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Research on PIMS System Upgrade and Development of Heat Consumption Deviation Analysis System in PLTU Kendari-3

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ABSTRACT

The increasing complexity of thermal power plant operations requires advanced digital systems capable of managing large-scale operational data to improve efficiency, reliability, and intelligent maintenance. The limitations of conventional Plant Information Management Systems (PIMS), including restricted data storage capacity, inadequate integration with Distributed Control Systems (DCS), and limited analytical capabilities, hinder effective operational decision-making. This study aimed to upgrade the PIMS infrastructure and develop an integrated heat consumption deviation analysis system supported by machine learning technology at PLTU Kendari-3. The research employed an applied engineering research design involving system diagnosis, hardware and software upgrades, DCS-PIMS integration, historical data migration, analytical module development, and post-implementation performance verification. The results showed that the upgraded PIMS successfully expanded historical data storage capacity from 90 days to more than five years, enabled real-time data integration, and provided automated heat consumption deviation analysis. Furthermore, the developed machine learning model achieved equipment fault prediction accuracy exceeding 85%. The implementation also contributed to an approximately 3% improvement in unit operating efficiency, a 5–8% reduction in maintenance costs, and an estimated 3–5-year extension of equipment service life. This study concludes that integrated PIMS modernization combined with intelligent analytics can significantly enhance thermal power plant operations and provide a practical framework for digital transformation toward intelligent operation and maintenance.

INTRODUCTION

With the continuous expansion of large-scale and intensive thermal power unit operations, production data has become a critical foundation for safe operation, economic dispatch, and refined management (Lin et al., 2025; Zang et al., 2024; Zheng et al., 2025). As the core platform for centralized production data management and analysis, the functionality, data storage capacity, and analytical capabilities of the Plant Information Management System (PIMS) directly influence the scientific basis and timeliness of operational decision-making in power plants. Reviews of maintenance practices in the power sector confirm that the transition from traditional engineering-knowledge-based maintenance toward IT-enabled and analytics-driven approaches has become a defining trend in modern plant management, primarily because centralized production data platforms facilitate this transformation (Moleda et al., 2023). This trend is further supported by case studies demonstrating that structured, data-driven operational management based on comprehensive production data platforms can measurably improve the thermal efficiency of large coal-fired units without requiring major hardware replacements (Ashraf et al., 2020).

The existing PIMS system at Kendari Power Plant was deployed at an early stage and is constrained by outdated hardware architecture and system design (Amannah, 2025; Lin et al., 2025). Historical data retention is limited to only 90 days, access depends on discontinued browser environments, and the platform lacks integrated analytical functions, requiring manual statistical processing for most operational analyses. This condition reflects a broader challenge identified in industrial data integration literature: legacy production monitoring platforms are often developed using inconsistent interface standards and proprietary data models, limiting real-time interoperability between distributed control systems and higher-level information platforms unless standardized communication protocols are deliberately implemented (Ioana & Korodi, 2021). Maintenance practice studies further indicate that platforms limited to data visualization without integrated diagnostic or predictive capabilities force plant personnel to rely on reactive, post-event analysis rather than proactive, condition-based approaches enabled by modern production data platforms (Moleda et al., 2023).

Among the analytical functions absent from the existing system, heat consumption (heat rate) deviation analysis is particularly important for operational management because even minor deviations in key operating parameters from design or commissioning baselines can directly increase fuel consumption and reduce unit efficiency. Detailed heat rate deviation studies of coal-fired power units have shown that specific equipment components, such as air heaters and feedwater heaters, can be ranked based on their contribution to overall heat rate deviation, providing plant management with a prioritized and financially quantified basis for maintenance decisions (Manmit Singh Jasbeer Singh et al., 2023). Similar deviation analysis conducted at an Indonesian coal-fired power plant, using a production data platform to compare actual performance test results with commissioning baselines, identified specific contributors to increased net plant heat rate and provided concrete recommendations for efficiency improvement (Yohanes et al., 2024). These findings demonstrate that heat consumption deviation analysis is most effective when integrated directly into a reliable, high-resolution production data platform rather than conducted as an independent periodic assessment.

Beyond deviation analysis, the integration of machine learning into production data platforms has increasingly supported equipment fault prediction and condition monitoring in thermal power plants (Deon et al., 2022; Garcia et al., 2025; Islam, 2025; Maican et al., 2025). Deep-learning-based condition monitoring frameworks applied to power plant auxiliary equipment have demonstrated that models trained using historical operational data can provide early fault warnings through adaptive thresholds, improving detection sensitivity and warning lead times compared with fixed-threshold approaches (Li et al., 2023). Similarly, machine learning algorithms trained on cleaned historian-derived process data have been used to predict thermal power plant process variables and identify abnormal operating conditions before they develop into equipment failures (Sultanov et al., 2022). Both approaches require sufficiently large and high-quality historical datasets, which is precisely the capability lacking in the existing Kendari Power Plant PIMS with its limited 90-day data retention period.

Despite the increasing importance of digital transformation, many existing thermal power plants continue to operate with legacy information systems that have limited analytical capabilities and insufficient integration with modern control systems. Similar challenges are observed at PLTU Kendari-3, where the existing PIMS architecture faces several limitations, including restricted historical data storage of only 90 days, dependence on outdated browser environments, limited system interoperability, and the absence of integrated analytical functions for operational optimization. These limitations reduce the ability of operators and engineers to conduct comprehensive performance evaluations, identify efficiency losses, and implement proactive maintenance strategies (Bafandegan Emroozi et al., 2024; Firdaus et al., 2023; Rakyta et al., 2024; West et al., 2024). Furthermore, operational analysis remains heavily dependent on manual statistical processing, resulting in delayed decision-making and increasing the risk of inefficiencies caused by undetected equipment degradation or abnormal operating conditions.

One of the most significant operational challenges in thermal power plants is maintaining optimal heat consumption performance (Chen et al., 2023; Soomar et al., 2022; Wang et al., 2022). Heat consumption deviation represents the difference between actual energy consumption and the expected optimal performance baseline, directly affecting fuel consumption, generation costs, and overall plant efficiency. Even relatively small deviations in operational parameters can result in substantial economic losses when accumulated during continuous large-scale operation. Previous studies have emphasized the importance of heat rate deviation analysis in identifying the primary contributors to efficiency degradation. Manmit Singh Jasbeer Singh et al. (2023) demonstrated that heat rate deviation analysis could prioritize equipment-related factors affecting thermal efficiency and provide a quantitative basis for maintenance decisions. Similarly, Yohanes et al. (2024) applied production-data-based analysis at an Indonesian coal-fired power plant and successfully identified contributing factors associated with increased net plant heat rate. However, these studies primarily focused on analyzing available operational data rather than improving the underlying data management infrastructure required to support such analysis.

In addition to performance optimization, the integration of machine learning into power plant information systems has emerged as an important approach for predictive maintenance and intelligent operation. Traditional maintenance strategies that rely on corrective actions after equipment failures are gradually being replaced by predictive approaches supported by historical operational data and artificial intelligence algorithms. Moleda et al. (2023) emphasized that the transition from corrective maintenance toward predictive maintenance in the power industry requires reliable data platforms capable of supporting continuous monitoring and advanced analytics. Furthermore, Li et al. (2023) developed a deep-learning-based condition monitoring framework for power plant auxiliary equipment and demonstrated that machine learning models using adaptive thresholds could improve early fault detection capabilities. Sultanov et al. (2022) also confirmed that machine learning algorithms trained using historical process data can predict thermal power plant conditions and identify abnormal operational patterns before failures occur.

Although previous studies have provided valuable insights into heat consumption analysis and machine learning applications, several research gaps remain. First, existing studies generally examine analytical models or optimization techniques using established and mature data platforms, while limited research has addressed the comprehensive modernization process required to develop such platforms. Second, previous research rarely integrates hardware upgrades, Distributed Control System (DCS)-PIMS communication enhancement, historical data migration, heat consumption deviation analysis, and machine learning-based fault prediction within a single operational transformation framework. Third, limited empirical evidence exists regarding how PIMS modernization can be implemented in an operating thermal power plant without disrupting production activities. Therefore, further research is needed to investigate an integrated approach that combines information system modernization and intelligent analytical development as a unified strategy for improving thermal power plant operational performance.

The urgency of this research is reinforced by the increasing demand for power plants to achieve higher efficiency, reliability, and competitiveness amid energy transition challenges. Thermal power plants must optimize existing assets while simultaneously reducing operational costs and improving maintenance effectiveness. Without adequate digital infrastructure, the large volumes of operational data generated by modern power plants cannot be effectively utilized to support strategic decision-making. The limitations of outdated PIMS systems may prevent operators from identifying hidden inefficiencies, predicting equipment failures, and implementing proactive optimization strategies. Therefore, upgrading PIMS infrastructure is not merely a technological improvement but a necessary transformation to support intelligent operation and maintenance practices in contemporary power generation systems.

This research introduces a novel approach by presenting an integrated framework for PIMS modernization combined with heat consumption deviation analysis and machine learning implementation at PLTU Kendari-3. Unlike previous studies that mainly focus on individual analytical methods, this study examines the complete transformation process, including hardware capacity enhancement, system architecture upgrades, Distributed Control System (DCS)-PIMS integration, historical data migration, development of real-time deviation analysis modules, and predictive modeling based on operational data. This research demonstrates how an outdated production information system can be transformed into an intelligent operational platform capable of supporting efficiency improvement and predictive maintenance. The implementation approach also provides practical insights into conducting digital transformation within an operational power plant environment while maintaining production continuity.

The main objective of this research was to design, implement, and evaluate an upgraded PIMS system integrated with heat consumption deviation analysis and machine learning-based operational intelligence at PLTU Kendari-3. Specifically, this research aimed to identify limitations in the existing PIMS architecture, develop an improved data management platform, establish reliable integration between DCS and PIMS, develop analytical functions for heat consumption deviation monitoring, and evaluate the effectiveness of machine learning models in supporting equipment fault prediction. Through these objectives, this research sought to provide empirical evidence regarding the effectiveness of integrated digital transformation in improving thermal power plant operations.

The contribution of this research lies in both academic and practical dimensions. Academically, this study expands existing knowledge regarding digital transformation in the power generation sector by demonstrating the relationship between information system modernization, operational analytics, and intelligent maintenance capabilities. Practically, this research provides a replicable implementation model for other thermal power plants facing similar challenges related to legacy systems, limited data availability, and inefficient maintenance approaches. The improvements achieved at PLTU Kendari-3, including the expansion of historical data storage from 90 days to more than five years, implementation of real-time deviation analysis, machine learning prediction accuracy exceeding 85%, approximately 3% improvement in operating efficiency, and a 5–8% reduction in maintenance costs, demonstrate the potential benefits of integrated PIMS modernization. Ultimately, this research contributes to the development of smarter, more efficient, and more sustainable power plant management systems aligned with the principles of Industry 4.0.

METHOD

Research Design

This study employed an applied engineering research design based on a real PIMS modernization project at Kendari Power Plant, integrating system diagnostic assessment, phased engineering implementation, and post-implementation performance verification. The research followed a sequential technical process involving hardware upgrades, platform deployment, system integration, functional development, and application verification. This approach was selected because the effectiveness of a production data platform upgrade could only be confirmed through evaluation of actual system performance and operational outcomes before and after implementation under real operating conditions.

System Diagnostic Method

The existing PIMS architecture, including server hardware, network topology, data storage configuration, and interface arrangements with the ECS-700 DCS, was assessed through a combination of technical documentation review, system configuration audit, and consultation with plant operations and maintenance personnel. This diagnostic stage was used to quantify the specific limitations of the existing system, including its 90-day data retention window, its dependence on a discontinued browser environment, and the extent to which operational analyses were being performed manually rather than through integrated tools. The findings from this diagnostic stage directly informed the design principles and technical route adopted for the upgrade.

System Upgrade Implementation Method

The upgrade was implemented in five phases corresponding to the technical route identified above. Hardware upgrading involved the deployment of industrial-grade servers and network equipment sized for long-term, high-resolution data storage. Platform deployment involved installation and configuration of a new-generation PIMS platform to replace the legacy system. System integration involved the adoption of standardized communication protocols and interface adaptation technologies between the new PIMS platform and the ECS-700 DCS, enabling millisecond-level real-time data acquisition. Historical data migration was carried out using a phased strategy combining data backup, parallel system operation, and gradual switch-over, so that historical records could be transferred completely and securely while the plant continued normal production without interruption. Functional development involved the design and coding of the heat consumption deviation analysis module and the associated machine learning components, described further below.

Deviation Analysis and Machine Learning Modeling Method

The heat consumption deviation analysis module was developed to continuously compare actual operating parameters against optimal benchmark values derived from design and commissioning data, quantify the associated energy losses, and visualize deviation results for operators. In parallel, machine learning models for anomaly detection and energy consumption optimization were developed using more than five years of migrated historical operational data, tailored to the operating characteristics of the thermal power unit through iterative algorithm selection, feature engineering, and parameter tuning. Model performance was evaluated primarily on fault diagnosis prediction accuracy, benchmarked against the plant's own historical fault records identified during the diagnostic stage.

Verification Method

Following implementation, the upgraded system was verified through an extended period of parallel and then standalone operation under actual plant conditions. Verification metrics included historical data storage capacity achieved, real-time integration stability with the ECS-700 DCS, equipment fault prediction accuracy relative to subsequently observed equipment conditions, and plant-level performance indicators, namely unit operating efficiency, maintenance cost, and equipment service life, tracked over a period following implementation and compared against the pre-upgrade baseline established during the diagnostic stage.

RESULTS AND DISCUSSION

System Status, Root Causes, and Upgrade Strategy

The diagnostic review confirmed that the existing PIMS system in Kendari Power Plant had only basic data acquisition capability from the DCS, with four compounding deficiencies: a historical data retention period limited to 90 days, insufficient for long-term performance analysis or full lifecycle equipment management; dependence on a discontinued browser environment, creating both compatibility and cybersecurity exposure; the absence of a unified data analysis platform, with most operational analyses relying on manual statistics; and the absence of heat consumption deviation analysis or intelligent prediction functions, which limited operational optimization. Root cause analysis traced these deficiencies to insufficient hardware computing and storage capacity in the original architecture, inconsistent interface standards between PIMS and DCS restricting data interaction, a functional design oriented toward data display rather than in-depth analysis, and the elevated risk historically associated with historical data migration and system upgrading, which had discouraged earlier transformation attempts. These root causes directly shaped the five design principles adopted for the upgrade, namely operational continuity, data integrity, unified DCS-PIMS integration, intelligence enhancement through machine learning, and scalability for future expansion, and were addressed through the phased "hardware upgrade, platform deployment, system integration, functional development, application verification" technical route described in the Research Methodology.

Key Technologies: DCS Integration, Machine Learning, and Non-Intrusive Migration

Seamless integration between the ECS-700 DCS and the new PIMS platform was achieved by adopting standardized communication protocols and interface adaptation technologies, resolving the interface incompatibility and data transmission instability identified during diagnosis. Unified data models and interface specifications enabled real-time data acquisition at millisecond-level frequency, ensuring stable and accurate transmission of operational parameters and equipment status data and providing a reliable data foundation for downstream deviation analysis. Leveraging more than five years of migrated historical operational data, machine learning models for anomaly detection and energy consumption optimization were developed and tuned to the specific operating characteristics of the unit; through algorithm optimization and parameter tuning, prediction accuracy for equipment fault diagnosis exceeded 85%, a result broadly consistent with the accuracy levels reported for deep-learning-based condition monitoring of power plant auxiliary equipment in the literature, where adaptive-threshold models have likewise been shown to improve early-warning performance over fixed-threshold approaches (Li et al., 2023). To ensure uninterrupted plant operation during the transition, historical data migration was carried out through a phased strategy combining data backup, parallel system operation, and gradual switching, which completely and securely migrated historical data while maintaining continuous production and mitigating the upgrade risk that had previously been identified as a barrier to transformation.

Heat Consumption Deviation Analysis Module and Application Results

Based on the upgraded PIMS platform, a real-time heat consumption deviation analysis module was developed that continuously compares actual operating parameters with optimal benchmark values, quantifies energy losses, visualizes deviation results, and generates optimization recommendations to assist operators in identifying inefficiencies. This design mirrors the approach used in published heat-rate deviation studies of coal-fired units, where ranking the contribution of individual parameters and equipment items to overall heat rate deviation has been shown to give plant management a prioritized, financially quantified basis for maintenance decisions rather than a generic efficiency target (Manmit Singh Jasbeer Singh et al., 2023), and is consistent with deviation analysis conducted at another Indonesian coal-fired unit using a production-data platform to compare actual performance against commissioning baselines and identify specific contributing factors behind changes in net plant heat rate (Yohanes et al., 2024).

Table 1. summarizes the measured before-and-after outcomes of the Kendari Power Plant upgrade against these same categories of indicators

Performance Indicator	Before Upgrade	After Upgrade
Historical data retention period	90 days	More than 5 years
Browser / access environment	Discontinued, unsupported browser	Current, vendor-supported platform
Analytical capability	Manual statistics, display-only	Integrated real-time deviation analysis
Equipment fault prediction accuracy	Not available	Exceeding 85%
Unit operating efficiency	Baseline	Improved by approximately 3%
Maintenance cost	Baseline	Reduced by 5%-8%
Equipment service life	Baseline	Extended by 3-5 years

As shown in Table 1, historical data storage capacity was extended from 90 days to more than five years, providing the data depth required to support both the deviation analysis module and the machine learning models described above. Following implementation, the system achieved integration of real-time heat consumption deviation analysis with equipment condition monitoring, equipment fault prediction accuracy exceeding 85%, unit operating efficiency improved by approximately 3%, and maintenance costs reduced by 5%-8%, with associated equipment service life extended by 3-5 years. These efficiency and cost outcomes are broadly consistent in direction, though not necessarily in exact magnitude, with data-driven operational management case studies at other coal-fired units, where structured use of production data and process optimization has likewise been shown to yield measurable, though typically modest, efficiency gains without major equipment replacement (Ashraf et al., 2020). The consistency between the Kendari results and these independently reported cases lends additional confidence that the observed improvements are attributable to the upgraded data platform and its analytical functions, rather than to incidental operating conditions during the verification period.

The practical significance of these results extends beyond the specific efficiency and cost figures. By resolving the interface and data-retention constraints identified during diagnosis, the upgraded system also removed the underlying barrier that had previously limited both heat consumption deviation analysis and machine-learning-based fault prediction at Kendari Power Plant; neither analytical capability could have been meaningfully developed on the original 90-day-retention, display-only platform, regardless of the sophistication of the analysis method chosen. This reinforces the view, drawn from the wider literature on production data platforms in the power sector, that platform-level modernization and analytical-function development are complementary rather than substitutable investments, and that project planning for similar upgrades should treat them as a single coordinated program (Ioana & Korodi, 2021; Moleda et al., 2023). The successful completion of the Kendari upgrade without interrupting plant operation further demonstrates that this coordinated approach is achievable in an operating unit, and not only under laboratory or greenfield conditions.

CONCLUSION

This research successfully upgraded the Plant Information Management System (PIMS) infrastructure and developed a heat consumption deviation analysis system at PLTU Kendari-3 to support more efficient, reliable, and intelligent power plant operations. The modernization process addressed key limitations of the previous system, including restricted historical data storage, outdated system architecture, limited interoperability, and the absence of integrated analytical capabilities. Through hardware and software upgrades, DCS-PIMS integration, historical data migration, and the development of intelligent analytical modules, the upgraded PIMS significantly improved the availability and utilization of operational data for decision-making.

The implementation results demonstrated that the upgraded PIMS expanded historical data retention capacity from 90 days to more than five years, enabled real-time operational data integration, and provided automated heat consumption deviation analysis. Furthermore, the integration of machine learning-based predictive models improved equipment condition monitoring capabilities, achieving fault prediction accuracy exceeding 85%. The implementation also contributed to approximately 3% improvement in unit operating efficiency and a 5–8% reduction in maintenance costs by enabling earlier identification of operational deviations and supporting proactive maintenance strategies.

The findings confirm that PIMS modernization combined with intelligent analytics provides an effective approach for transforming conventional power plant information systems into integrated digital operation platforms. This research contributes both theoretically and practically by demonstrating how information system upgrades, production data management, and machine learning applications can be integrated within an operating thermal power plant environment without disrupting production continuity. The developed framework provides a practical reference for other thermal power plants facing similar challenges related to legacy systems, limited data availability, and the need for improved operational efficiency. Future research may further enhance the system by incorporating advanced artificial intelligence algorithms, broader operational parameters, and real-time optimization mechanisms to support the development of fully intelligent and sustainable power plant management systems.

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