EXPERIMENTAL VALIDATION OF LOG-BASED DIAGNOSTIC METHODS FOR FREEZE-DRYING EQUIPMENT USING DISTRIBUTED LABORATORY TEST PLATFORM

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Abstract. Reliable operation of freeze-drying equipment used in agricultural and food-processing applications depends on coordinated performance of vacuum, thermal, and control subsystems. Early detection of abnormal operating conditions is essential to prevent process disruptions and product quality degradation. Log-based diagnostics provide a non-intrusive approach for monitoring complex equipment without modifying control algorithms. This paper presents an experimental validation of log-based diagnostic methods using a distributed laboratory test platform. The approach is based on event–telemetry correlation, where time-synchronized sensor data and control event logs are analysed to reconstruct system behaviour and detect deviations from expected process dynamics. A laboratory platform consisting of six simulator nodes was developed to emulate freeze-drying units under controlled conditions. The system enabled execution of normal operation, fault injection, and communication disturbance scenarios. In total, 21 fault scenarios were tested, including vacuum degradation, thermal instability, sensor anomalies, and control sequence inconsistencies. Experimental validation results demonstrate that the proposed diagnostic method achieved 100% detection of predefined fault scenarios after rule refinement, with no false-positive detections during extended normal operation tests. The system provided fault detection within 2–5 seconds after deviation occurrence. The platform operated with heterogeneous logging configurations, including sampling intervals of 0.1 s and 1 s across nodes, and relative timestamp precision of approximately 1 ms. Diagnostic functionality remained stable under communication conditions with millisecond-level latency. The results confirm that log-based diagnostics provide an effective, scalable, and non-intrusive solution for condition monitoring of distributed agricultural processing equipment.

Keywords: fault detection, log-based diagnostics, freeze-drying, distributed systems, condition monitoring.

1. Introduction

Modern agricultural and food-processing equipment is increasingly characterized by distributed and software-intensive systems. Freeze-drying installations represent a particularly demanding class of equipment, requiring precise coordination of vacuum, thermal, and control subsystems to ensure product quality and process stability [1; 2].

Traditional diagnostic approaches rely on direct integration with control systems or manual inspection. These methods are difficult to scale and may interfere with normal system operation. At the same time, small and medium manufacturers often lack the resources required for comprehensive verification and fault analysis procedures typical of high-integrity industries.

Log-based diagnostics provide a practical alternative by enabling reconstruction of system behaviour from operational data without modification of control logic. Such approaches are aligned with condition-based maintenance strategies and Industry 4.0 concepts [1; 3; 4]. The integration of IoT technologies further enhances the ability to collect and process operational data from distributed equipment [4; 5]. These developments support the transition toward intelligent and interconnected diagnostic systems. However, raw telemetry alone lacks sufficient context for reliable fault detection.

This work proposes a diagnostic approach based on **event–telemetry correlation**, where sensor data are interpreted together with control event logs [6]. This enables detection of anomalies that cannot be identified from either data source independently.

The objective of this study is to experimentally validate the proposed approach using a distributed laboratory test platform, emulating freeze-drying equipment.

The main contributions of this paper are:

- implementation of event-correlated log-based diagnostics within an FDIR framework;
- development of a distributed laboratory validation platform;
- experimental evaluation under controlled fault scenarios;
- assessment of robustness in distributed operating environments.

The overall system concept is illustrated in Fig. 1.

The following section describes the diagnostic method and its implementation.

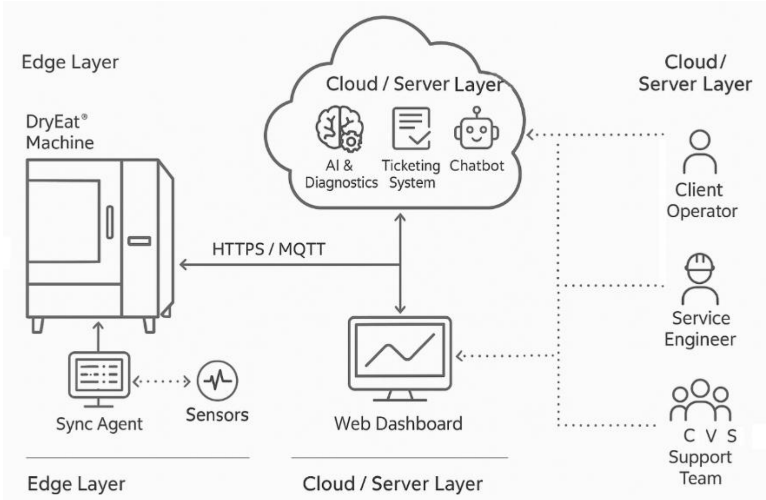

Fig. 1. **System concept**

2. Diagnostic method

The proposed diagnostic approach is based on the analysis of log data generated by distributed system nodes. Logs include time-stamped records of sensor values, control actions, and system events.

Log-based and data-driven diagnostic approaches are widely used in industrial monitoring systems, enabling detection of anomalies without direct access to internal control logic [1; 7; 8]. In contrast to purely data-driven methods, the proposed approach employs rule-based logic, providing transparency and interpretability.

Event–telemetry correlation

The core principle of the method is the correlation between control events and the measured system response. For example, during a vacuum phase, a control event ("pump activated") is recorded in logs, and telemetry provides pressure evolution over time.

A fault is detected when the expected system response (pressure decrease) does not occur within a defined time interval. This allows identification of anomalies that cannot be detected using threshold-based monitoring alone.

Machines are connected via a centralized service infrastructure enabling aggregation of telemetry and diagnostic data from distributed nodes. Advanced service tools may enable maintainers and customers to query machine status conversationally via messaging platforms and through user interfaces.

FDIR-based diagnostic logic

The diagnostic approach follows the Fault Detection, Isolation and Recovery (FDIR) paradigm established in aerospace and industrial automation [9].

Detection relies on correlating timestamped telemetry with event logs. Both data streams share a common time base, enabling precise alignment of sensor readings with control actions. By measuring elapsed time from a control event (e.g., "pump activated") to an expected state change (e.g., "pressure below threshold"), the system can detect anomalies that would be invisible to either data source alone.

Within the ČetriS system, the FDIR paradigm is implemented as follows.

- **Detection**: identification of abnormal system behaviour.
- **Isolation**: differentiation between possible root causes.
- **Recovery**: generation of appropriate system or operator actions.

Diagnostic rules are implemented in several categories: threshold, sequence, temporal, and consistency rules, corresponding to parameter limits, event order validation, timing constraints, and cross-parameter consistency.

The rule-based approach enables traceability, as each diagnostic decision can be linked to specific log entries and rule conditions.

Figure 2 illustrates the application of the method to a vacuum step scenario.

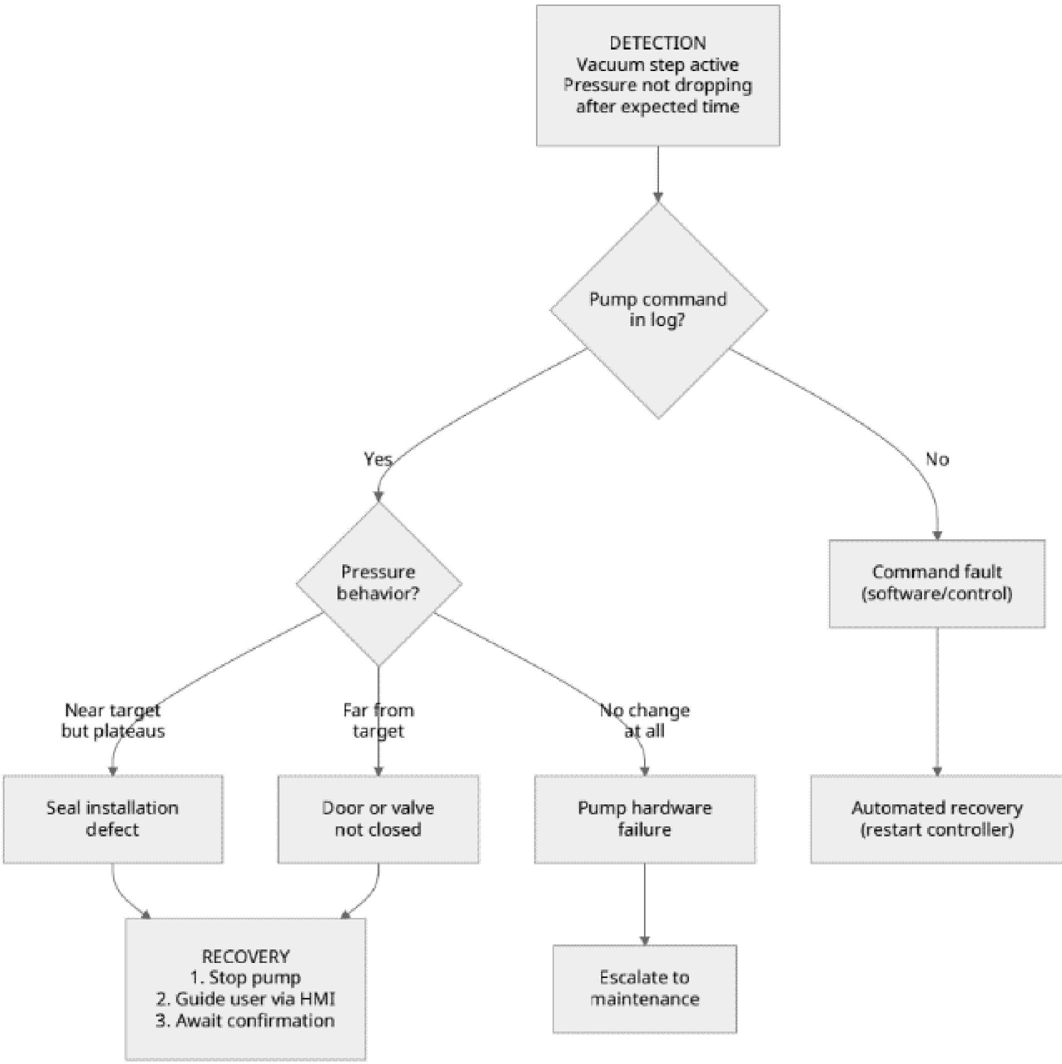

Fig. 2. **Example of FDIR Decision Flow-Fault detection, isolation and recovery flow vacuum step anomaly. Telemetry and log correlation enables differential diagnosis of root cause**

3. Laboratory test platform

To validate the proposed method, a distributed laboratory test platform was developed (Fig. 3).

The platform consists of six independent simulator nodes representing freeze-drying units. The nodes are interconnected via a TCP/IP network, forming a distributed system comparable to real deployments.

Each simulator node includes: an embedded control unit based on microcontroller or single-board computer platforms (ARM, Intel, and compatible architectures), a local human–machine interface (HMI) with a touch display, a communication module supporting TCP/IP data exchange, software components for process simulation, logging, and interaction with the diagnostic system.

The use of heterogeneous hardware (ARM and Intel platforms) enables cross-platform hardware-independent validation of the system and ensures independence from specific hardware configurations.

Each simulator node generates operational logs and telemetry data, which are processed locally and transmitted through the network. Diagnostic results, including alerts and recommendations, are displayed on the local interface.

In addition to automated diagnostics, the system includes a maintenance and deep-analysis mode, providing access to detailed system logs, manual inspection and analysis of process data, system control functions (restart, software update, configuration), prioritized control access with authentication mechanisms.

The developed platform enables simultaneous operation of multiple virtual machines, providing a scalable environment for testing distributed diagnostic methods under realistic conditions.

Fig. 3. **Laboratory test platform**

The platform includes a process emulator capable of simulating freeze-drying phases and events, generating realistic sensor data and injecting fault conditions.

A central management system enables coordinated scenario execution and data collection.

The experimental configuration and data acquisition parameters are defined as follows.

To ensure repeatability and quantitative evaluation of the proposed diagnostic method, the laboratory test platform was configured with defined operational and data acquisition parameters.

The distributed system consisted of six independent simulator nodes interconnected via a local TCP/IP network. Each node emulated a freeze-drying unit, including process logic, sensor behaviour, and control event generation. Nodes were implemented on heterogeneous embedded platforms representing typical AVR-, ARM-, and x86-based architectures, ensuring hardware-independent validation.

Each node generated two synchronized data streams: telemetry data (including pressure, temperature and system states) and event logs (including control actions and system events).

Data acquisition was performed using two configurations: nodes 1-3 operated with a sampling interval of 0.1 s, while nodes 4-6 operated with a sampling interval of 1 s.

All log entries were time-stamped using a common system clock, providing relative timestamp precision of approximately 1 ms. This enabled accurate alignment of telemetry and event data for correlation-based diagnostics.

Communication between nodes and the central processing system was performed under local network conditions with millisecond-level latency. Communication disturbance scenarios were emulated by introducing artificial delays, data loss, and temporary disconnections.

The experimental campaign included three scenario categories: normal operation, fault injection, and communication disturbances.

In total, 21 predefined fault scenarios were implemented. These included vacuum system degradation (e.g., insufficient pressure decrease), thermal instability, sensor anomalies (out-of-range values and noise), and control sequence inconsistencies.

Each scenario was executed multiple times across different nodes to verify consistency of diagnostic behaviour. Diagnostic performance was evaluated based on detection correctness, response time, absence of false positives, and robustness under communication disturbances.

4. Experimental methodology

Validation was conducted using predefined operational scenarios derived from real equipment behaviour.

Three categories of scenarios were implemented:

1. normal operation scenario: simulation of standard freeze-drying process stages with stable sensor readings and expected system behaviour;
2. fault injection scenario: introduction of abnormal conditions, including sensor anomalies (out-of-range values and noise), process deviations (temperature instability, incorrect phase transitions), and system-level faults (component malfunction simulation);
3. communication disturbance scenario: emulation of network-related issues such as temporary loss of connectivity, delayed data transmission, and incomplete data streams.

In total, 21 fault scenarios were tested under controlled conditions.

Each simulator node was configured independently, allowing simultaneous execution of different scenarios across the distributed system. Each node continuously generated logs including sensor measurements, control actions, system events, and communication status.

The diagnostic system was evaluated based on its ability to detect abnormal system behaviour, correctly identify fault conditions, generate appropriate alerts, and provide diagnostic recommendations. Both automated diagnostics and manual verification were applied, including rule-based analysis and manual inspection using the maintenance and deep-analysis mode.

Diagnostic performance was evaluated based on the following principles: correctness of fault detection, response time, absence of false positives, robustness under network disturbances.

Validation criteria were derived from project requirements and included reliability of data acquisition, correctness of fault detection, responsiveness of alert generation, robustness under communication disturbances, and consistency across hardware platforms.

The following sources of measurement uncertainty and platform limitations were identified.

The laboratory test platform is based on process simulation and software-generated telemetry, and therefore differs from real industrial systems in terms of physical measurement uncertainty. However, several sources of uncertainty relevant to diagnostic performance were identified and analysed.

The primary source of uncertainty is related to temporal resolution and synchronization. Although log entries were generated with a relative timestamp precision of approximately 1 ms, effective diagnostic resolution is influenced by the sampling interval of telemetry data (0.1 s and 1 s). This may introduce a delay in detecting rapid transient events, particularly in lower-resolution nodes.

A second source of uncertainty arises from communication effects. In the laboratory setup, network latency was within the millisecond range; however, communication disturbance scenarios included artificial delays, packet loss, and temporary disconnections. These conditions may affect the completeness and timing of available data, potentially influencing diagnostic response time but not detection capability.

Model-based simulation of process variables introduces an additional limitation. While the emulator reproduces expected system dynamics and fault patterns, it cannot fully capture all physical phenomena present in real freeze-drying processes, such as complex heat and mass transfer effects or hardware-specific nonlinearities.

To minimise the impact of these uncertainties, the diagnostic method is based on event–telemetry correlation over time intervals rather than instantaneous measurements. This reduces sensitivity to short-term fluctuations, noise, and timing jitter. In addition, diagnostic rules incorporate temporal thresholds and consistency checks, improving robustness under varying data quality conditions.

The use of heterogeneous sampling rates across nodes provided additional validation of method stability. Consistent diagnostic performance across different temporal resolutions indicates that the approach is not critically dependent on high-frequency data acquisition.

Overall, while the laboratory platform does not replicate all aspects of real industrial systems, it provides a controlled and repeatable environment for systematic validation of diagnostic logic. The identified limitations do not affect the correctness of fault detection but may influence detection latency under certain conditions.

5. Results and analysis

The experimental validation was carried out using the developed platform under the scenarios defined in Section 4. The results demonstrate the capability of the log-based diagnostic approach to detect abnormal conditions and support system analysis in a distributed environment. Stable system operation under normal conditions and reliable detection of fault scenarios were confirmed. The diagnostic system identified abnormal sensor values, deviations in process sequences, and simulated equipment faults.

To support the qualitative analysis, the diagnostic performance was evaluated using quantitative indicators derived from the experimental scenarios. The results are summarised in Table 1.

Table 1

Diagnostic performance metrics under experimental conditions

Metric	Value	Description
Number of simulator nodes	6	Distributed test platform
Number of fault scenarios	21	Predefined and repeatable
Fault detection rate	100%	All fault scenarios successfully detected
False positive rate	0%	No false alarms during normal operation
Detection time	2-5 s	Time from fault occurrence to detection
Sampling interval	0.1 s/1 s	High and standard-resolution nodes
Timestamp precision	~1 ms	Relative synchronization accuracy
Communication latency	ms-level	Local network conditions
Robustness to disturbances	High	Maintained functionality under delay/loss
Cross-platform consistency	Confirmed	Same behaviour across hardware types

The quantitative results confirm that the proposed diagnostic approach provides reliable and stable performance under all tested conditions. In particular, the absence of false-positive detections during extended normal operation demonstrates robustness of the rule-based logic, while the consistent detection time across different sampling configurations indicates low sensitivity to data acquisition parameters.

The results also show that communication disturbances primarily affect detection latency rather than detection correctness, confirming the suitability of the method for distributed environments with non-ideal network conditions.

All 21 fault scenarios were successfully detected following iterative rule refinement. Normal operation produced no false positives across extended test runs. These results align with established findings in industrial condition monitoring, where rule-based approaches offer transparency advantages over black-box machine learning methods [1; 8].

Normal operation: during nominal scenarios, all six nodes executed freeze-drying process phases with stable sensor readings and expected state transitions. The diagnostic system correctly identified normal conditions and produced no false-positive alerts. Log synchronization across the distributed platform remained consistent throughout extended test runs.

Fault detection: fault injection scenarios validated each rule category. For example, the vacuum step anomaly (Fig. 2) triggered correctly when pressure failed to drop within expected time, with the system isolating root causes (seal defect, valve issue, or pump failure) based on log correlation. Alerts were generated within seconds of detection, and diagnostic recommendations supported operator response. The system detected sensor anomalies, process deviations, and simulated equipment faults.

Event–telemetry correlation enabled differentiation between fault types, improving diagnostic precision compared to threshold-based methods.

Communication disturbances: the system maintained functionality under network disruptions, with delayed but consistent data transmission and preserved log integrity. Diagnostic functionality remained operational under partial data availability, confirming suitability for distributed environments.

Cross-platform consistency: diagnostic behaviour remained consistent across heterogeneous hardware platforms, confirming system scalability.

These results are consistent with established approaches in industrial condition monitoring, where rule-based methods provide reliable fault detection and high interpretability [1; 8]. Compared to machine learning-based approaches [7; 10], the rule-based method offers higher transparency and simpler implementation in early-stage systems.

6. Discussion

The results demonstrate that the proposed log-based diagnostic approach provides an effective and non-intrusive solution for monitoring distributed agricultural processing equipment. The integration of event–telemetry correlation within an FDIR framework enables reliable detection and interpretation of abnormal system behaviour without requiring modification of control algorithms.

A key advantage of the proposed approach lies in its non-intrusive nature, allowing deployment on existing equipment without redesign of control systems. This is particularly important for small and medium manufacturers, where access to full system-level verification and diagnostic infrastructures is limited. In such contexts, the presented method provides a practical pathway to improve operational reliability without significant additional system complexity.

Another important aspect is the transparency of rule-based diagnostics. Unlike machine learning approaches, where diagnostic decisions may be difficult to interpret, the proposed method ensures traceability by linking each decision to specific log entries and rule conditions. This is critical for engineering validation, troubleshooting, and certification-related activities.

At the same time, the results highlight the complementary role of rule-based and data-driven approaches. While machine learning methods [7; 10] offer advantages in handling large-scale datasets and complex patterns, they typically require extensive training data and computational resources. In contrast, the proposed rule-based approach is well suited for early-stage systems (TRL4–5), where data availability is limited and system behaviour is still being characterized.

The use of a distributed laboratory platform enabled systematic validation under controlled conditions, including fault injection and communication disturbances. This confirms the robustness of the approach in distributed environments, where network instability and partial data availability are common challenges. The ability to maintain diagnostic functionality under such conditions is essential for real-world deployment.

From a system engineering perspective, the proposed approach can be interpreted as a form of operational-level DFMEA (Design Failure Mode and Effects Analysis), where fault detection rules are derived from expected system behaviour and continuously refined based on observed data. This provides a structured methodology for evolving diagnostic capabilities alongside system development.

The scalability of the approach is demonstrated through consistent behaviour across heterogeneous hardware platforms and multiple simulator nodes. This indicates that the method can be extended to fleet-level monitoring of distributed equipment, supporting Industry 4.0 concepts of interconnected and intelligent systems.

Despite these advantages, several limitations were identified. The rule-based approach depends on predefined fault scenarios and may require iterative refinement as new failure modes are observed. In addition, laboratory validation cannot fully replicate the variability and complexity of real industrial environments. Finally, diagnostic performance depends on the quality and completeness of log data.

Future work should focus on hybrid diagnostic approaches, combining rule-based methods with data-driven techniques to improve adaptability and detection accuracy. Integration with real industrial systems and long-term operational validation will be essential for further development and commercialization.

Conclusions

1. The developed distributed laboratory platform, consisting of six simulator nodes, enabled repeatable experimental validation of log-based diagnostic methods for freeze-drying equipment under controlled conditions.

2. The proposed event–telemetry correlation approach demonstrated reliable fault detection capability, achieving 100% detection of all 21 predefined fault scenarios after rule refinement.
3. The diagnostic system showed high robustness during normal operation, with no false-positive detections observed across extended test runs.
4. Fault detection was achieved within 2–5 seconds after deviation occurrence, confirming the suitability of the method for near real-time monitoring applications.
5. The diagnostic approach maintained functionality under communication disturbances, indicating applicability in distributed environments with non-ideal network conditions.
6. The use of heterogeneous sampling configurations (0.1 s and 1 s) did not significantly affect diagnostic correctness, demonstrating low sensitivity to data acquisition parameters.
7. The results confirm that log-based diagnostics provide a scalable and non-intrusive solution for condition monitoring of distributed agricultural processing equipment, particularly suitable for small and medium-scale systems.

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Author contributions:

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