning, allowing them to capture dynamic network information—such as topology variations, user mobility, and changing service demands—in real time. These capabilities make them particularly valuable for intelligent network operation and maintenance, enabling faster diagnosis, optimized resource scheduling, and proactive security protection.

The construction of a knowledge graph for wireless networks represents a systematic transformation process from raw data to structured knowledge. This process includes three main stages: ontology modeling, data mapping, and knowledge graph management and application. First, ontology modeling serves as the "structural blueprint" of the knowledge graph. During this stage, core entities, attributes, and relationships of the wireless networking domain are defined to establish a unified semantic framework. This ensures that subsequent data transformation follows consistent and domain-specific semantic standards.

Next, data mapping is conducted. For the multi-source heterogeneous data present in wireless networks, technologies such as entity recognition and relation extraction are used to convert raw information into triples that conform to the predefined ontology. Entity recognition and relation extraction are implemented using a lightweight rule- and template-based approach tailored to structured network logs and configuration data. This design choice avoids the overhead of large-scale model training while ensuring robustness and interpretability in network management scenarios. Entity alignment and relation disambiguation are then applied to ensure semantic accuracy and avoid redundant or conflicting representations. Finally, the resulting knowledge is stored in a graph database, and dynamic update mechanisms ensure that new network events and state changes are continuously incorporated. An overview of the overall construction framework is illustrated in **Figure 2**.

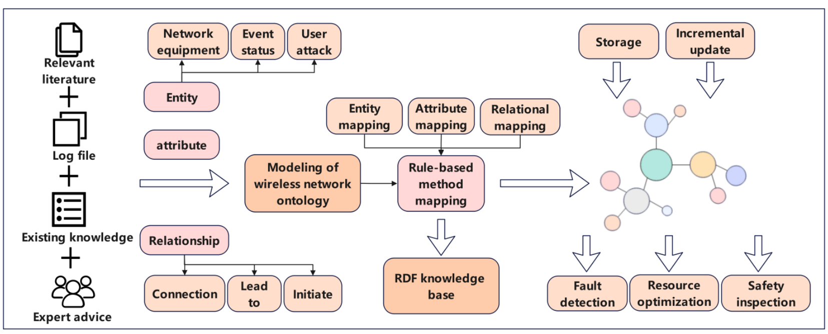

Figure 2. Structure diagram of the knowledge graph construction.

To clearly illustrate the core processing logic of the proposed framework, **Algorithm 1** summarizes the main steps involved in knowledge graph construction and incremental update:

Algorithm 1. Knowledge Graph Construction and Incremental Update.

- Input: Network logs, configuration data
- Output: Updated knowledge graph
- Step 1: Extract entities using predefined templates
- Step 2: Map entities to ontology using rules
- Step 3: Resolve conflicts based on rule priority
- Step 4: Insert or update affected nodes and edges

As shown in **Algorithm 1**, the framework starts by extracting structured entities from network logs and configuration data using predefined templates. These entities are then mapped to the ontology through rule-based mapping, where potential conflicts are resolved based on rule priority and semantic specificity. The knowledge graph is constructed or updated incrementally in response to network events, such as faults or topology changes, by modifying only the affected nodes and relations. This event-driven and fine-grained update mechanism enables efficient knowledge maintenance and supports near real-time network management.

To clearly explain the above construction process, this chapter is divided into three subsections: knowledge representation, data mapping, and the management and application of the knowledge graph. By presenting these components step by step, this chapter provides a comprehensive view of how the wireless network knowledge graph is designed, constructed, and utilized.

3.1. Data Sources and Types

The construction of a wireless network knowledge graph relies on multi-source heterogeneous data that jointly describe the structure, operation, and management logic of the network. According to the characteristics of data origin and semantic granularity, the sources used in this study can be categorized into four major types: relevant literature, log files, existing knowledge, and expert advice, as illustrated on the left side of **Figure 2**. Each type of data provides complementary information for entity extraction, relationship construction, and rule definition, enabling a comprehensive representation of wireless network knowledge.

- Relevant Literature: Academic publications, technical reports, and standard specifications in wireless communication, network management, and artificial intelligence provide rich textual resources. These documents contain conceptual definitions, hierarchical structures, and technical relationships that can be transformed into the ontological framework of the knowledge graph. Using natural language processing techniques such as named entity recognition and relation extraction, this theoretical and standardized knowledge can be formalized into semantic triples that enrich the conceptual layer of the graph.
- Log Files: Operational logs generated by base stations, routers, user terminals, and monitoring platforms provide real-time records of alarms, fault events, throughput indicators, and signaling interactions. These logs reflect the dynamic operational state of the wireless network and serve as an essential basis for identifying causal relationships and event patterns. Through structured parsing and pattern recognition, entities and relationships can be extracted to construct an event-oriented semantic chain that supports fault diagnosis and performance analysis.
- Existing Knowledge: This category includes previously organized structured or semi-structured information such as equipment configuration databases, network topology records, and public domain ontologies. These resources offer prior knowledge and relational templates that help maintain semantic consistency during knowledge integration. By aligning the wireless network ontology with existing knowledge bases, redundant representations and semantic conflicts can be minimized, ultimately enhancing interoperability.
- Expert Advice: Domain experts contribute experiential and heuristic knowledge that is often absent from raw data. Through expert annotation, rule definition, and ontology refinement, hidden associations—such as the influence of environmental conditions on performance anomalies—can be incorporated into the knowledge graph. Such expert-derived knowledge ensures semantic completeness and interpretability, especially in scenarios where data-driven extraction alone is insufficient.

These data are collected through network monitoring interfaces, configuration management systems, and performance logging modules at regular intervals. Collectively, these four types of data form the foundational information sources for the wireless network knowledge graph. Their complementarity—literature providing theoretical structure, logs contributing real-time dynamics, existing knowledge ensuring semantic continuity, and expert input enriching domain logic—enables the construction of a comprehensive, scalable, and semantically grounded knowledge representation.

However, acquiring high-quality and timely knowledge presents significant challenges. Issues such as licensing restrictions and compliance requirements may inhibit the direct use of certain proprietary resources; raw records often contain sensitive information that must be anonymized or filtered to meet privacy standards. Additionally, the presence of noise, redundancy, and inconsistencies in large-scale data necessitates strict screening and quality control. Ensuring the timeliness of knowledge also requires efficient incremental updates and traceability mechanisms. Therefore, the construction and maintenance of a reliable knowledge base demand continuous verification, standardized governance, and rigorous curation of data sources.

3.2. Knowledge Representation

Knowledge representation is a fundamental component in the construction of wireless network knowledge graphs. Its core objective is to define entities, attributes, and relationships within the domain in a standardized, machine-interpretable manner, thereby forming a coherent semantic framework. Given the high complexity and dynamic characteristics of wireless networks, knowledge representation must ensure both structural clarity and compatibility with reasoning mechanisms.

Based on the requirements of wireless network fault detection and security protection, the ontology first defines the core conceptual system of the domain, establishing the "basic vocabulary" and "semantic rules" of the knowledge graph. The ontology provides standardized definitions of entity types, entity attributes, and relationship types, ensuring semantic consistency across all stages of data processing.

Entity types: According to the structural and operational characteristics of wireless networks, entities are categorized into three major groups: network device entities, event and state entities, and user and attack entities, as shown in **Table 1**. These categories capture the essential components required for accurately modeling network behaviors, device interactions, and potential security threats. The selection of entity categories is guided by common abstractions in wireless network management, where devices, services, and events represent the core elements required for monitoring, analysis, and decision-making. This design balances expressiveness and complexity to support efficient reasoning and querying.

Table 1. Entity types.

Entity Type	Meaning	The Key Sub-type
Network device entity	The hardware and logical components that make up a network are the core objects of fault detection	Base stations; optical cable; core network equipment
Event and state entities	Dynamic events reflecting the operational status of the network serve as the direct basis for fault and safety analysis	Fault events; alarm information
Users and attack entities	Link network users with potential threat sources to support attack traceability in security protection scenarios	Legitimate users; malicious terminals; attack behaviors

Entity attributes: Entity attributes describe the key characteristics of entities, including both static parameters and dynamic parameters. Attribute values are designed to be quantifiable or classifiable to support efficient computation, comparison, and reasoning.

Relationship type: Relationship types define the semantic associations between entities, such as hierarchical relationships, causal relationships, and interactive relationships. These relationships form the logical backbone of the knowledge graph, enabling deeper semantic interpretation and facilitating inference mechanisms such as fault propagation analysis or attack path prediction.

To provide a more intuitive illustration of the semantic framework defined by the ontology, a partial visualization of the ontology model is presented in **Figure 3**. The diagram illustrates how high-level concepts in the wireless network domain are decomposed into specific sub-entities, and how semantic linkages between these entities are represented through well-defined relationships.

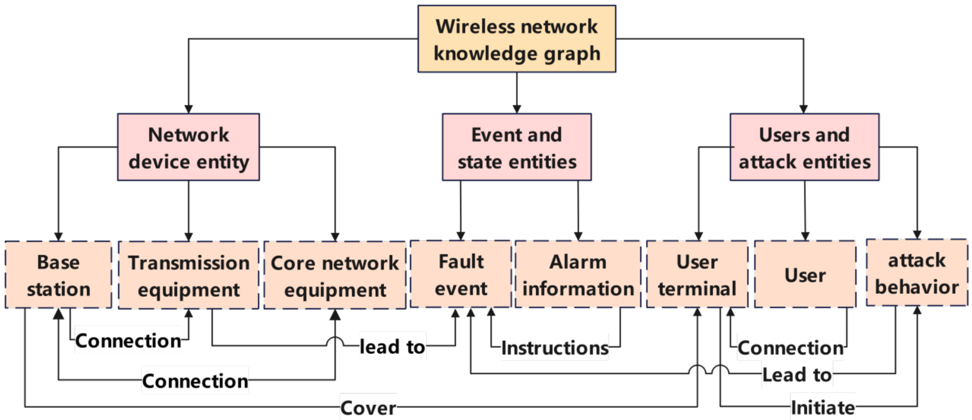

Figure 3. Partial schematic diagram of the ontology model.

Overall, the knowledge representation framework ensures that the wireless network knowledge graph captures essential domain semantics, supports logical reasoning, and provides a consistent foundation for subsequent processes such as data mapping, graph storage, and intelligent applications.

3.3. Data Mapping

Data mapping is a critical step in constructing the knowledge graph, serving as the bridge between raw data and the domain ontology. Its core function is to align the extracted entities, attributes, and relationships with the semantic structure defined in the ontology, ensuring that unstructured or semi-structured information is transformed into standardized knowledge representations. Because the extracted results may contain semantic ambiguity, format inconsistencies, or duplicate expressions, the data mapping process plays an essential role in ensuring accuracy, consistency, and interpretability.

After applying knowledge extraction techniques to raw wireless network data, a set of preliminary entities, attributes, and relationships is obtained. However, these elements often contain variations such as multiple expressions of the same concept—for example, "weak signal," "poor signal," and "signal attenuation"—or ambiguous relationships such as "cause" being used for both causal and correlative associations. To eliminate ambiguity and unify representation, this study adopts a rule-based mapping strategy, which defines explicit correspondences between data fields and ontology elements, offering strong interpretability and clear logical boundaries.

Mapping rules can be defined in a formal way. For entity mapping, the rules are expressed as:

$$R_{entity}(d.field, C) \rightarrow (O.Class, e.ID)$$

where $d.field$ is the data source field, C is the condition that the field needs to meet, such as format and value range, $O.Class$ is the target class in the ontology, and $e.ID$ is the unique identifier of the mapped entity.

The attribute mapping rule is:

$$R_{attr}(e.ID,\ d.field,\ C) \rightarrow (O.Attribute,\ v)$$

where $e.ID$ is the entity identifier, $O.Attribute$ is the ontology attribute, and v is the attribute value.

The relation mapping rule is:

$$R_{relation}(e_1.ID,\ e_2.ID,\ d.relation\_field,\ C) \rightarrow O.relation$$

$e_1.ID$ and $e_2.ID$ are the identifiers of associated entities, and $O.relation$ is the ontology relationship.

For instance, from the report text "On October 1, 2023, optical cable L-002 was damaged during construction, resulting in a weak signal at base station BS-1001 and affecting user UE-2023 communication", the entities "Optical cable L-002", "Weak signal at BS-1001", and "UE-2023" were extracted, along with their relationships "cause" and "affect".

According to the mapping rules:

Relation ($e_1.ID$ = Optical cable L-002, $e_2.ID$ = Weak signal at BS-1001, d.Text includes "cause") → Ontology relation: causes.

Relation ($e_1.ID$ = Weak signal at BS-1001, $e_2.ID$ = UE-2023, d.Text includes "affect") → Ontology relation: affects.

These mappings construct a clear causal chain—Optical cable damage → Weak signal → User communication degradation—accurately reflecting the ontology-defined semantic structure for "device–event–impact." To address potential conflicts and ambiguities among mapping rules, a priority-based mechanism is adopted. Rules with higher semantic specificity and domain relevance are assigned higher priority, while conflicting rules with lower priority are suppressed. In addition, consistency checks are performed to ensure that the generated entities and relations do not violate predefined ontology constraints.

Through rule-based mapping, all extracted information is ultimately converted into standardized RDF triples that strictly adhere to the ontology semantics. These triples form the core knowledge units of the graph, supporting reliable storage, efficient querying, and intelligent reasoning in subsequent applications.

3.4. Management of Knowledge Graphs

The management of knowledge graphs aims to ensure real-time adaptability to network changes while maintaining the accuracy, completeness, and consistency of the stored knowledge. Given the large scale of wireless networks and the frequent updates of entities and relationships, the management framework must support efficient storage, fast updates, and high-quality governance.

The management of knowledge graphs needs to adapt to the dynamics and scale of wireless networks. The core modules include storage architecture, incremental updates, and quality control.

Storage architecture: A suitable graph database must be selected to accommodate the vast number of triples representing entities such as base stations, users, fault events, and device relationships. In this work, Neo4j [24] is employed due to its support for high-concurrency queries, scalable storage, and efficient graph traversal. A hierarchical storage strategy is adopted—static knowledge is stored offline, while dynamic knowledge is cached in an in-memory database—achieving a balance between storage efficiency and real-time performance.

Incremental update mechanism: Wireless networks exhibit strong temporal dynamics, with frequent changes in topology, user behavior, and operational events. To maintain timely knowledge synchronization, a triggered update mechanism is implemented: whenever device logs, signaling data, or performance indicators are updated, the corresponding entity recognition, relation extraction, and mapping procedures are automatically activated. The updated triples are then inserted into the graph. The incremental update mechanism is event-driven. When changes such as fault occurrences, topology updates, or configuration modifications are detected, only the affected entities and relations are updated, rather than reconstructing the entire graph. This fine-grained update strategy significantly reduces update overhead and supports near real-time knowledge maintenance. In addition, timestamp labeling and version control are employed to preserve historical states, enabling traceable reasoning such as fault evolution analysis or anomaly pattern discovery.

Quality control strategy: Knowledge quality is evaluated based on consistency, completeness, and timeliness. Inconsistent or outdated knowledge is identified through rule validation and periodic checks, and corresponding entities are corrected or deprecated accordingly. Due to the noisy and heterogeneous nature of wireless network data, robust quality control is essential. Rule-based validation is applied to eliminate contradictory or logically impossible triples—for example, preventing mappings that violate domain rules such as attributing "weak base station signal" to irrelevant causes. Machine-learning-based entity disambiguation is also utilized to resolve conflicts in entity references and ensure accurate linking. Through these mechanisms, the knowledge graph maintains high semantic fidelity and supports reliable inference, even in complex and dynamic operational environments.

4. Implement the Knowledge Graph for Wireless Networks

The previous sections have presented the construction process of the wireless network knowledge graph, including ontology-based knowledge representation, rule-driven data mapping, and dynamic management mechanisms. Building on this foundation, this chapter illustrates how the knowledge graph is applied in real wireless network scenarios to address practical challenges in fault detection, resource optimization, and security protection. For large-scale graphs, query efficiency is improved through indexed entity attributes and localized subgraph traversal. By limiting queries to relevant subgraphs based on context constraints, unnecessary global scans are avoided, enabling scalable query performance. This chapter demonstrates how structured semantic knowledge is transformed into actionable intelligence.

In wireless network operation and maintenance, fault events often trigger a chain reaction that makes diagnosis difficult. By constructing an association network of "device–event–impact," the knowledge graph enables rapid identification of root causes and supports fault propagation analysis. For example, when users within the area report "signal interruption", the knowledge graph automatically activates the dependency chain of "user terminal → access base station → transmission link → core network equipment", and combines historical fault triples such as "optical cable damage → weak base station signal" and "core network overload → regional network disconnection" to infer potential fault points. If the knowledge graph detects an abnormal connection relationship between "Base Station BS-2001" and "Optical Cable L-056", and the optical cable has recent construction records, it will prioritize pushing the root cause judgment of "optical cable construction damage" and link the "fault - Solution" associated data to assist technicians in handling it quickly.

Resource optimization in wireless networks requires dynamic allocation of spectrum, computing, and storage resources based on real-time conditions and user demands [25]. Similar to the Internet of Vehicles, where reinforcement learning has been applied to optimize handover and resource allocation [26], traditional static resource allocation methods struggle under highly dynamic network conditions such as fluctuating user density and diverse service types. By integrating relationships among "user clusters," "network nodes," and "resource pools," the knowledge graph constructs a semantic model that supports fine-grained, demand-aware resource scheduling. In high-density scenarios such as concerts or sporting events, the graph can match user service types with resource requirements to ensure stable and fair service quality. This optimization logic is also supported by insights from cross-domain dynamic prediction models. For example, multi-feature attention mechanisms used in traffic prediction can be adapted to prioritize key influencing factors in wireless networks, such as emergency communication, high-definition video, or control signaling [27]. Likewise, hybrid models designed for sparse traffic prediction can inspire methods to enhance resource scheduling for edge nodes with limited user data [28]. These cross-domain strategies extend the reasoning capabilities of the knowledge graph and improve its effectiveness in dynamic resource allocation.

In security protection, emerging cyberattacks exhibit increasing stealth and complexity. By constructing a security-oriented knowledge graph linking "user," "device," and "attack behavior," potential threat paths and risk patterns can be identified through semantic inference. For instance, if "Terminal T-102" sends an unusually large number of forged identity requests, the knowledge graph traces its historical behavior and identifies that it frequently co-accesses base station BS-500 with "Terminals T-103" and "T-104," with similar communication characteristics. The graph infers that these terminals may belong to an attack group. In this work, reasoning refers to the process of inferring implicit relationships and potential network states by traversing explicit entity–relation paths and applying predefined logical rules over the knowledge graph. In the event of node failure, the corresponding entities are marked as inactive, and related relations are temporarily disabled. Once recovery is detected, the graph is incrementally updated to restore consistency without requiring full reconstruction. Furthermore, by linking "attack behavior" with "vulnerability type"—such as mapping forged requests to authentication protocol weaknesses—the graph predicts potential risks for similar base stations, such as BS-501 and BS-502, and automatically issues patch update recommendations.

These application scenarios are quantitatively evaluated through experiments, as reported in Section 5, demonstrating their effectiveness under different network scales. Overall, the knowledge graph transforms multi-source data into an interpretable, actionable intelligence network, enabling enhanced fault localization, efficient resource scheduling, and proactive security defense in wireless networks. This demonstrates its strong potential to support next-generation intelligent network management.

5. Experimental Evaluation

5.1. Experimental Setup

To quantitatively evaluate the effectiveness of the proposed knowledge-graph-based framework for wireless network management, a series of experiments is conducted. Considering the privacy and availability constraints of real operational data, wireless network data are generated that reflect realistic network management scenarios.

The network consists of user equipment (UE), base stations (BS), backhaul links, and abstracted core network components. Network events, including fault occurrences and traffic load fluctuations, are injected in a controlled manner. The effectiveness of this application scenario is quantitatively evaluated in the experimental section. Each event is recorded in the form of structured logs and performance indicators, which serve as the input to different management methods.

To examine scalability, four network scales are evaluated: small (30 users), medium (100 users), large (500 users), and very large (1000 users). For each scale, the corresponding number of base stations and links is increased proportionally to maintain realistic network density. The proposed method is compared with a baseline rule-based monitoring approach that relies on direct threshold matching and local correlation, without leveraging graph-based semantic relationships.

The following evaluation tasks are considered:

(1) Fault localization accuracy
(2) Resource utilization efficiency
(3) Query latency and scalability

5.2. Fault Localization Performance

Fault localization is a fundamental task in wireless network management, where the objective is to accurately identify the root cause of observed service degradation. In the experiments, fault events such as optical link failures or base station malfunctions are injected, and the system is required to infer the most probable fault source based on observed symptoms.

Table 2 presents the fault localization accuracy achieved by the baseline method and the proposed knowledge-graph-based approach under different network scales. The results demonstrate that the proposed method consistently outperforms the baseline across all evaluated scenarios, achieving an absolute accuracy improvement of approximately 18–20%. While the baseline approach relies on isolated rule matching, the knowledge graph enables fault propagation reasoning along "device–event–impact" paths, which significantly improves root cause identification, especially in large-scale networks.

Table 2. Fault Localization Accuracy under Different Network Scales.

Number of Users	Baseline Accuracy	KG-Based Accuracy
30	0.557	0.738
100	0.559	0.758
500	0.562	0.754
1000	0.564	0.752

Moreover, the performance of the proposed method remains stable as the network size increases, indicating that the reasoning process is robust to network expansion.

5.3. Resource Utilization Evaluation

Efficient resource utilization is critical for maintaining service quality in dynamic wireless environments. In this experiment, network traffic demands are dynamically generated to emulate variations in user behavior and service requirements. Resource utilization is measured as the ratio of effectively allocated resources to the total available capacity.

Table 3 compares the resource utilization achieved by the baseline approach and the proposed method. The knowledge-graph-based framework improves overall resource utilization by approximately 10–14%, owing to its ability to incorporate semantic relationships among users, base stations, and service requirements.

The proposed approach enables more informed resource allocation decisions than static rule-based strategies. This advantage becomes more pronounced in medium and large-scale networks, where local optimization alone is insufficient to capture global resource dependencies.

Table 3. Resource Utilization Comparison.

Number of Users	Baseline Utilization	KG-Based Utilization
30	0.598	0.731
100	0.593	0.740
500	0.620	0.764
1000	0.591	0.740

5.4. Scalability and Query Performance

Scalability is a critical requirement for practical deployment in large wireless networks. To evaluate scalability, the query latency of network management operations is measured under increasing network sizes. Query latency refers to the time required to retrieve and reason over relevant knowledge graph entities in response to a management request.

Table 4 summarizes the average query latency for both methods. The proposed approach exhibits lower query latency than the baseline across all scales, despite maintaining richer semantic information. This result can be attributed to structured graph indexing and localized traversal enabled by the graph database.

Table 4. Query Latency Scalability Analysis.

Number of Users	Baseline Latency (ms)	KG-Based Latency (ms)
30	12.8	6.0
100	17.9	11.6
500	66.5	44.6
1000	127.2	83.9

As the number of users increases from 30 to 1000, query latency grows approximately linearly for both methods, but with a significantly lower growth rate for the knowledge-graph-based approach. These results indicate that the proposed framework is capable of supporting large-scale wireless network management with acceptable response times.

5.5. Discussion

The experimental results demonstrate that integrating structured knowledge graphs into wireless network management yields measurable performance benefits in fault localization accuracy, resource utilization efficiency, and scalability. Unlike traditional rule-based approaches, the proposed framework captures complex semantic relationships and supports reasoning over interconnected network entities. The current experiments primarily target enhanced Mobile Broadband (eMBB) and Ultra-Reliable and Low Latency Communications (URLLC) scenarios [29], while massive machine-type communications (mMTC) will be explored in subsequent studies.

From a computational perspective, the proposed framework primarily incurs linear complexity with respect to the number of graph entities during update and query operations. The storage requirement grows proportionally with the network scale and can be supported by distributed graph databases in practical deployments. The architecture is compatible with distributed processing paradigms commonly adopted in large-scale network management systems. The proposed framework is designed to support near real-time network management through event-driven updates and localized graph queries, making it suitable for low-latency and high-throughput wireless environments.

Overall, the results provide quantitative evidence supporting the effectiveness and scalability of the proposed method, addressing the key limitations identified in existing network management approaches.

6. Conclusions

This paper focuses on the pain points in the field of wireless networks and proposes a construction and application scheme of knowledge graphs. Firstly, the efficiency and accuracy issues existing in traditional fault detection, resource optimization and security protection were analyzed, and the adaptability of knowledge graph technology was demonstrated. Secondly, the construction process of the knowledge graph of wireless networks is elaborated in detail, including the realization of knowledge representation through ontology modeling, rule-based multi-source data mapping, and the graph management mechanism that supports dynamic updates; Finally, the application effects of knowledge graphs in fault location, resource scheduling and security protection were demonstrated in combination with actual scenarios, verifying their value in enhancing the intelligence level of wireless networks. The current evaluation focuses on eMBB and URLLC scenarios, while extending the framework to mMTC remains an important direction for future work. The framework is designed to operate under typical network management hardware constraints. Lightweight rule-based processing and incremental updates reduce computational overhead, enabling deployment on commodity servers or edge computing platforms.

Future work will investigate distributed deployment strategies, further optimization of incremental update efficiency, and cross-domain knowledge integration. In addition, the trade-off between ontology expressiveness and query efficiency, as well as consistency maintenance under concurrent updates, will be explored, and can be combined with large language [30] models to provide more powerful support for the intelligent operation and maintenance of the next-generation networks.

Author Contributions

W.L. led the overall conceptualization, methodology design, and manuscript preparation. Y.L. (Yinguo Liu) and Y.S. assisted in data collection, validation, and visualization. Y.L. (Ying Li) provided supervision, critical review, and project administration as the corresponding author. All authors have read and approved the final manuscript.

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Not applicable.

Data Availability Statement

The data used in this experiment was not made public due to privacy and other reasons.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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