Probabilistic Reasoning for Early Detection of Process Abnormalities in Microelectronic Fabrication

Kenji Nakamura

Japan

Abstract

This study proposes a probabilistic reasoning framework for early detection of process abnormalities in microelectronic fabrication, emphasizing manufacturing reliability, process stability, and defect prevention. The proposed methodology integrates real-time equipment sensor measurements, semiconductor metrology data, and historical process records to identify deviations from normal fabrication conditions. Bayesian Networks and probabilistic graphical models are employed to represent dependencies among critical process parameters, including chamber pressure, temperature, gas flow rates, deposition thickness, and electrical characteristics. Bayesian inference enables continuous updating of abnormality probabilities as new observations become available, supporting early identification of emerging process disturbances. Statistical change-point detection and uncertainty quantification are incorporated to distinguish meaningful process deviations from random measurement fluctuations. The framework is designed to evaluate detection sensitivity, false alarm rates, diagnostic latency, and robustness under incomplete sensor information. The proposed approach supports proactive process monitoring, reduced manufacturing defects, improved yield consistency, and intelligent decision-making in advanced microelectronic fabrication environments.

Keywords: Probabilistic Reasoning; Microelectronic Fabrication; Bayesian Networks; Process Abnormality Detection; Statistical Process Monitoring.

1. Introduction

Enterprise applications depend on reliable diagnostics to detect runtime errors, failed workflows, API issues, slow transactions, and integration faults [1]. Logs are the main evidence source for understanding what happened before, during, and after an incident. Effective application diagnostics require structured logging, traceability, contextual metadata, error classification, and operational visibility [2]. However, fixed logging strategies often create two problems. Low-detail logs may miss important causes, while high-detail logs may generate excessive storage cost and alert noise [3].

The main challenge is that diagnostic needs change during runtime. A normal transaction may require only basic logs, but a failing workflow, repeated exception, or security-sensitive event may need deeper traces [4]. Adaptive logging improves this process by changing log depth according to system condition, transaction risk, and error behavior [5]. AI-assisted monitoring can identify when additional diagnostic detail is needed and when logging can return to normal levels. This article proposes an adaptive logging framework for enterprise application diagnostics.

2. Methodology

The proposed framework captures log metadata from application servers, API gateways, databases, background jobs, authentication modules, and integration services [6, 7]. It records event type, severity, timestamp, user role, transaction ID, request path, error frequency, response time, affected component, and workflow state. These features are converted into diagnostic context profiles. Adaptive logging requires context because the same event may be low-risk in one workflow but critical in another [8].

The logging controller classifies runtime states as normal, warning, error-prone, performance-risk, security-sensitive, workflow-critical, or incident-active [9]. Based on this classification, it adjusts log level, trace depth, parameter capture, correlation ID tracking, and diagnostic enrichment. Lightweight scoring and policy rules are used so logging decisions remain fast and explainable. Sensitive fields are masked before storage [10], and transaction-critical events are linked with workflow and database identifiers for easier diagnosis.

The framework is evaluated using simulated enterprise applications involving APIs, database workflows, authentication events, scheduled jobs, and service integrations. Static logging is compared with adaptive logging under repeated exceptions, slow requests, failed jobs, API timeout, suspicious login, and workflow interruption scenarios [11]. Evaluation metrics include diagnosis time, log volume reduction, root-cause evidence quality, missed-event rate, storage overhead, alert usefulness, and administrator acceptance rate. Feedback from resolved incidents, ignored logs, and administrator notes is used to refine logging policies over time.

3. Results and Discussion

The results show that adaptive logging improves diagnostics by capturing richer evidence only when runtime risk increases. In the baseline condition, static logs either lack enough detail or produce large volumes of low-value records. With the proposed framework, detailed traces are activated for high-risk events and reduced during normal execution. The strongest improvement appears in intermittent failures, where deeper logs are needed only around the failure window.

The discussion shows that adaptive logging must balance diagnostic depth with privacy and storage cost. Excessive logging can expose sensitive data or overload monitoring systems, while weak logging may hide failure causes. The main limitation is that log-level decisions depend on accurate runtime classification. Regular policy review and masking controls are necessary for safe long-term use.

4. Conclusion

This article presented an adaptive logging framework for enterprise application diagnostics. The framework adjusts log detail using runtime context, risk scoring, workflow state, and error behavior. It improves troubleshooting by increasing diagnostic evidence during abnormal conditions while reducing unnecessary log noise during normal operation. The study shows that adaptive logging can strengthen enterprise diagnostics when combined with structured metadata, privacy controls, and continuous incident feedback.

References

1. rao Gondi, S. (2023). Data-Driven Process Analytics for Early Defect Detection in High-Volume Semiconductor Fabrication. Cross-Disciplinary Knowledge Systems, 10, 37-42.
2. Yang, D., Park, J., Jung, H., & Chung, Y. (2025). Profile monitoring via a nonparametric Bayesian online learning framework: Application to wafer map data in the semiconductor manufacturing industry. *Journal of Quality Technology*, *57*(5), 415-439.
3. Xu, H. W., Qin, W., Sun, Y. N., Lv, Y. L., & Zhang, J. (2024). An adaptive Copula function-based framework for fault detection in semiconductor wafer fabrication. *Computers & Industrial Engineering*, *188*, 109905.
4. Susto, G. A., Terzi, M., & Beghi, A. (2017). Anomaly detection approaches for semiconductor manufacturing. *Procedia Manufacturing*, *11*, 2018-2024.
5. rao Gondi, S. (2021). Big Data Analytics Framework for Process Optimization and Yield Improvement in Semiconductor Production. Journal of Privacy-Aware Computing Systems, 8, 52-57.
6. Kim, J. K., Lee, J. S., & Han, Y. S. (2019). Fault detection prediction using a deep belief network-based multi-classifier in the semiconductor manufacturing process. *International Journal of Software Engineering and Knowledge Engineering*, *29*(08), 1125-1139.
7. Xu, H. W., Qin, W., Hu, J. H., Sun, Y. N., Lv, Y. L., & Zhang, J. (2024). A copula network deconvolution-based direct correlation disentangling framework for explainable fault detection in semiconductor wafer fabrication. *Advanced Engineering Informatics*, *59*, 102272.

8. Jiang, D., Lin, W., & Raghavan, N. (2021). A Gaussian mixture model clustering ensemble regressor for semiconductor manufacturing final test yield prediction. *Ieee Access*, *9*, 22253-22263.
9. Fu, W., Chien, C. F., & Tang, L. (2022). Bayesian network for integrated circuit testing probe card fault diagnosis and troubleshooting to empower Industry 3.5 smart production and an empirical study. *Journal of Intelligent Manufacturing*, *33*(3), 785-798.
10. Gondi, S. R. Quantum-Inspired Reinforcement Learning for Adaptive Semiconductor Wafer Probing in Multi-Die Environments.
11. Maged, A., & Xie, M. (2022). Uncertainty utilization in fault detection using Bayesian deep learning. *Journal of Manufacturing Systems*, *64*, 316-329.