

Advances and Prospects of Knowledge-Base-Driven Intelligent Applications for Electronic Test Instruments

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Abstract: A paradigm shift is transforming electronic test instruments from rule-based systems into knowledge-base-driven intelligent platforms. This survey reviews intelligent application technologies for such instruments built on knowledge-base architectures. We delineate the domain's knowledge-intensive characteristics, examine knowledge-base construction (architecture design, multi-source acquisition, ontology modeling, and heterogeneous data fusion), and analyze three core technologies—intelligent fault diagnosis combining case-based and rule-based reasoning, intelligent parameter configuration through data-driven recommendation, and intelligent test process planning via automated task decomposition. We then identify key challenges in data security, knowledge maintenance, and technical compatibility, and outline trends including Internet of Thing (IoT) and cloud computing convergence, expansion into fields such as 5G/6G and aerospace, and industrial standardization.

Keywords: Electronic test instruments; Knowledge base; Intelligent application; Fault diagnosis; Parameter optimization; Test automation; Ontology modeling.

1. Introduction

Electronic test instruments are the backbone of modern electronic engineering, underpinning performance verification and quality assurance from consumer electronics to aerospace. Conventional systems, built on deterministic algorithms and manually encoded rules, suffer from three shortcomings [1][2][3][4]: (i) heavy reliance on human expertise for configuration and fault interpretation, causing inconsistency and high labor cost, (ii) rigid procedures that cannot adapt to different models or conditions, and (iii) fragmented knowledge management, with diagnostic experience locked in individual engineers' tacit knowledge rather than captured and reused.

Knowledge-base-driven framework, combined with advances in AI and natural language processing, addresses these limits [5][6][7]. A knowledge base which is a structured repository of facts, rules, procedures, and case histories lets intelligent tools reason, learn from experience, and provide decision support. Integrated with machine learning, knowledge graphs, and retrieval-augmented generation, it turns passive measurement devices into active partners capable of autonomous diagnosis, adaptive optimization, and context-aware planning. Although several architectures for electronic test instruments knowledge management have been proposed, intelligent testing platforms deployed in production and field-service settings, the field remains fragmented across instrument categories.

The remainder of this paper is organized as follows. Section 2 discusses domain characteristics. Section 3 introduces knowledge base construction. Section 4 elaborates typical intelligent applications. Section 5 looks ahead to future development trends and prospects.

2. Electronic test instruments: domain characteristics

Electronic test instruments, such as oscilloscopes,

spectrum Analyzer, vector network analyzers, multimeters, signal generators, and logic analyzers, act as the sensory apparatus of electronic engineering, converting physical quantities into measurable signals. Their diversity of types and scenarios shapes the design of intelligent applications.

Table 1. Classification and Characteristics of Electronic Test Instruments

Instrument Type	Primary Function	Knowledge Intensity	Typical Application Domain
Oscilloscope	Time-domain signal visualization	High	Circuit debugging, signal integrity
Spectrum Analyzer	Frequency-domain analysis	High	RF testing, EMC compliance
Vector Network Analyzer	S-parameter measurement	High	Antenna design, filter characterization
Multimeter	Basic electrical measurements	Low	General-purpose testing
Signal Generator	Controlled signal generation	Medium	System stimulation, calibration
Logic Analyzer	Digital signal acquisition	Medium	Digital circuit verification
Power Supply	Programmable power delivery	Low	Device powering, efficiency testing

As Table 1 shows, knowledge intensity varies widely: high-knowledge instruments such as network analyzers demand extensive expertise for configuration and interpretation, creating barriers for novices. Heterogeneous environments with proprietary protocols and fast-evolving models further underscore the need for knowledge-base-driven systems that unify disparate ecosystems [1][7][8].

Instrument operation involves several knowledge-intensive

tasks suited to automation [2][9]. Fault diagnosis mainly associates symptoms with causes within the large fault mode space; parameter configuration matches test requirements with instrument capabilities and programmable test parameters; test flow planning decomposes objectives into executable sequences satisfying dependency relationships. All these tasks rely on declarative knowledge and procedural knowledge, so knowledge-base representation is more suitable.

3. Construction of electronic test instrument knowledge base

A well-structured knowledge base is the key foundation of intelligent application. Construction proceeds in three phases: architecture design, knowledge acquisition, and knowledge

processing [10][11].

3.1. Knowledge Base Architecture Design

The architecture must support efficient storage, retrieval, reasoning, and updating of heterogeneous knowledge. It is mainly divided into three layers. The data layer is used for persistent storage of structured, semi-structured and unstructured data. The logic layer implements ontology, rule engines and graph databases to support semantic reasoning. The application layer provides knowledge services externally through standardized APIs.

Modularity is a key principle, the knowledge base should comprise independent yet interoperable modules covering different instrument families and test methodologies, as summarized in Table 2.

Table 2. Core Modules of Electronic Test Instrument Knowledge Base

Module	Content Description	Knowledge Representation	Update Frequency
Test Method Library	Standardized test procedures and protocols	Workflow graphs, SOP documents	Quarterly
Instrument Parameter Library	Device specifications and configuration templates	Relational database, JSON schemas	Monthly
Fault Case Library	Historical fault records and resolution strategies	Case-based reasoning frames	Weekly
Component Knowledge Base	Component characteristics and failure modes	Ontology, knowledge graph	Bi-annually
Environmental Model	Operating condition constraints	Rule-based expressions	As needed

3.2. Knowledge Acquisition and Sources

Knowledge acquisition is the most labor-intensive stage, which relies on structured data sources such as relational business databases, test logs and calibration certificates, as well as unstructured data sources including manuals and expert reports. Transformer-based natural language processing techniques have greatly improved the capability of automatic extraction of structured knowledge through methods such as named entity recognition, relation extraction and event extraction.

Expert elicitation remains critical for tacit knowledge, structured interviews and case-based walkthroughs can be adopted to capture diagnostic reasoning processes from senior engineers and formalize them into rules or case frameworks.

3.3. Knowledge Processing and Fusion

Raw knowledge must be processed to ensure its consistency and interoperability. OWL description logic ontology supports automatic classification and consistency checking. Knowledge fusion adopts confidence-weighted aggregation, scoring assertions according to the reliability and timeliness of data sources. Conflicts are resolved by means of majority voting, temporal ordering and expert review to construct a unified semantic knowledge graph.

4. Typical intelligent applications

4.1. Intelligent Fault Diagnosis

Intelligent fault diagnosis is a highly representative application of domain-knowledge-base-driven retrieval-augmented generation (RAG) in the field of electronic test instruments. The standard diagnostic pipeline consists of sequential standardized operations: symptom acquisition, fault isolation, root cause identification, and maintenance suggestion generation [9].

A RAG-powered fault diagnosis system runs according to the following pipeline. To begin with, technicians input instrument fault descriptions in natural language. The retrieval component then queries the fault diagnosis knowledge repository, mainly containing historical fault instances and maintenance handbooks, and fetches the top-k past fault records with the highest similarity to the ongoing fault alongside corresponding troubleshooting workflows. Afterwards, the generative module integrates the retrieved materials and outputs diagnostic reports. These reports rank possible fault hypotheses, offer suggested diagnostic workflows and supply maintenance guidelines.

The fault diagnosis knowledge repository comprises four categories of resources: (1) structured fault code databases maintained by instrument vendors; (2) instrument user guides, maintenance documents and fault records; (3) unstructured service log files; and (4) troubleshooting guides contributed by community users.

4.2. Intelligent Parameter Configuration and Optimization

Proper tuning of instrument panel test parameters is essential to acquire precise measurement data efficiently. Poor parameter settings may trigger measurement inaccuracies. Typical causes include inappropriate input range selection, insufficient averaging counts, and incorrect analysis bandwidth or trigger configurations [7]. Such mistakes result in invalid measurement outputs, increased repeated debugging overhead and reduced test throughput.

The working mechanism of domain-knowledge-base-driven adaptive test parameter configuration assistant is described below. First, it interprets natural-language test requirements and confirms the target measurement task. An example requirement: “Measure the signal characteristics of the radar signal simulator, including signal amplitude, pulse width and pulse repetition period, with an operating

frequency of 5.5 GHz.” Second, the assistant retrieves relevant configuration recommendations from instrument technical specifications and rule-based knowledge bases. Third, it produces stepwise configuration workflows and parameter key-value pairs customized for the target instrument model and measurement scenario.

The domain knowledge base forms a multi-dimensional parameter space. Each dimension maps to one programmable instrument setting, including frequency span, reference level, sampling frequency, resolution bandwidth, video bandwidth, detector mode and sweep duration. The adaptive configuration workflow creates suitable parameter schemes for assigned measurement tasks via test requirement parsing, case library retrieval and rule-base matching.

4.3. Intelligent Test Process Planning

Test process planning aims to convert abstract test requirements into executable, measurable and controllable systematic action plans. Combining information such as instrument manuals, specifications and historical test data, the planning process covers all necessary measurements, verifications and compliance checks. In contrast, retrieval from technical documents requires operators to locate specific information within lengthy instrument handbooks, application notes and standards.

Complex scenarios demand multi-instrument measurement sequences with dependency relationships and resource constraints [2] [12]. The knowledge base for electronic test instruments can effectively organize and manage the associations among test scenarios, test tasks, test instruments, test constraints and test methods via rules or graph structures. With this knowledge base, upon receiving input of test tasks, the system can understand and decompose test tasks, match test resources, autonomously perform flow planning under test constraints, and generate logically consistent and parameter-matched test sequences. This greatly improves the efficiency of test support.

5. Development trends and prospects

There is a trend of technology convergence. Integration with the Internet of Things enables real-time monitoring and predictive maintenance. Networked instruments transmit telemetry data to cloud platforms, and anomaly detection triggers corresponding maintenance workflows. Cloud computing further strengthens such capability by offering scalable resources, supporting knowledge management and AI reasoning, and serving thousands of users with centralized version control.

Application scenarios keep expanding. The scope of applications is extending from laboratories to 5G/6G and aerospace testing fields. In the 5G domain, the characteristics of massive MIMO arrays and millimeter waves exceed manual inspection capacity. Therefore, systems incorporating professional RF testing expertise are highly valuable. The aerospace sector imposes stringent requirements on reliability and traceability, and thus prefers systems capable of generating audit-compliant and fully traceable records to satisfy rigorous certification requirements.

Explainability and trust are critical in safety-critical test applications. For safety-critical applications of electronic test instruments such as aerospace, medical devices and test support, retrieval attribution as well as traceability of processes and results must be verifiable and traceable back to authoritative sources [13] [14].

Edge deployment brings both opportunities and challenges. For field service applications where network connectivity may be limited, deploying intelligent assistant systems equipped with compressed models and localized knowledge bases on edge devices requires breakthroughs in model compression, quantization, and efficient retrieval on resource-constrained hardware [15].

Conflicts of interest

The authors declare that they have no conflict of interest.

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