Adaptive Energy Scheduling for Battery Storage and Solar Photovoltaic Systems Using Predictive Analytics

Lars Johansson

Sweden

Abstract

This study proposes an adaptive energy scheduling framework for integrated battery storage and solar photovoltaic systems using predictive analytics to improve renewable energy utilization, operational efficiency, and power supply reliability. The proposed methodology combines solar generation forecasting, electricity demand prediction, and battery state-of-charge estimation within an intelligent energy management architecture. Machine learning algorithms are employed to predict short-term photovoltaic output and load variations using historical generation records, meteorological conditions, and consumption patterns. A model predictive control strategy dynamically optimizes battery charging and discharging schedules based on forecasted energy availability, electricity tariffs, battery degradation constraints, and operational requirements. The optimization framework aims to minimize grid dependency, energy costs, and unnecessary battery cycling while maintaining system stability. Performance evaluation considers forecasting accuracy, renewable energy self-consumption, peak demand reduction, battery utilization, and scheduling efficiency. The proposed approach supports sustainable energy management and reliable operation of distributed solar photovoltaic and battery storage systems.

Keywords: Adaptive Energy Scheduling; Solar Photovoltaic Systems; Battery Energy Storage; Predictive Analytics; Model Predictive Control.

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, 5]. Adaptive logging improves this process by changing log depth according to system condition, transaction risk, and error behavior [6]. 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 [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, 10]. 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 [11], 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 [12]. 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. Sorour, A., Fazeli, M., Monfared, M., Fahmy, A. A., Searle, J. R., & Lewis, R. P. (2021). Forecast-based energy management for domestic PV-battery systems: A UK case study. *Ieee Access*, *9*, 58953-58965.
2. Nair, U. R., Sandelic, M., Sangwongwanich, A., Dragičević, T., Costa-Castello, R., & Blaabjerg, F. (2021). An analysis of multi objective energy scheduling in PV-BESS system under prediction uncertainty. *IEEE Transactions on Energy Conversion*, *36*(3), 2276-2286.
3. Sorour, A., Fazeli, M., Monfared, M., Fahmy, A., Searle, J., & Lewis, R. (2021, October). Enhancing Self-consumption of PV-battery Systems Using a Predictive Rule-based Energy Management. In *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)* (pp. 1-6). IEEE.
4. rao Gondi, S. (2023). Data-Driven Process Analytics for Early Defect Detection in High-Volume Semiconductor Fabrication. Cross-Disciplinary Knowledge Systems, 10, 37-42.
5. Hua, W., Jiang, J., Sun, H., Tonello, A. M., Qadrdan, M., & Wu, J. (2022). Data-driven prosumer-centric energy scheduling using convolutional neural networks. *Applied Energy*, *308*, 118361.
6. Tobajas, J., Garcia-Torres, F., Roncero-Sánchez, P., Vázquez, J., Bellatreche, L., & Nieto, E. (2022). Resilience-oriented schedule of microgrids with hybrid energy storage system using model predictive control. *Applied Energy*, *306*, 118092.
7. Gondi, S. R. (2023). AI-Assisted Fault Localization in Semiconductor Wafer Testing and Manufacturing Operations. Perception, Navigation and Intelligent Devices, 10, 1-8.

8. Guo, M., Ren, M., Chen, J., Cheng, L., & Yang, Z. (2023). Tracking photovoltaic power output schedule of the energy storage system based on reinforcement learning. *Energies*, *16*(15), 5840.
9. Aksan, F., Suresh, V., & Janik, P. (2024). Optimal capacity and charging scheduling of battery storage through forecasting of photovoltaic power production and electric vehicle charging demand with deep learning models. *Energies*, *17*(11), 2718.
10. Cao, X., Yang, X., Li, L., Shen, L., Ma, W., Yang, R., & Zou, H. (2024). Prediction model-assisted optimization scheduling strategy for renewable energy in the microgrid. *Processes*, *12*(9), 1786.
11. Kim, S., & Lee, J. (2024). Optimal scheduling strategy for distribution network with mobile energy storage system and offline control PVs to minimize the solar energy curtailment. *Energies*, *17*(9), 2234.
12. rao Gondi, S. (2025). Multi-Modal AI-Driven Electrical and Optical Characterization Framework for Sub-5 nm Semiconductor Defect Localization. Research Briefs on Information and Communication Technology Evolution, 11, 188-198.