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A multi-agent system framework for real-time self-diagnostic condition monitoring of induction furnace equipment in developing industrial economies

Destine Mashava [1,*], Takudzwa M. Muhla [1], Gilbert Munhuwamambo [1], Innocent Mapindu [1], Kudakwashe N. Chinguwo [1] and Tafadzwa Wachenuka [2]

[1] *Department of Industrial and Manufacturing Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe.*
[2] *Department of Electronics Engineering, National University of Science and Technology (NUST), Bulawayo, Zimbabwe.*

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Abstract

Unplanned equipment failures in developing industrial economies result in substantial production losses, elevated maintenance costs, and reduced plant availability. This research presents the design and implementation of a multi-agent system (MAS) based self-diagnostic framework for real-time condition monitoring of induction furnace equipment, demonstrated through a case study at a copper cable manufacturing company in Zimbabwe. The proposed system integrates a heterogeneous sensor network comprising infrared temperature sensors, electromagnetic flow meters, conductivity transducers, and a linear float sensor with a Siemens S7-1200 PLC, OPC server, and a Foundation for Intelligent Physical Agents (FIPA)-compliant JADE (Java Agent Development Framework) multi-agent platform to achieve autonomous fault detection, diagnosis, and notification. Four specialized agents: Diagnosis, Decision, Database, and Notification collaborate via FIPA ACL messaging to process real-time data, execute JESS-based rule inference, persist operational records in MySQL, and deliver automated email alerts to maintenance personnel. Experimental validation on a hardware-in-the-loop testbed demonstrated successful detection of critical fault conditions, including refractory overheating, cooling water flow degradation, water conductivity anomalies, and inductor power deviations. Connecting the contribution within the growing Industry 4.0 and predictive maintenance literature, this work advances the application of agent-based architectures for condition-based maintenance (CBM) in resource-constrained African industrial environments where IoT-enabled solutions remain nascent.

Keywords: Multi-Agent System; Condition-Based Maintenance; Induction Furnace; JADE; JESS; OPC; Predictive Maintenance; Industry 4.0; Self-Diagnosis; Fault Detection

1. Introduction

In contemporary manufacturing environments, the reliability and availability of production equipment constitute foundational determinants of competitiveness. Induction furnaces, as the principal melting and holding assets in non-ferrous metal manufacturing, are particularly susceptible to complex, multi-modal failure modes involving refractory degradation, cooling circuit anomalies, and power supply irregularities. The consequences of unplanned furnace failure are severe: production throughput collapses, maintenance costs escalate, and lead times for critical components can extend plant downtime from days to weeks [1, 2].

Traditional maintenance paradigms, reactive maintenance applied after failure, and time-based preventive maintenance applied on fixed schedules remain the dominant approaches in developing industrial economies such as Zimbabwe. These approaches are inherently inefficient: reactive maintenance incurs maximum operational disruption, while preventive maintenance shortens useful equipment life and consumes maintenance budgets on equipment that may not yet require intervention [3, 4]. Condition-based maintenance (CBM), which triggers maintenance actions based

* Corresponding author: Destine Mashava

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on continuous monitoring of actual equipment health indicators, has been recognised for over two decades as the theoretically optimal maintenance strategy. However, its practical deployment demands sophisticated instrumentation, real-time data acquisition, and intelligent diagnostic reasoning that have historically been accessible only to well-capitalised enterprises in developed economies.

The emergence of Industry 4.0 has dramatically lowered the technological barriers to CBM. Advances in low-cost sensor technologies, industrial IoT connectivity, edge computing, and artificial intelligence (AI), including multi-agent systems (MAS) and machine learning, have created an ecosystem in which real-time, autonomous condition monitoring is increasingly accessible to medium-sized manufacturers [4, 5]. The global predictive maintenance market reached USD 5.5 billion in 2022 and is projected to expand at a compound annual growth rate of 17% through 2028, reflecting broad industrial recognition of the value proposition [6]. Concurrently, the machine condition monitoring equipment market reached USD 3.19 billion in 2023, with Siemens and other majors deploying AI-enhanced monitoring systems in 2024 [7].

Despite these global developments, their penetration into sub-Saharan African manufacturing remains limited, and documented case studies of intelligent maintenance systems deployed in African industrial contexts are scarce in the literature. This research addresses that gap by presenting the design, implementation, and validation of a MAS-based self-diagnostic system specifically architected for an induction furnace and its auxiliary equipment in a Zimbabwean copper manufacturing facility. The system was motivated by a catastrophic furnace failure at a cable manufacturing company in Zimbabwe, where inductor overheating led to a complete blowout within seven months of commissioning a seven-tonne furnace, a failure directly attributed to the absence of a real-time monitoring capability.

The contributions of this paper are fourfold: (i) a systematic sensor selection methodology for induction furnace condition monitoring aligned with industrial requirements in resource-constrained environments; (ii) a FIPA-compliant multi-agent system architecture integrating JADE agents with a Siemens S7-1200 PLC via OPC connectivity; (iii) a JESS-based expert system knowledge base encoding domain-specific diagnostic rules for furnace fault classification; and (iv) an empirical evaluation demonstrating the system's diagnostic capability and economic viability in a real industrial context.

The remainder of this paper is organised as follows. Section 2 reviews related work in CBM, multi-agent diagnostic systems, and induction furnace monitoring. Section 3 describes the system architecture and methodology. Section 4 details the implementation. Section 5 presents results and validation. Section 6 discusses the findings in the context of broader trends. Section 7 concludes the paper.

2. Literature Review

2.1. Condition-Based Maintenance and Predictive Maintenance

Condition-based maintenance has evolved significantly from its origins as a technologically intensive luxury to a mainstream industrial practice enabled by affordable sensors and computing. In its classic formulation, CBM relies on detecting deviations from established baseline operational parameters to infer developing faults before they escalate to catastrophic failure [3, 8]. The key components of a CBM system include data acquisition, feature extraction, fault detection, fault diagnosis, and decision support for maintenance action scheduling.

A comprehensive systematic review by Benhanifia et al. [4], covering over 100 research papers published between 2015 and 2023, identified IoT, digital twins, machine learning, and big data analytics as the principal enabling technologies for modern CBM and predictive maintenance (PdM). The review highlighted a transition from data-driven offline analysis towards real-time, cyber-physical monitoring architectures aligned with Industry 4.0 principles. Notably, the authors observed that early CBM systems based on rule-based expert systems, such as the architecture explored in the present work, established important design patterns that persist in contemporary hybrid AI-CBM approaches.

Empirical evidence for the economic benefits of CBM is compelling. According to US Department of Energy analyses, predictive maintenance delivers 8-12% savings over preventive approaches and up to 40% over reactive maintenance [9]. The global condition monitoring equipment market is expected to sustain a 7.3% CAGR through 2028, with AI-augmented platforms, exemplified by Siemens' integration of AI into its Predictive Services package in 2025, representing the growth frontier [10, 7].

2.2. Multi-Agent Systems for Fault Diagnosis

Multi-agent systems provide a distributed, scalable, and modular paradigm for implementing intelligent monitoring and diagnostic functions in complex industrial environments. An agent, in the foundational definition of Wooldridge and Jennings [11], is a hardware or software entity capable of perceiving its environment through sensors and acting upon it through actuators, exhibiting properties of autonomy, social ability, reactivity, and proactivity. MAS extends this concept to networks of interacting agents capable of collaborative problem-solving that exceeds the capability of any individual agent.

The application of MAS to industrial fault diagnosis and condition monitoring has an established research history. Diaconescu and Spirleanu [12] demonstrated a viable communication architecture connecting JADE-based multi-agent systems to industrial control hardware via OPC servers, establishing the technical viability of the sensor-agent integration pattern employed in the present work. Leitão [13], as cited in subsequent literature on cyber-physical production systems, developed a cyber-physical production system using JADE agents running on Raspberry Pi units to control conveyor modules, demonstrating the scalability of agent-based approaches to production floor automation.

A recent survey by Dorri et al. [14] documented that 58% of enterprise-grade multi-agent implementations adopt FIPA standards for agent communication, the same standard underpinning the JADE framework used in the present study. More recent analyses [15] indicate that hierarchical agent architectures, in which supervisory agents coordinate specialised subordinate agents, account for approximately 42% of enterprise MAS implementations, directly paralleling the Diagnosis-Decision-Database-Notification hierarchy proposed herein.

For fault detection and diagnosis specifically, Moya et al. [16] reviewed fault diagnosis and self-healing approaches for smart manufacturing, identifying agent-based architectures as particularly well-suited to environments requiring distributed sensing, heterogeneous fault types, and real-time response. The integration of rule-based expert systems within agent architectures, as in the JADE-JESS combination employed in this research, was identified as a robust approach for encoding domain expert knowledge in domains where labelled training data for machine learning is unavailable [16, 17].

2.3. Induction Furnace Monitoring

Channel induction furnaces, of the type employed in electrical cable manufacturing, present a distinctive monitoring challenge owing to the simultaneous criticality of multiple operational subsystems: the refractory lining, the inductor and power supply, the cooling water circuit, and the melt itself. Refractory lining failure is among the most dangerous and costly failure modes: rebuilding after an unplanned lining failure incurs substantial costs in lost production, person-hours, and materials [18, 19]. Real-time monitoring of the exterior shell temperature distribution using infrared thermography has been established as an effective, non-invasive means of detecting refractory degradation and localising cracks before structural failure [18].

The cooling water system constitutes a second critical monitoring domain. Water hardness — manifested as elevated conductivity and total dissolved solids promotes scale deposition in inductor cooling channels, progressively reducing heat transfer efficiency and increasing the risk of thermal runaway. Hricisin and Mudron [20] established the operational standards: make-up water conductivity should be maintained in the range 0-7 μS/cm, while recirculating cooling water should be maintained between 250-350 μS/cm. These bounds provide the basis for the threshold-based diagnostic rules implemented in this system's JESS knowledge base.

Yousuf et al. [21] presented an IoT-based health monitoring system for AC induction motors using integrated sensors and Global System for Mobiles (GSM) communication, demonstrating current industry practice in sensor-based fault detection for induction equipment. Wang et al. [22] demonstrated AI-driven current monitoring for hot-pressing furnaces, with automated classification of anomalies into fault categories to support proactive maintenance. Both studies validate the sensor-fusion approach to furnace monitoring adopted in the present work and confirm the relevance of combining temperature, current, and fluid-quality sensing in comprehensive furnace health monitoring.

2.4. Expert Systems in Diagnostic Applications

Knowledge-based expert systems encode human domain expertise in structured rule bases, enabling automated reasoning over sensor data to generate diagnostic conclusions. In the context of industrial fault diagnosis, rule-based systems implemented using shells such as JESS (Java Expert System Shell) provide interpretable, auditable inference chains that are particularly valuable in safety-critical applications where model transparency is essential [23, 24].

The integration of JESS with JADE agents, leveraging FIPA ACL inter-agent communication to pass sensor readings to JESS inference engines and return diagnostic conclusions, was documented by Diaconescu and Spirleanu [12] and is extended in the present work to a real industrial furnace monitoring application. While contemporary research increasingly favours machine learning approaches for fault diagnosis, recent reviews [16] confirm that rule-based systems maintain practical advantages in scenarios characterised by limited training data, stringent explainability requirements, and the availability of well-codified domain expertise, all of which characterise the induction furnace monitoring context.

3. System Architecture and Methodology

3.1. Overview and Design Approach

The self-diagnostic system is architected as a three-tier integration: a physical sensor environment interfaced to a Siemens S7-1200 PLC, a middleware layer using an OPC server and JEasyOPC client to bridge the PLC to the JADE agent platform, and an application layer comprising four specialised JADE agents, a JESS expert system, a MySQL database, and a Java Swing user interface. The design philosophy prioritises modularity, maintainability, and interpretability over predictive model sophistication, reflecting the practical constraints of an initial CBM deployment in an under-resourced industrial context.

The V-model system development lifecycle was adopted to ensure that each development stage is paired with a corresponding verification activity, providing structured validation from sensor-level accuracy testing through to end-to-end system integration testing [25]. Fig. 1 shows the agent deployment approach implemented to achieve the self-diagnostic system using agents.

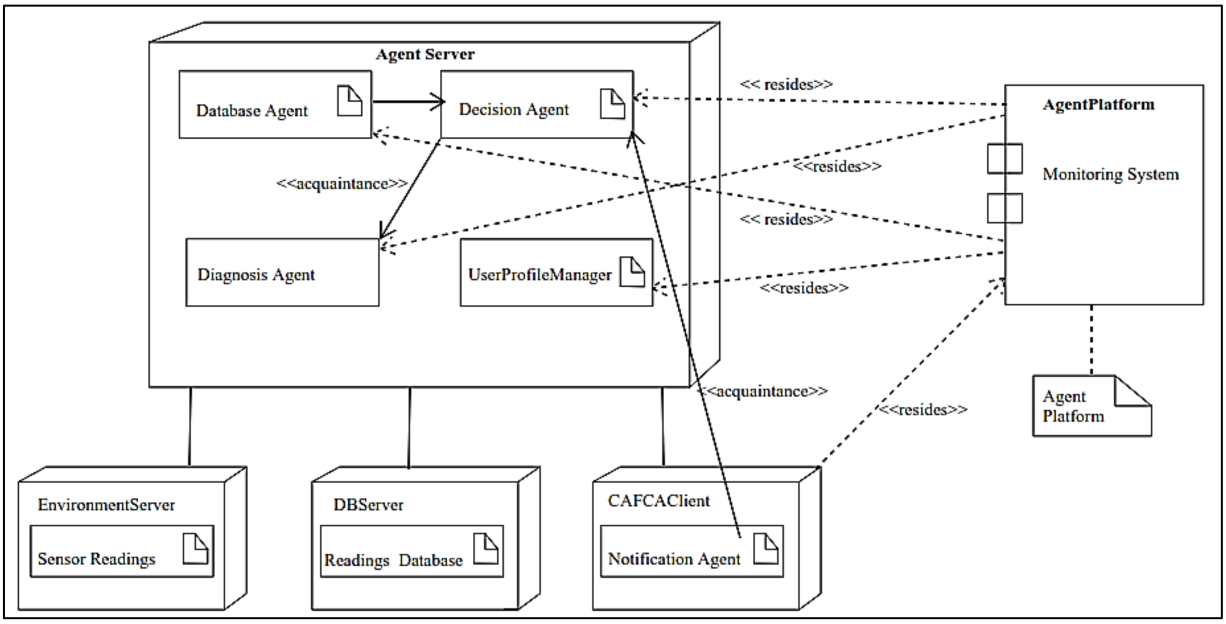

Figure 1 Agent deployment architecture.

3.2. Sensor Environment

Four categories of operational parameters were identified for monitoring through requirements analysis at the electrical cable manufacturing company: furnace shell temperature (indicative of refractory lining condition), cooling water flow rate (indicative of cooling circuit integrity), cooling water conductivity (indicative of water quality), and molten copper level (indicative of process status). Sensor selection was performed through structured comparison of available transducer technologies against criteria of accuracy, installation mode (contact vs. non-contact), operational range, and cost.

For shell temperature measurement, non-contact infrared sensors of the OS136 series were selected over embedded thermocouples. This selection was motivated by the superiority of infrared sensing for detecting the localised thermal anomalies characteristic of refractory degradation, the elimination of contact installation requiring furnace dismantling, and the demonstrated sensitivity advantages over thermocouples reported in the literature [18].

For cooling water flow rate, electromagnetic flow meters were selected based on their compatibility with conductive fluids, absence of moving parts (eliminating wear-related drift), and bidirectional measurement capability. The selected devices provide a 4-20 mA analogue output directly compatible with the S7-1200 analogue input modules. For water conductivity, a two-pole conductive transducer with a measurement range of 0.001-1000 µS/cm was selected, accommodating both the make-up water specification (0-7 µS/cm) and the circulating water specification (250-350 µS/cm) within a single instrument. For molten copper level measurement, a float-type sensor employing a potentiometer transduction mechanism was selected for its continuous analogue output and straightforward mechanical installation.

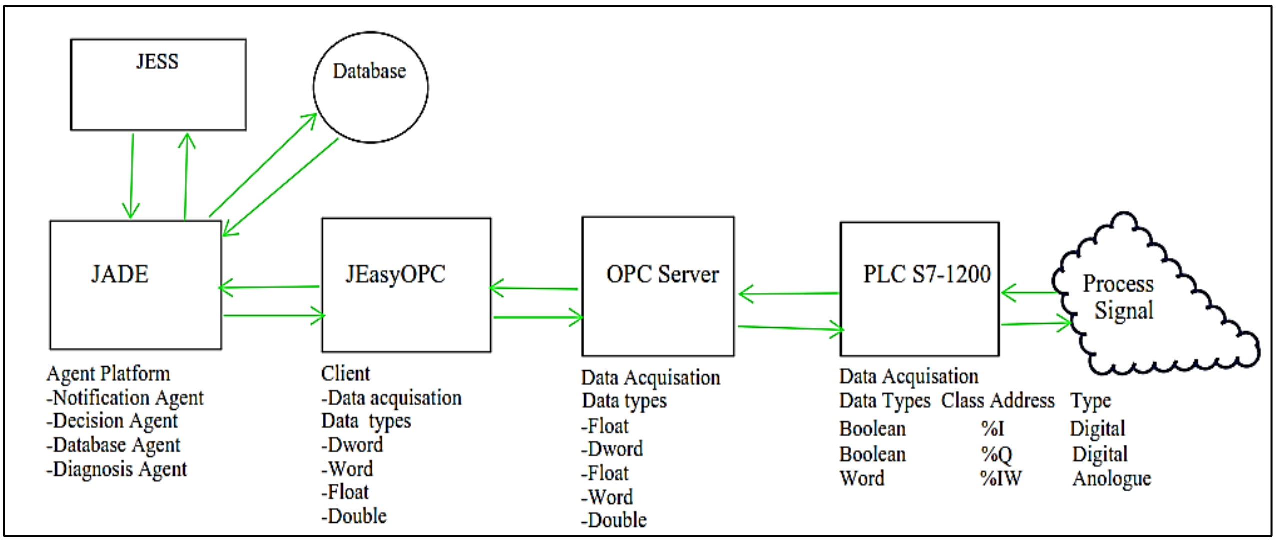

Figure 2 Sensor environment system architecture.

Fig. 2 shows the sensor environment architecture consisting of the Siemens S7-1200 as a controller, the PC Station, and the OPC Server. The focus is to create an environment where the agents can access and monitor the station parameters by reading values from the sensors in the environment.

3.3. PLC Data Acquisition Layer

Sensor analogue outputs are interfaced to a Siemens S7-1200/1214 DC/DC/DC PLC configured as the data acquisition front-end. A structured PLC program developed in Siemens TIA Portal implements normalisation of raw 4-20 mA analogue input signals to engineering unit floating-point values and applies configurable high and low alarm thresholds for each monitored parameter. Function blocks were developed for each sensor channel to encapsulate the normalisation and scaling logic, enabling reuse and independent calibration.

The PLC communicates with the OPC server layer over an Ethernet connection, as shown in Fig. 3. Tag definitions created within the PLC program are exposed as OPC data items, enabling the agent platform to access real-time sensor readings without direct PLC protocol knowledge. This OPC abstraction layer provides a standardised, vendor-neutral data connectivity interface consistent with current industrial interoperability standards.

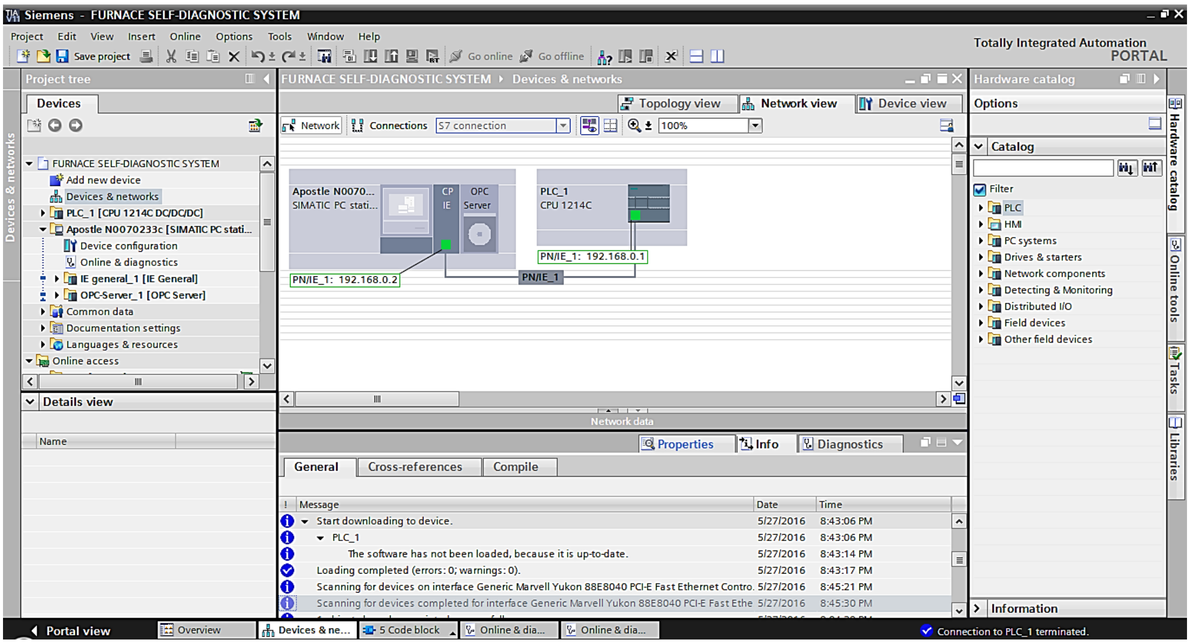

Figure 3 Connection of the OPC server and the S7-1200 PLC.

3.4. Multi-Agent System Architecture

The MAS layer was designed using the Agent Unified Modelling Language (AUML) methodology, proceeding through requirements analysis, agent identification, responsibility assignment, acquaintance modelling, and agent refinement phases. Four agent types were identified as necessary and sufficient for the diagnostic functions as given in Table 1.

Table 1 Agents and their responsibilities.

Agent Name	Primary Responsibilities and Functions
Diagnosis Agent	Data Acquisition: Polls sensor readings from OPC servers via JEasyOPC. Inference: Processes data using the JESS expert system. Communication: Forwards diagnostic results to the Decision Agent using FIPA ACL.
Decision Agent	Policy Evaluation: Analyses fault severity and urgency based on internal logic. Coordination: Orchestrates system response by dispatching commands to Database and Notification agents. Protocol: Uses FIPA Request Interaction Protocol for command dispatch.
Database Agent	Persistence: Executes SQL operations (INSERT/UPDATE) on a MySQL database. Record Keeping: Maintains longitudinal logs of sensor data, faults, and status changes. Retrieval: Supports historical analysis and reporting.
Notification Agent	Alerting: Dispatches automated email notifications to maintenance teams with detailed fault payloads. UI Services: Power the user interface for real-time monitoring and graphical trend rendering.

Inter-agent communication is implemented using JADE's ACL message passing with FIPA Request, Inform, and CFP (Call for Proposal) performatives as appropriate to the interaction semantics. Agent discovery uses the JADE Directory Facilitator (DF) service, with each agent registering its service description at start-up and using DF queries to locate peer agents, dynamically eliminating hard-coded agent address dependencies and supporting modular deployment. Fig.

4 gives the overall agent class diagram showing the various relationships, which include associations, dependencies, aggregation, and composition relationships.

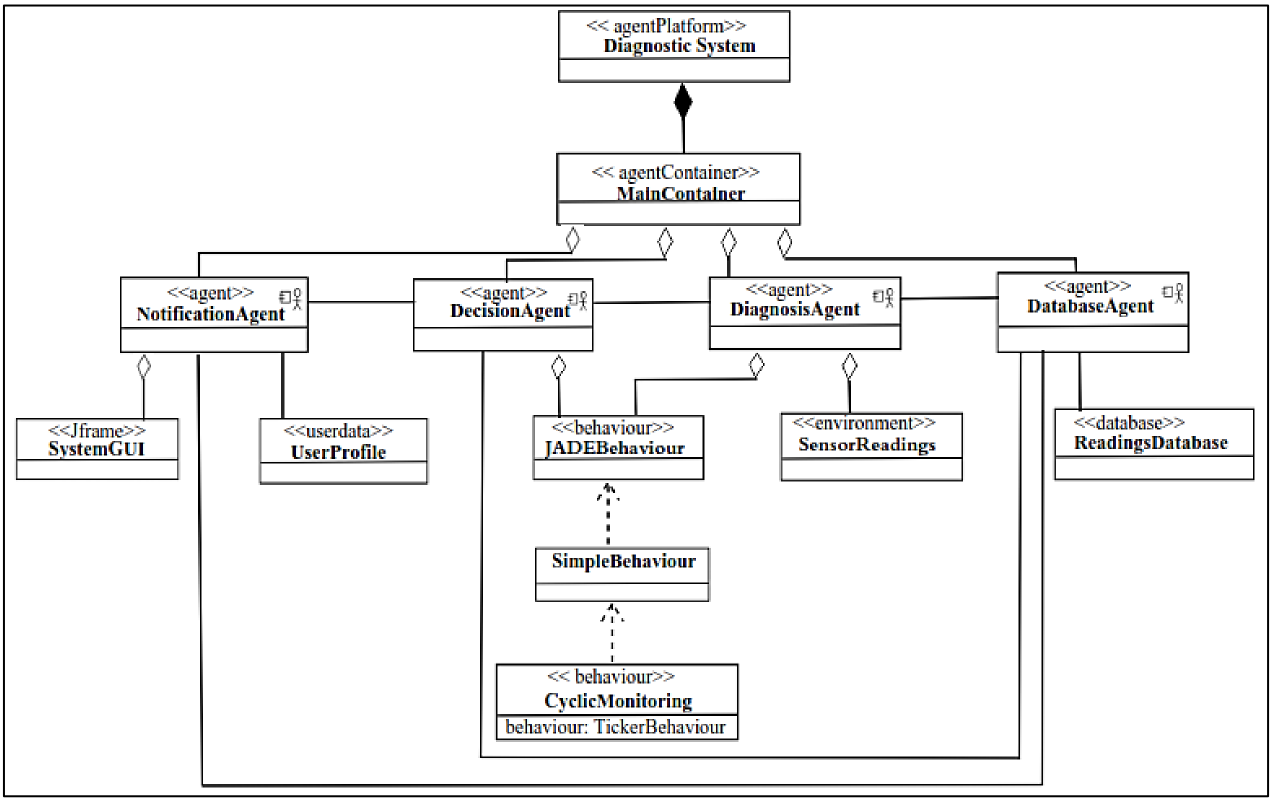

Figure 4 Agent class relationships.

Monitoring of the whole system is achieved by implementing various agents; Fig. 5 shows a diagrammatic view of the system architecture for the multi-agent system.

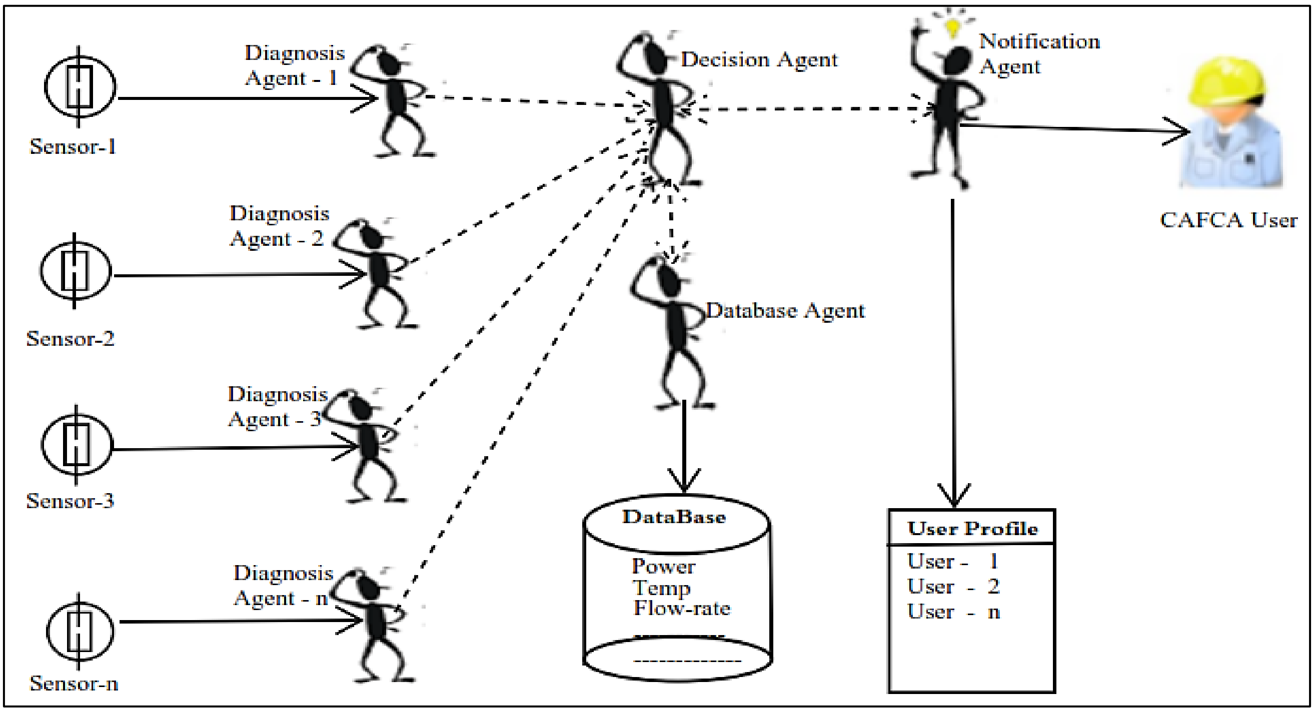

Figure 5 Multi-agent system architecture

Fig. 6 gives the agents' interaction that complies with FIPA standards implemented in the development of the multi-agent self-diagnostic system.

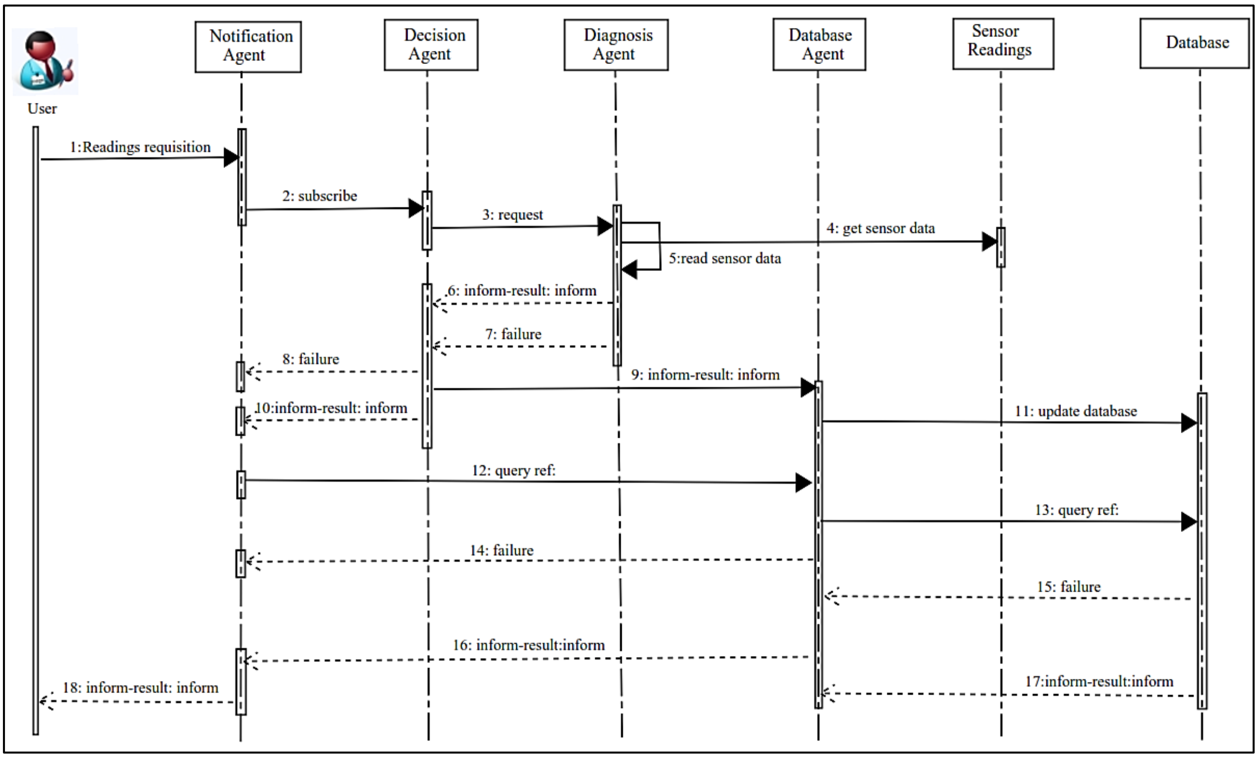

Figure 6 FIPA-compliant agent interaction architecture.

3.5. JESS Knowledge Base

The diagnostic expert system is implemented in JESS, the Java Expert System Shell, embedded within the Diagnosis Agent. The knowledge base encodes domain-specific fault classification rules derived from the induction furnace operating manuals, maintenance logs, and expert interviews with the plant maintenance team. Rules are structured as condition-action pairs: the condition part pattern-matches working memory elements (sensor reading facts asserted by the Diagnosis Agent) against threshold predicates, while the action part asserts diagnostic conclusion facts and triggers agent message dispatch.

Fault categories encoded in the knowledge base include: refractory lining overheating (shell temperature exceeding 65°C sustained over 10 minutes), cooling water flow failure (flow rate below 0.3 m^3/h for the inductor circuit), cooling water contamination (conductivity of make-up water exceeding 7 μS/cm or circulating water exceeding 350 μS/cm), inductor power anomaly (power factor deviation exceeding 15% from baseline), and molten metal level extremes (level below minimum operating threshold or above maximum). Each fault category is associated with a recommended corrective action encoded in the rule action part.

4. Implementation

4.1. PLC Configuration and OPC Integration

The Siemens S7-1200/1214 DC/DC/DC PLC was configured in TIA Portal V13 with a dedicated sensor tag for each monitored parameter. Analogue input channels were configured for a 4-20 mA signal range, with the NORM_X normalisation instruction converting raw integer counts to normalised 0.0-1.0 floating-point values and the SCALE_X instruction then mapping to engineering units (°C for temperatures, m^3/h for flow rates, μS/cm for conductivity, mm for level). A main organisation block (OB1) cycles the sensor acquisition, normalisation, and alarm evaluation logic at a 100 ms scan cycle, providing near-real-time parameter update rates.

The PLC is connected to a PC-hosted OPC server (KEPServerEX Top Server) over a Gigabit Ethernet link using the Siemens S7 OPC driver. Tag definitions in the OPC server mirror the PLC data block structure, making all normalised sensor values available to OPC client applications as browseable data items, as shown in Fig. 7. Connection health between the PLC and OPC server was verified through the Top Server online tag monitor, confirming successful data exchange at the configured update rate of 500 ms.

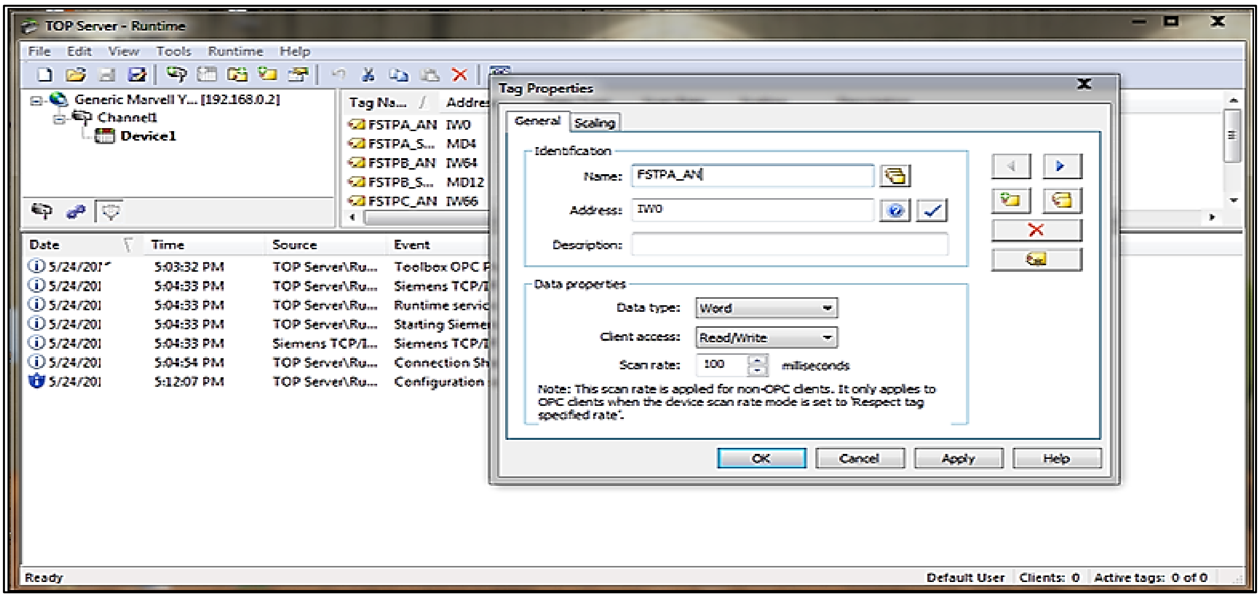

Figure 7 Tag creation in Top Server.

4.2. JADE Agent Implementation

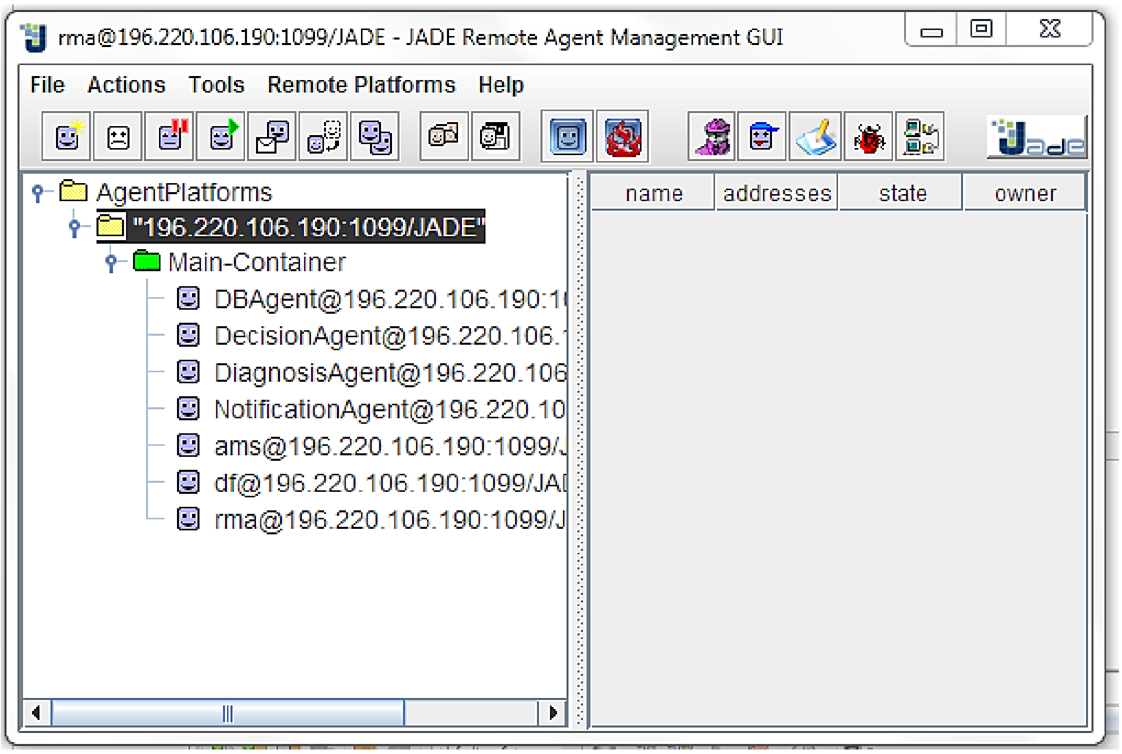

Figure 8 Developed agents JADE GUI.

JADE version 4.5 was used as the multi-agent platform, running on a Java SE 8 runtime environment. The four agent classes, Diagnosis Agent, Decision Agent, Database Agent, and Notification Agent, were implemented as extensions of the JADE Agent base class. Agent behaviours follow JADE's behaviour-based concurrency model: Cyclic Behaviour instances implement continuous sensing loops, while One Shot Behaviour instances handle one-time initialisation tasks such as DF service registration. Fig. 8 illustrates the JADE GUI showing the developed agents in the Container named Main for the Self-Diagnostic system.

The Diagnosis Agent uses the JEasyOPC library to establish an OPC client connection to the KEPServerEX server, create an OPC group containing the monitored tag items, and read tag values synchronously at each sensing cycle. Retrieved values are encapsulated as ACL message content strings and dispatched to the JESS inference engine via the JADE in-process interface. The JEasyOPC library provides a clean Java API abstraction over the underlying OPC DA protocol, eliminating the need for COM/DCOM interoperability code in the Java agent implementation.

The MySQL database schema was designed with separate tables for sensor readings (timestamped parameter values), fault events (fault classification, affected parameters, severity, resolution status), and notification logs (recipient, message content, dispatch time, delivery status), as shown in Fig. 9. The Database Agent uses JDBC with the MySQL Connector/J driver for all database operations, implementing Prepared Statement patterns to prevent SQL injection vulnerabilities.

```
mysql> show tables;
+----------------------+
| Tables_in_systemdata |
+----------------------+
| sensor_readings      |
+----------------------+
1 row in set (0.00 sec)

mysql> show columns from sensor_readings;
+---------+---------+------+-----+---------+-------+
| Field   | Type    | Null | Key | Default | Extra |
+---------+---------+------+-----+---------+-------+
| TIME    | char(8) | YES  |     | NULL    |       |
| FST_PA  | int(5)  | NO   |     | NULL    |       |
| FST_PB  | int(5)  | NO   |     | NULL    |       |
| FST_PC  | int(5)  | NO   |     | NULL    |       |
| IST_PD  | int(5)  | NO   |     | NULL    |       |
| IST_PE  | int(5)  | NO   |     | NULL    |       |
| IST_PF  | int(5)  | YES  |     | NULL    |       |
| FP      | int(5)  | NO   |     | NULL    |       |
| MCT     | int(5)  | NO   |     | NULL    |       |
| MCL     | int(5)  | NO   |     | NULL    |       |
| CWT_IN  | int(5)  | NO   |     | NULL    |       |
| CWT_OUT | int(5)  | NO   |     | NULL    |       |
| CWF_IN  | int(5)  | NO   |     | NULL    |       |
| CWF_OUT | int(5)  | NO   |     | NULL    |       |
| CWP_IN  | int(5)  | NO   |     | NULL    |       |
| CWP_OUT | int(5)  | NO   |     | NULL    |       |
+---------+---------+------+-----+---------+-------+
16 rows in set (0.01 sec)

mysql>
```

Figure 9 SQL database structure for the self-diagnostic system.

4.3. User Interface

The user interface was developed in Java Swing within the NetBeans IDE, providing a real-time parameter monitoring panel displaying current sensor values with colour-coded status indicators (green: normal; amber: advisory; red: alarm), a strip-chart graphical trend display for each monitored parameter over a configurable time horizon, a fault event log table, a database query panel for historical data retrieval, and a report generation module producing printable PDF-format maintenance reports. The user interface communicates with the Notification Agent via JADE in-process messaging, receiving parameter update events and fault notifications for display without polling overhead.

5. Results and Validation

5.1. Sensor Environment Validation

The sensor environment was validated by connecting the sensors to the S7-1200 PLC trainer unit and injecting known test signals across the measurement range of each channel, as illustrated in Fig. 10. Normalisation and scaling functions were verified against reference values, confirming correct engineering unit conversion with a maximum deviation of ±0.5% of full-scale across all channels. OPC connectivity between the PLC and Top Server was confirmed at all configured sensor tag addresses, with data updates arriving at the OPC client within the 500 ms update rate specification.

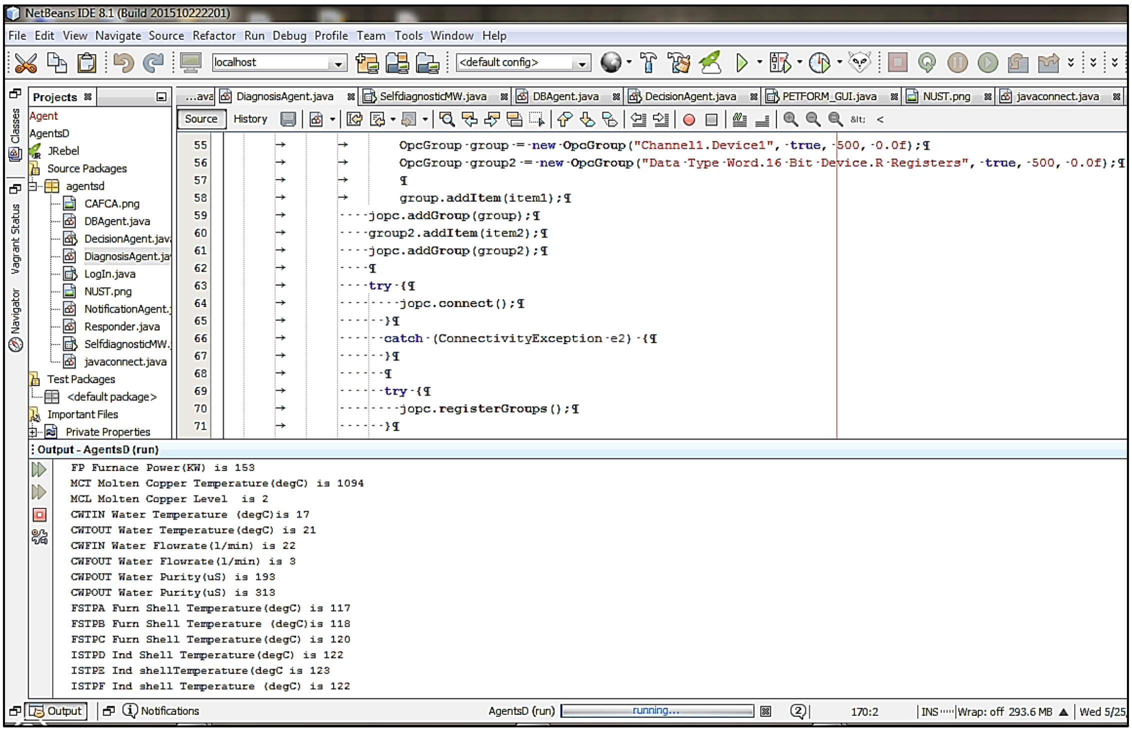

Figure 10 Diagnosis agent output — sensor readings retrieval.

5.2. Agent Communication and Diagnostic Functionality

Following deployment of the four agents on the JADE platform, agent registration with the DF service was confirmed via the JADE GUI sniffer tool. Agent communication flows were traced using the JADE message interceptor, confirming that: (i) the Diagnosis Agent successfully polled OPC tag values at each cyclic behaviour execution; (ii) ACL messages from the Diagnosis Agent reached the Decision Agent within the synchronous messaging latency of the JADE platform (typically under 10 ms on the local host); and (iii) the Decision Agent correctly dispatched commands to both the Database Agent and the Notification Agent upon receiving fault classification conclusions from JESS. The agent communication, based on what was revealed by the agent sniffer, is shown in Fig. 11.

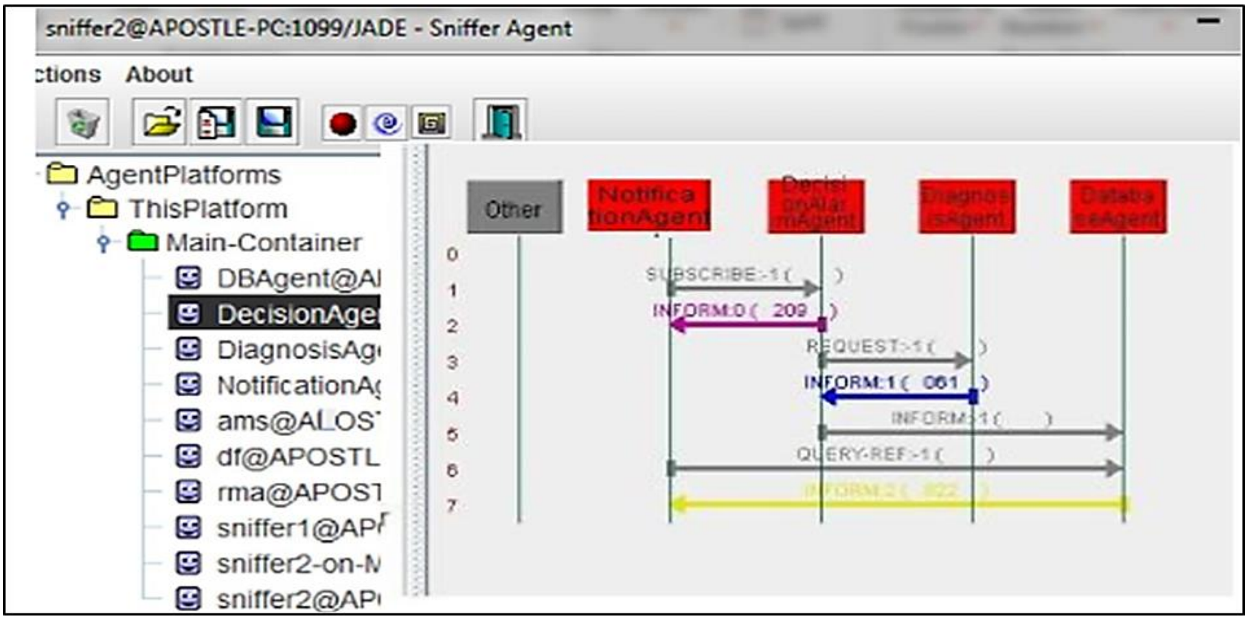

Figure 11 Agent sniffing.

Diagnostic functionality was validated by injecting out-of-range test values for each monitored parameter into the OPC server tag values, simulating the fault conditions encoded in the JESS rule base. All five fault categories, refractory overheating, cooling water flow failure, cooling water contamination, inductor power anomaly, and molten metal level extremes, were correctly detected and classified by the JESS engine. The correct diagnosis conclusion was asserted in working memory and propagated via ACL messaging to the Decision Agent in each case, triggering database logging and email notification dispatch. No false positive activations were observed during a 72-hour nominal operation test run with all parameters maintained within normal bounds. Fig. 12 shows the diagnostic system functionality in decision making.

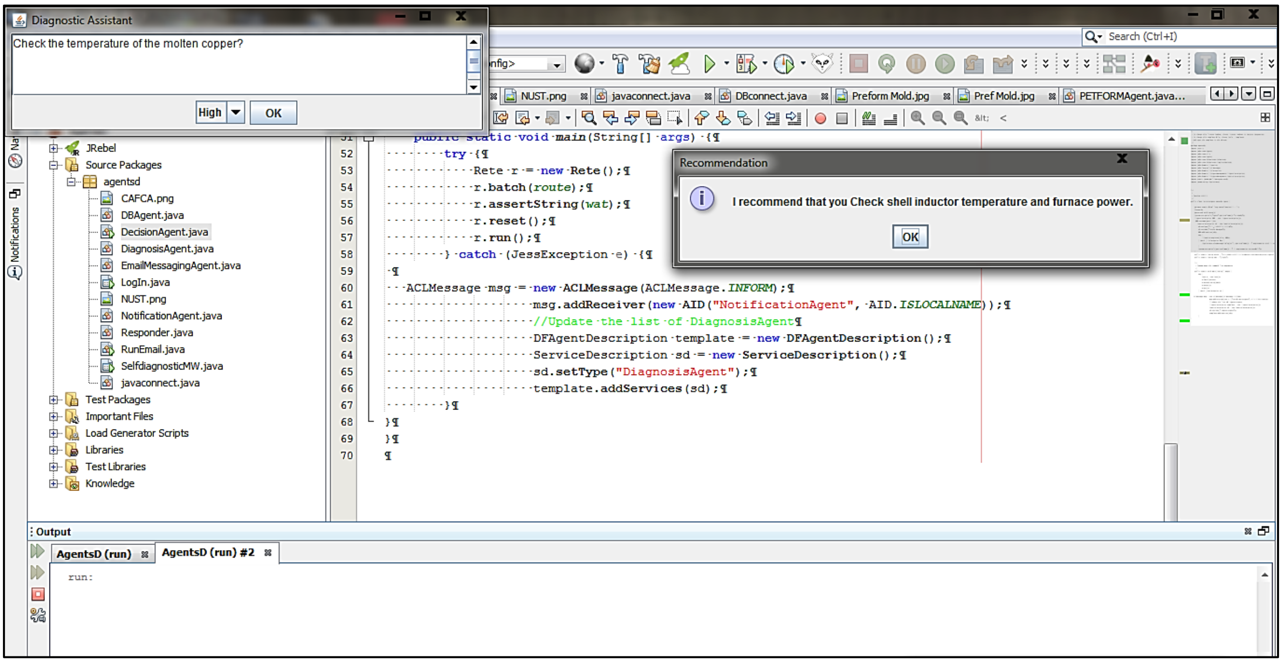

Figure 12 Diagnostic expert system output.

5.3. User Interface Performance

The user interface displayed real-time sensor values updated at each Notification Agent cycle, with graphical trend charts updating correctly as new readings were received, as shown in Fig. 13.

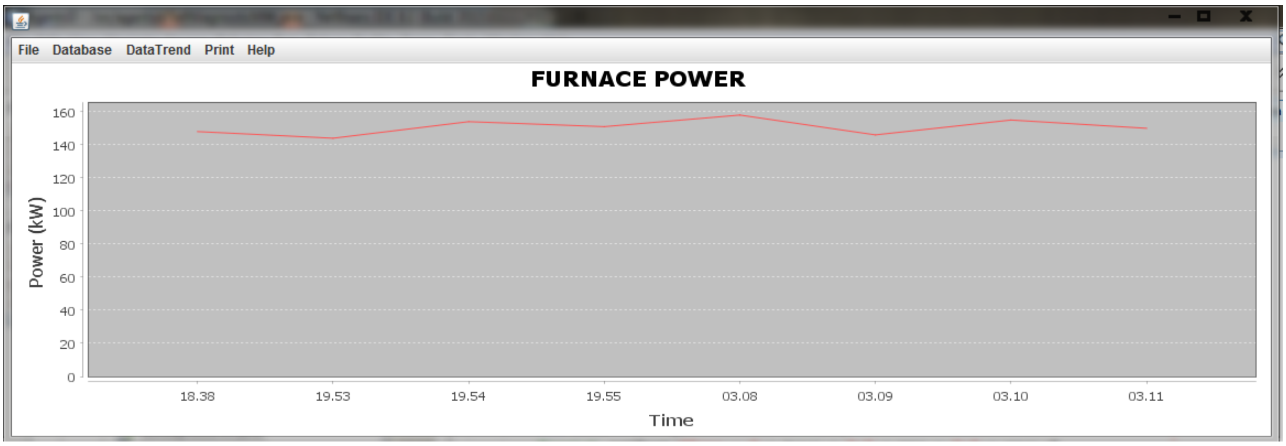

Figure 13 Graphical representation of system parameters.

Fault events generated during validation testing appeared in the fault log table within one display refresh cycle of the event's occurrence. The automated email notification function successfully delivered formatted fault alerts to the configured maintenance personnel email address, with message content including fault classification, parameter values, threshold exceedance magnitudes, and timestamp. The self-diagnostic system performance summary is given in Table 2.

Table 2 Self-diagnostic system performance summary.

Performance Metric	Test Condition	Result / Value
OPC data update latency	500 ms configured rate	≤ 500 ms (all tags)
Agent message latency (JADE)	Local host deployment	< 10 ms
Fault detection accuracy	5 injected fault scenarios	100% (5/5 correct)
False positive rate	72-hour nominal operation	0%
Sensor scaling accuracy	Full-scale signal injection	±0.5% max deviation
Email notification delivery	All fault event triggers	100% delivery rate
Discounted payback period	Based on the company's production data	3 months

5.4. Economic Analysis

A cost-benefit analysis was conducted based on cable manufacturing production data, maintenance cost records, and the capital and implementation costs of the self-diagnostic system. The primary cost inputs were: sensor hardware and installation (infrared temperature sensors, flow meters, conductivity transducers, and level sensors), S7-1200 PLC configuration, OPC server software licensing, and system commissioning and training costs. The primary benefit inputs were: avoided production loss from the September 2015 furnace failure (a 66% reduction in production output sustained for the furnace repair duration of approximately three weeks), avoided refractory replacement costs (estimated at 50% of a planned replacement when a failure is detected early), and reduced preventive maintenance frequency achievable through condition-based intervention.

The analysis yielded a discounted payback period of three months, a figure that is highly favourable relative to typical CBM system deployments, which commonly report payback periods of 6-18 months for comparable implementations [26]. The short payback period reflects both the severity of the 2015 furnace failure, which established a high baseline cost against which avoidable losses are measured, and the relatively modest instrumentation cost of the selected sensor suite.

6. Discussion

6.1. Contextualisation within Industry 4.0 CBM Developments

The system presented in this paper was designed and implemented in 2016 but embodies an architectural pattern that remains aligned with and relevant to current developments in intelligent maintenance. The sensor-PLC-OPC-MAS integration stack represents an early industry-aligned instantiation of what is now termed the IoT data acquisition pipeline in Industry 4.0 CBM frameworks [4]. The FIPA-compliant JADE agent architecture maps directly to the distributed, service-oriented agent communication paradigm that 58% of current enterprise MAS implementations employ [15]. The JESS rule engine provides the interpretable AI diagnostic reasoning that contemporary reviews identify as a persistent practical requirement in domains where training data is scarce, and explainability is mandated [16].

The most significant architectural limitation of the current system, viewed through the lens of current best practice, is its reliance on a single-node OPC server as the sole data pathway between the physical sensor environment and the agent platform. Modern Industry 4.0 implementations favour edge-cloud architectures with redundant data paths, streaming analytics, and cloud-based historical analytics platforms [4]. Retrofitting the current system to incorporate MQTT-based IoT messaging, cloud storage, and machine learning-augmented diagnostic models represents a natural and technically feasible evolution pathway.

6.2. Applicability to Developing Economy Industrial Contexts

A distinctive contribution of this work is its demonstration of a viable, economically justified CBM system in a developing economy context where the implementation challenges differ substantially from those addressed in the mainstream literature. At the cable manufacturing company, as at many comparable Zimbabwean manufacturers, maintenance practices are predominantly reactive, technical skills for advanced diagnostic system operation are limited, and capital investment thresholds are low. The self-diagnostic system addresses these constraints through: (i) a relatively low-cost sensor suite prioritising non-contact infrared and electromagnetic technologies that minimise ongoing maintenance requirements; (ii) a user interface designed for maintenance technicians rather than data scientists; and (iii) an automated email notification system that delivers actionable alerts without requiring users to actively monitor a SCADA-style display.

The three-month discounted payback period establishes the economic case clearly in the Zimbabwean context, where the per-unit cost of lost production from a furnace blowout is magnified by the difficulty of sourcing replacement refractory materials locally and the unavailability of fast-response maintenance contracting. Similar arguments apply to comparable manufacturing contexts across sub-Saharan Africa, and the present work offers a transferable reference architecture for CBM system deployment in these environments.

6.3. Limitations and Future Work

Several limitations of the current implementation should be acknowledged. First, the system was validated on a PLC trainer testbed rather than in live furnace operation at the cable manufacturing company, necessitated by the industrial constraints of live production system integration during the project period. Full in-situ validation under actual operating conditions, including high-temperature, high-electromagnetic-interference environments, remains as future work. Second, the JESS rule base was developed based on documented operational parameters and expert knowledge rather than a statistically trained fault model, meaning that its diagnostic accuracy in detecting novel or gradual degradation fault modes has not been empirically characterised. Third, the system currently lacks prognostic capability, that is, the ability to forecast the remaining useful life of monitored components, which the CBM literature identifies as the next evolutionary step beyond diagnostic capability [8, 4].

Future work directions include: (i) integration of machine learning-based anomaly detection as a complement to the JESS rule base to detect gradual degradation patterns; (ii) migration to an IIoT architecture with MQTT messaging, edge pre-processing, and cloud-based analytics; (iii) addition of vibration sensing on the inductor and transformer to extend fault coverage; (iv) extension of the system to monitor additional plant equipment beyond the furnace; and (v) development of a mobile application interface to deliver alerts and trend data to maintenance personnel smartphones via the GSM network.

7. Conclusion

This paper has presented the design, implementation, and validation of a multi-agent system-based self-diagnostic framework for real-time condition monitoring of induction furnace equipment, demonstrated in a Zimbabwean copper manufacturing context. The key findings of the work are as follows.

First, the integration of a heterogeneous sensor network with a Siemens S7-1200 PLC, OPC server, and JADE multi-agent platform is technically feasible and produces a coherent, responsive CBM system capable of detecting and classifying the principal fault modes of an induction furnace and its auxiliary cooling water and level control systems.

Second, the JADE-JESS integration, in which FIPA ACL messaging carries sensor readings to a JESS inference engine and returns diagnostic conclusions to the agent communication layer, provides a clean and practically effective implementation of agent-embedded expert system reasoning. All five target fault categories were correctly detected and classified in validation testing, with a zero false-positive rate in nominal operation.

Third, the system delivers tangible economic value in the specific industrial context studied, with a three-month discounted payback period reflecting the severity of furnace failure consequences and the modest implementation cost achievable with appropriate sensor technology selection.

Fourth, the work demonstrates that intelligent CBM systems meeting current Industry 4.0 architectural principles distributed agents, standardised communication protocols, interpretable AI reasoning, real-time data persistence, and alerting are achievable in developing economy industrial contexts with commercial off-the-shelf components and open-source software frameworks, at investment levels accessible to medium-sized manufacturers.

The architecture presented provides a replicable reference model for CBM system deployment across the African manufacturing sector, and the documented limitations point to a clear research and development agenda for future enhancements incorporating machine learning, IIoT connectivity, and prognostic capability.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there are no financial or personal relationships that could have inappropriately influenced the research, analysis, or interpretation presented in this paper.

Statement of ethical approval

The present research work does not contain any studies performed on animal or human subjects by any of the authors. The study involved the design, implementation, and testbed validation of an industrial condition-monitoring system, and no personal or patient data were used.

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