Jurnal Penelitian dan Aplikasi Sistem dan Teknik Industri (PASTI)
Vol. XIX, No. 3, Desember 2025, 429-443
p-ISSN 2085-5869/ e-ISSN 2598-4853

# Designing an IoT-Based EMIS using Linear Regression and CUSUM for Real-Time Anomaly Detection in Pharmaceutical Industry

**Freska Lionia Darlion[1], Muhammad Isa Lufti[2*]**
[1] Department of Digital Business, Institut Pariwisata Tedja Indonesia, Jakarta, Indonesia
[2]Department of Industrial Engineering, Universitas Mercu Buana Jakarta, Indonesia
Email: isa.lufti@mercubuana.ac.id

(Diterima: 17-02-2025; Direvisi: 30-12-2025; Disetujui: 31-12-2025)

**_Abstrak_**

*Industri farmasi merupakan sektor dengan intensitas energi tinggi yang membutuhkan stabilitas operasional yang ketat. Namun, banyak perusahaan masih mengandalkan metode pemantauan energi manual yang menyebabkan latensi informasi. Studi kasus pada sebuah perusahaan farmasi multinasional di Indonesia mengungkap adanya inefisiensi beban dasar (baseload) sebesar 14,3 kW di luar jam operasional yang tidak terdeteksi akibat sistem manajemen energi yang masih bersifat ad-hoc. Penelitian ini bertujuan untuk merancang arsitektur Energy Management Information System (EMIS) berbasis IoT guna mentransformasi proses bisnis dari reaktif menjadi proaktif-prediktif. Sistem ini dirancang dengan mengintegrasikan model regresi linier ($R^2$=0.80) untuk penentuan Energy Performance Indicators (EnPI) dan algoritma Cumulative Sum (CUSUM) untuk deteksi anomali waktu-nyata (real-time). Kelayakan investasi dievaluasi menggunakan analisis tekno-ekonomi. Implementasi EMIS membutuhkan investasi sebesar Rp225.000.000 dengan potensi penghematan tahunan sebesar Rp44.172.687. Meskipun Simple Payback Period (SPP) mencapai 5,1 tahun, proyek ini dinilai layak karena nilai strategisnya dalam transparansi data, mitigasi risiko operasional, dan kepatuhan ISO 50001. Selain itu, transformasi digital ini mendukung pencapaian Sustainable Development Goals (SDG 7, 9, dan 12) dengan mendorong efisiensi energi dan produksi industri yang bertanggung jawab. Digitalisasi sistem energi bukan sekadar penggantian alat, melainkan transformasi strategis yang mengubah data energi menjadi aset keputusan bisnis yang krusial.*

***Kata Kunci:*** *Energy Management Information System* (EMIS); *Transformasi Digital*; IoT; CUSUM; *Efisiensi Energi*; SDGs

**Abstract**

The pharmaceutical industry is a high energy-intensity sector requiring strict operational stability. However, many companies still rely on manual energy monitoring methods, leading to information latency. A case study at a multinational pharmaceutical company in Indonesia revealed a baseload inefficiency of 14.3 kW during non-operational hours, which remained undetected due to an ad-hoc energy management system. This study aims to design an IoT-based Energy Management Information System (EMIS) architecture to transform the energy management business process from reactive to proactive-predictive. The study utilizes secondary data from the 2025 Energy Audit Report. The system design integrates a linear regression model ($R^2$=0.80) for Energy Performance Indicators (EnPI) determination and the Cumulative Sum (CUSUM) algorithm for real-time anomaly detection. Investment feasibility is evaluated using techno-economic analysis. The implementation of EMIS requires an investment of IDR 225,000,000 with potential annual energy cost savings of IDR 44,172,687. Although the Simple Payback Period (SPP) is 5.1 years, the project is considered feasible due to its strategic value in data transparency, operational risk mitigation, and ISO 50001 compliance. Furthermore, this digital transformation supports the achievement of Sustainable Development Goals (SDG 7, 9, and 12) by promoting energy efficiency and responsible industrial consumption. Digitizing energy systems is not merely a tool replacement but a strategic transformation that turns energy data into critical business decision assets.

**Keywords:** *Energy Management Information System* (EMIS); *Digital Transformation*; *IoT; CUSUM*; *Energy Efficiency*; *SDGs*

## BACKGROUND

The pharmaceutical industry is a manufacturing sector characterized by high energy consumption intensity. This energy demand is driven by stringent regulatory requirements regarding air quality control (HVAC), sterility, and temperature stability within production processes (Gao et al., 2019). Amidst fluctuating global energy prices and pressures to comply with Environmental, Social, and Governance (ESG) standards, pharmaceutical companies are compelled to decarbonize their energy systems without compromising productivity (Beck et al., 2025). Consequently, the optimization of key energy metrics becomes crucial for maintaining corporate operational competitiveness (Chen et al., 2022).

Despite the high urgency of energy efficiency, many companies in this sector still rely on conventional or manual monitoring methods. The use of manual recording (logsheets) often leads to information gaps, where energy consumption data is only available periodically rather than in real-time. This delay in data analysis risks leaving inefficiencies undetected for extended periods (Cesarotti, 2016). In the context of Industry 4.0, the shift from reactive maintenance to monitoring based on the Internet of Things (IoT) has become an absolute solution for enhancing data visibility and decision-making accuracy (Reichardt, 2023; Jagtap et al., 2021). According to the Ministry of Energy and Mineral Resources (2025), energy audits in the industrial sector have revealed potential savings of tens of millions of kWh. With energy costs accounting for 20-30% of total production costs, efficiency is a top priority for decarbonization (Kementerian ESDM, 2025). This research is also designed to align corporate operational strategies with the Sustainable Development Goals (SDGs), specifically in promoting sustainable industrial infrastructure and energy efficiency.

### Problem Identification

This case study was conducted at a production facility belonging to a multinational pharmaceutical company in Indonesia (hereinafter referred to as the 'Object of Study'). Based on an energy performance evaluation conducted in 2025, it was identified that the company's energy management maturity level remains in the 'Ad Hoc' phase. This approach is characterized by efficiency initiatives that are reactive, fragmented, and heavily reliant on periodic physical audits, thereby failing to guarantee the long-term sustainability of energy performance.

The limitations of this conventional approach were confirmed through an analysis of the daily electrical load profile. Monitoring data indicated an anomalous baseload phenomenon, where energy consumption persisted at an average of 14.3 kW continuously, even during non-operational periods.

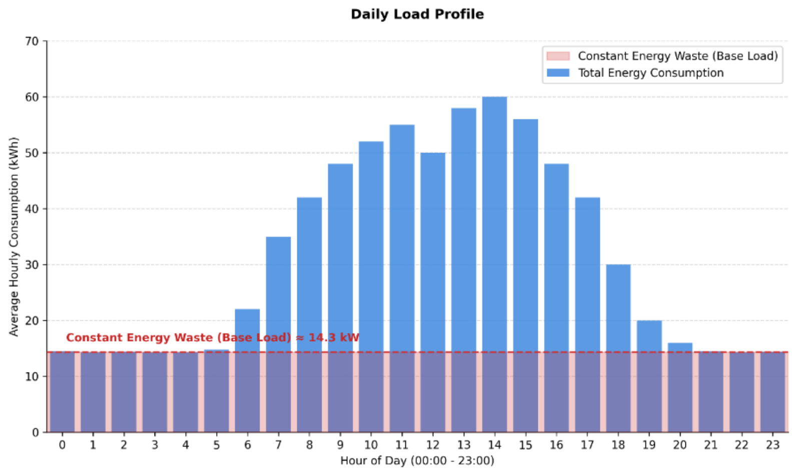


**Figure 1. Daily Load Profile Showing High Baseload During Non-Operational Hours**

Based on the daily load profile analysis shown in Figure 1, significant energy waste anomalies are visible, which remain undetected by the current facility management system.

**Table 1. Estimated Energy Waste and Potential Cost Savings**

| Energy Performance Parameter | Value | Unit |
|---|---|---|
| **A. Existing Load Profile** | | |
| Existing Load Profile | 14,3 | kW |
| Load Duration | 8.760 | Hours/year |
| Total Annual Baseload Consumption | 125.268 | kWh/year |
| **B. Efficiency Target** | | |
| Benchmark Target Baseload | 5,0 | kW |
| Target Consumption | 43.800 | kWh/year |
| **C. Value Analysis** | | |
| Energy Saving Potential | **81.468** | **kWh/year** |
| Industrial Electricity Tariff | 1.114,7 | Rp/kWh |
| **Estimated Opportunity Loss** | **Rp 90.812.379** | **per year** |

The baseline urgency of this problem is emphasized by the 14.3 kW baseload anomaly that accumulates into a loss of Rp90,812,379/year (Table 1), with a saving potential of 81,468 kWh via a tariff of Rp1,114.7/kWh. Although related studies have discussed IoT and smart audits, the main gap is the lack of CUSUM integration for specific baseload detection in pharmaceuticals. Without a real-time EMIS, baseload energy performance cannot be detected accurately, as manual systems only capture periodic data that fails to reveal daily anomalies like 14.3 kW during non-operational hours. The root cause of this inefficiency is information latency due to the absence of real-time monitoring systems. This is evidenced by audit findings where the 14.3 kW phantom load at the Study Object was not detected by internal management until external measurements were conducted. The energy performance evaluation report shows that without granular data visibility (such as the lack of hourly production logging on boilers and minimal sub-metering on the user side) management lacks a data foundation for timely operational interventions. Consequently, if this condition persists without digital technology intervention, this baseload inefficiency will accumulate into a significant operational expenditure (OPEX) burden, as reflected in Table 1.

**Urgency of Digital Business Transformation**

The issues described above demonstrate that the energy issue at the Object of Study is not merely a technical electrical problem, but an information management problem. There is an urgent need to shift the energy management paradigm through digital transformation. Energy data should no longer be treated as mere administrative records but must be transformed into "Strategic Assets" that support data-driven decision-making. The implementation Energy Management Information System (EMIS) serves as a strategic step to bridge the gap between physical audits and intelligent systems (Abidin, 2025). This transformation also aligns with modern facility management readiness, which demands system integration for improved responsiveness (Naji, 2024).

This study aims to design an EMIS architecture capable of detecting anomalies in real-time and to analyze the investment feasibility of the system from the perspectives of business value and operational sustainability. Without a real-time EMIS, baseload anomalies remain statistically invisible despite periodic energy audits.

**State-of-the-Art and Conceptual Context**

To fully address these operational gaps, it is essential to contextualize EMIS within the broader Smart Factory ecosystem. In the Industry 4.0 era, the paradigm of manufacturing energy management has shifted from passive manual recording to cyber-physically integrated systems. Tesch da Silva et al. (2020) define this shift as energy transparency, which forms the foundation of the Smart Factory (Vetrivel S.C, 2024). Specifically, an effective EMIS architecture must provide real-time data visibility to detect inefficiencies in specific sub-systems, rather than merely tracking total electricity bills (IoT-IEEMS, 2021; Prudenzi, 2019). Furthermore, integrating Internet of Things (IoT) technologies transforms the audit process from static to dynamic (Abidin, 2025).

From a strategic perspective, this transition represents true digitalization—altering how an organization responds to energy inefficiencies, rather than mere digitization of data (Reichardt, 2023). Modern IoT-based systems also serve as early warning mechanisms for power quality issues, minimizing costly production downtime (Garrido-Zafra, 2022) and laying the groundwork for predictive maintenance (Jeevitha D, 2023).

To translate this real-time data into valid technical decisions, standardized methodologies like ISO 50001 are required. This involves determining Energy Performance Indicators (EnPI) and baselines tailored to pharmaceutical load characteristics (Chen et al., 2022; Pokane, 2023).

While previous studies have discussed IoT implementation for energy efficiency, a distinct research gap remains regarding the specific integration of statistical process control algorithms with real-time IoT architectures in the pharmaceutical context. Table 2 summarizes the state-of-the-art of this research compared to previous studies, highlighting the specific novelty of integrating the CUSUM algorithm to automate phantom load detection, supplemented by a comprehensive techno-economic analysis (LCCA)

Although previous studies have discussed IoT implementation for energy efficiency (Reichardt, 2023; Jagtap et al., 2021) and smart energy audit frameworks (Abidin et al., 2025), there is scarce literature discussing the specific integration of the CUSUM algorithm with an IoT-based EMIS architecture for detecting baseload anomalies in the pharmaceutical industry. Furthermore, most studies focus on technical aspects without including a deep techno-economic analysis (LCCA). This research fills that gap by designing an EMIS system validated using real energy audit data and investment profitability analysis.

**Table 2. State of the Art Comparison Table**

| Author/Year | Focus | Detection Method | Pharmaceutical Compliance Integration | Gap |
|---|---|---|---|---|
| **Reichardt (2023)** | IoT for General Efficiency | Dashboard Monitoring | No | Only visualization, no automated statistical analysis. |
| **Abidin et al. (2025)** | Smart Audit Framework | Conceptual/Framework | Conceptual/ Framework | Theoretical in nature, no economic validation (LCCA). |
| **Chen et al. (2022)** | KPI Energy Pharmaceutical | Linear Regression | Yes | Focus on production, does not detect phantom load during holidays. |
| **This Study** | **Real-time EMIS for Pharma** | **Integrated CUSUM + IoT** | **Strong (GMP & ISO 50001)** | **Full validation: Technical, Statistical, & Economic.** |

**Energy Management Information System (EMIS) in the Smart Factory Ecosystem**

In the Industry 4.0 era, the paradigm of manufacturing energy management has shifted from passive manual recording to cyber-physically integrated systems. Tesch da Silva et al. (2020) define this shift as energy transparency, where efficiency decisions are no longer based on assumptions or historical data alone, but on connected actual data. This concept is the foundation of the Smart Factory, which demands interconnectivity between production machines, utility systems, and management layers to achieve optimal operational efficiency (Vetrivel S.C, 2024).

An Energy Management Information System (EMIS) is defined as an integrated system combining hardware (sensors/meters), communication networks, and software to collect, visualize, and analyze energy consumption data. Research by IoT-IEEMS (2021) emphasizes that an effective EMIS architecture must be capable of providing real-time data visibility. Specifically for industrial facilities with wide load distribution, a smart distributed energy monitoring approach becomes crucial. This enables facility managers to detect inefficiencies in specific sub-systems, such as administrative building baseloads or anomalies in specific distribution panels, rather than merely viewing the total electricity bill (Prudenzi, 2019).

Furthermore, Abidin (2025) highlights that the integration of Internet of Things (IoT) and Digital Twin technologies into energy audits can transform the audit process from static (periodic) to smart, dynamic, and continuous. Thus, EMIS is not merely a recording tool but a primary operational control instrument in a smart factory. Conventional approaches fail to detect actual baseload energy performance, as proven in the Object of Study where a 14.3 kW phantom load was missed by manual logsheets.

**Digital Business Value: From Digitization to Digitalization**

In the context of strategic management, it is important to distinguish between digitization (converting analog data to digital) and digitalization (leveraging digital technology to transform business models or work processes). Implementing sensors on electrical panels is merely the digitization stage. The true digital business value is created through the digitalization process, which occurs when that data is used to alter how the organization responds to energy inefficiencies (Reichardt, 2023).

Modern IoT-based monitoring systems are not limited to reading energy consumption (kWh) but have evolved to include power quality monitoring, such as voltage and harmonics, via cloud-based platforms (Garrido-Zafra, 2022). From a business perspective, this capability transforms physical assets into "smart assets" capable of providing early warning systems, thereby minimizing the risk of costly production downtime. Additionally, data accumulation from this system serves as a foundation for future Artificial Intelligence (AI) applications for load prediction and predictive maintenance, significantly increasing the long-term technology investment value (Jeevitha D, 2023).

### Energy Performance Indicators (EnPI) and Measurement Methodology

To ensure data generated by EMIS can be translated into valid technical decisions, standardized performance measurement methodologies are required, such as those regulated in the ISO 50001 framework. Key components include the determination of Energy Performance Indicators (EnPI) and Energy Baselines (EnB) relevant to pharmaceutical production characteristics (Chen et al., 2022). In digital system architecture, a modular approach is needed to integrate operational data (such as production quantity or working hours) with energy data to generate accurate EnPIs (Pokane, 2023). Linear regression analysis is often used to model the relationship between energy consumption and its influencing variables (drivers) so that energy performance evaluation remains objective in the Industry 4.0 era (Tesch da Silva et al., 2020). The designed EMIS system must be capable of visualizing the deviation between actual consumption and the modeled baseline (CUSUM method). This allows the engineering team to verify energy savings in real-time and identify consumption anomalies (waste) uncorrelated with production activities, such as high loads during holidays.

## RESEARCH METHODOLOGY

### Research Object and Location

This research was conducted through a case study at a production facility owned by a multinational pharmaceutical company located in Indonesia (hereinafter referred to as the 'Study Object'). The selection of the object is based on the characteristics of the pharmaceutical industry, which has high energy intensity and strict operational requirements. The research focus is limited to the transformation of energy management systems in two critical areas identified in the energy audit, namely the Low Voltage Main Distribution Panel (LVMDP) and the Administration Building (Admin Building). These areas were chosen due to indications of significant but undetected baseload inefficiencies by the current manual monitoring system.

### Conceptual Framework and Research Flow

This research adopts a framework approach that integrates conventional auditing with smart system design. This approach refers to the methodology of transforming static energy audits into IoT-based continuous monitoring as outlined by Abidin (2025). The research flow starts from diagnosing the existing condition (As-Is), designing the proposed system (To-Be), to feasibility analysis. The systematic research stages are presented in Figure 2.

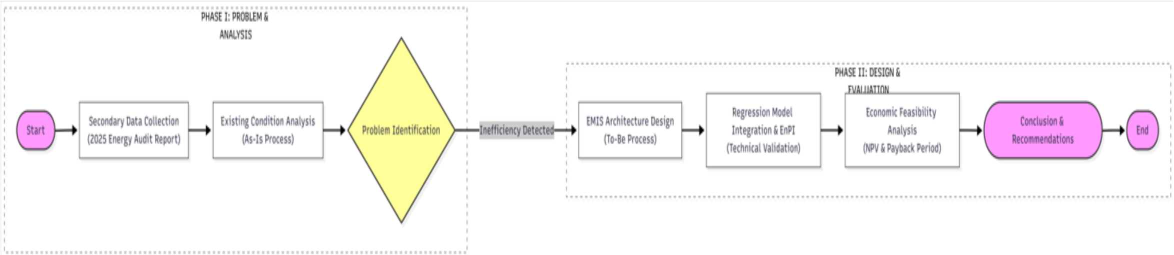


**Figure 2. Research Flow Diagram**

## Data Collection

The data used in this research are secondary data sourced from the 2025 Energy Audit Report (Investment Grade Audit). The use of this historical operational data is important for forming valid energy consumption patterns (Prudenzi, 2019). Data classification includes:

a. Electrical Load Profile: Hourly energy consumption data at the Study Object to identify baseload anomalies outside operational hours.

b. Energy Drivers: Monthly production data and total energy consumption for regression model formation.

c. Financial Data: Estimated costs for hardware and software investment in the Advanced Energy Monitoring system amounting to Rp 225,000,000, as well as annual saving potential (referring to audit recommendations).

## EMIS System Architecture Design (System Design)

This stage designs the Energy Management Information System (EMIS) architecture to address information latency in manual systems. The design refers to a modular architecture that separates the physical layer (sensors), network layer, and management application layer (Pokane, 2023).

- As-Is Process Mapping: Identifying bottlenecks in manual recording processes (logsheets) that cause delays in energy waste detection.
- To-Be Process Design: Designing automated data flows using smart meters connected to a cloud database to enable real-time analysis.

EMIS enables baseload energy performance detection via real-time IoT data from LVMDP and the Administration Building, replacing manual logsheets that cause latency. Without real-time EMIS, baseload energy performance cannot be detected accurately, so this architecture is designed modularly to integrate sensors, cloud, and regression algorithms for automated baselines (Pokane, 2023).

## Data Analysis and Validation

Data analysis is conducted using two approaches to ensure technical and economic feasibility:

1. Determination of Energy Performance Indicators (EnPI):

Using a simple linear regression model validated in the audit report with the equation $Y=3.5569x+6691$ and $R^2=0.80$. This statistical approach is used to establish an accurate Energy Baseline (EnB) in accordance with manufacturing load characteristics (Chen et al., 2022). This baseline will be embedded in the EMIS algorithm for automatic consumption deviation detection.

2. Techno-Economic Analysis:

Evaluating digital system investment feasibility using simple Life Cycle Cost Analysis (LCCA) and Payback Period methods. This evaluation not only calculates energy savings (kWh) but also considers management process efficiency as part of the transformation value towards Industry 4.0 (Tesch da Silva et al., 2020).

## RESULTS AND DISCUSSION

### Business Process Gap Analysis

This analysis evaluates the transformation from conventional energy management to digital-based systems. Referring to the framework by Abidin et al. (2025), this transition is essential to eliminate data latency that hinders operational decision-making. Referring to the Smart Energy Audit framework developed by Abidin et al. (2025), modern energy management consists of a layered architecture.

a. Sensing Layer: The physical foundation where IoT sensors replace human roles in recording energy parameters (kWh, V, A, PF).

b. Data Processing Layer: Where mathematical models (such as Linear Regression EnPI) are embedded to process raw data into meaningful information.

c. Application Layer: The interface for management to view real-time energy status and receive early warnings.

In this research, implementation at the Study Object is focused on shifting the company's business processes from the 'Traditional Audit' quadrant to 'Smart Energy Audit', as illustrated in Figure 3.

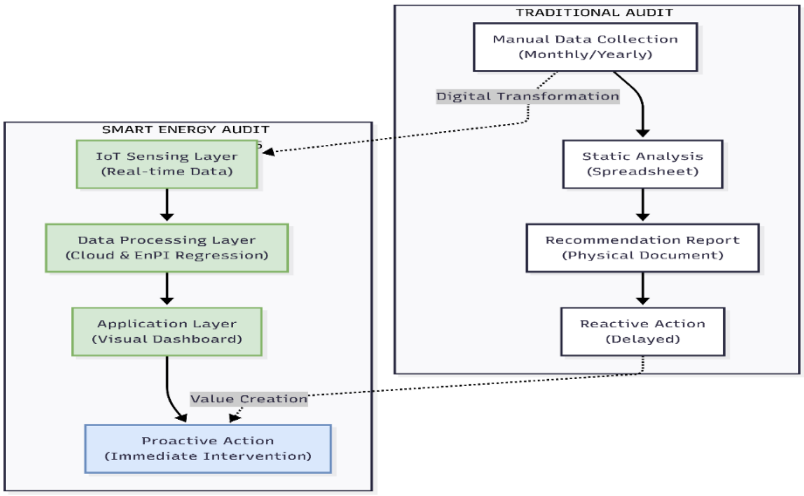


**Figure 3. Abidin Framework Adaptation: Transformation (Traditional vs Smart)**

a. Existing Condition: Limitations of Manual Monitoring

Based on field observations, energy monitoring processes at the Study Object still rely on manual recording (logsheets) and monthly recapitulation. This method creates operational blind spots where daily inefficiencies are not detected directly. This aligns with findings by Jagtap et al., stating that the absence of real-time data is the main barrier to energy efficiency in manufacturing industries. Empirical evidence of this weakness is seen in the Study Object's load profile (Figure 1). Audit data shows an average baseload consumption of 14.3 kW occurring continuously, including on holidays and at night. Without an early warning system, this waste persists without intervention, resulting in accumulated energy losses.

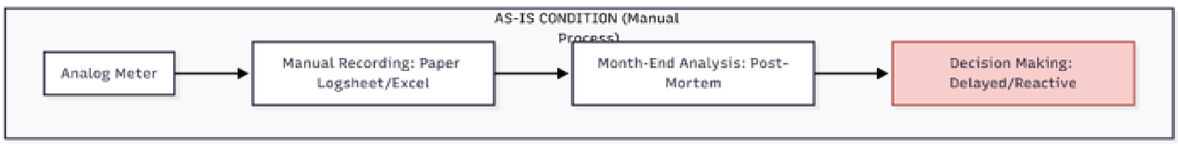


**Figure 4. As-Is Condition**

b. Proposed Condition: Smart System Architecture

To mitigate these risks, an Energy Management Information System (EMIS) architecture integrating IoT sensors with cloud computing is designed. As explained by Reichardt (2023), IoT implementation enables data transparency that changes work patterns from corrective to proactive.

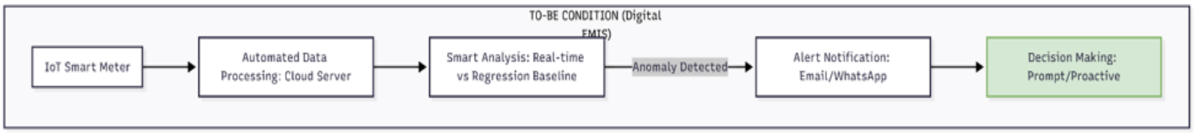


**Figure 5. To-Be Condition**

To mitigate these risks, an Energy Management Information System (EMIS) architecture integrating IoT sensors with cloud computing is designed. As explained by Reichardt (2023), IoT implementation enables data transparency that changes work patterns from corrective to proactive.

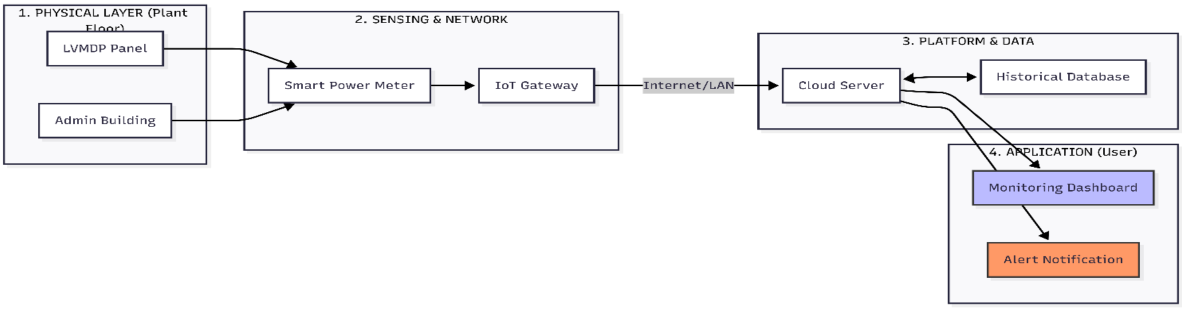


**Figure 6. Proposed EMIS System Topology Architecture Based on IoT at the Study Object**

**EMIS as a Critical Tool for Baseload Visibility: As-Is and To-Be Comparison**

In comparison to the As-Is condition which relies on monthly logsheets, results in an invisible baseload, and uses post-mortem audits, the To-Be (EMIS) architecture provides 15-minute real-time data visibility, detects baseload anomalies, and serves as an early warning system.

**Design of Energy Performance Indicators (EnPI) and System Validation: Determination of Energy Baseline (EnB)**

A smart EMIS system requires algorithms to distinguish between reasonable consumption (due to production) and waste. Using the methodology recommended by Chen et al. (2022) for the pharmaceutical industry, this research establishes a linear regression model as the base algorithm. The baseline period must be long enough to include changes caused by production patterns and product demand conditions. The production and energy consumption data examined as the base year are historical data from 2022-2023, as they have a better $R^2$ value than other periods. The baseline and baseload are obtained by correlating energy consumption with production. The baseload value is determined by the y-intercept of the baseline line equation, i.e., by setting X = 0. Thus, the baseload for energy consumption at the Study Object is 6691 GJ per month. Meanwhile, the baseline, which is the monthly energy consumption at the Study Object, follows the equation:

$$Y = 3{,}5569x + 6691$$

Where:

- $Y = \text{Estimated Energy Consumption (GJ/month)} \left(\frac{\text{GJ}}{\text{month}}\right)$
- $x = \text{Production volume (Ton)}$
- $6691 = \text{Fiixed Energy/}$
  $\text{Baseload (Energy consumption when production is zero)}$

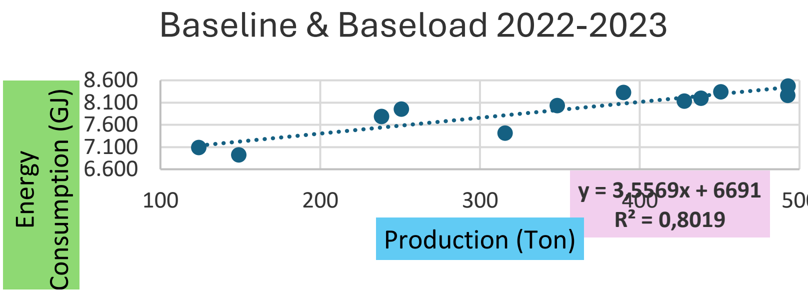


**Figure 7. Linear Regression Model as the Base EMIS Algorithm**

This model has a coefficient of determination ($R^2$) of 0.8019 (Table 3), meeting statistical validity requirements ($R^2 \geq 0.75$) to be used as a baseline in EMIS software.

**Table 3. Results of Regression Model Validation**

| Indicator | Value | Recommendations |
|---|---|---|
| Coefficient of Determination ($R^2$) | 0.8 | ≥ 0.75 |
| Coefficient of Variation of RMSE | 0.03 | < 0.2 |
| T-statistic (for Production) | 6.36 | > 2 |
| Baseload Value per Month | 6,691 | ≥ 0 |
| Bias Model | 0% | < 0.0005% |

**Statistical-Based Anomaly Detection Method (CUSUM Algorithm)**

To ensure objectivity in energy performance verification, the EMIS system is designed using the Cumulative Sum of Deviations (CUSUM) algorithm. This method was chosen for its high sensitivity in detecting small shifts in process performance that are often undetected by standard control charts (Abujiya et al., 2013).

a. Algorithm Formulation and Baseline Integration

The algorithm works by comparing actual energy consumption data (E_actual) recorded by IoT sensors with predicted energy consumption (E_predicted). The predicted value is obtained from the validated linear regression model in the energy audit, namely:

$$\boldsymbol{E_{predicted} = 3,5569(P) + 6691}$$

Where P is the production variable (Ton). This model has a baseload baseline of 6.691 GJ/month that must be maintained. Based on the framework by Mahandari et al. (2025), integrating static baselines into dynamic monitoring systems is key to accurate measurement and verification (M&V).

The CUSUM calculation in the system is formulated as follows:

$$\boldsymbol{CUSUM_t = \sum_{i=1}^{t} (E_{actual,i} - E_{predicted,i})}$$

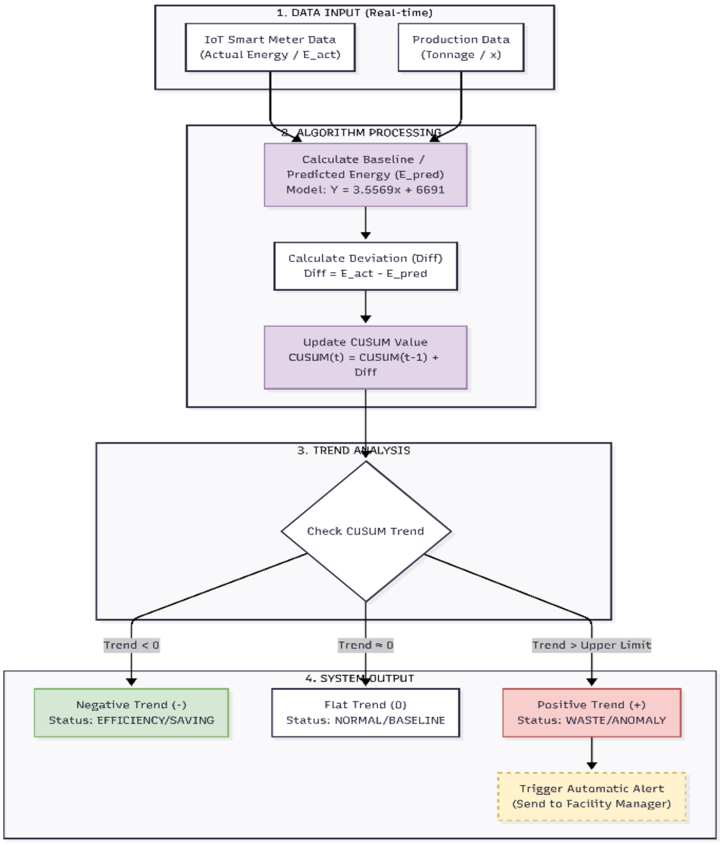


**Figure 8. Logic Flowchart of CUSUM Algorithm for Anomaly Detection in EMIS**

Figure 8 illustrates the system's computational logic. Actual production data is input into the regression equation (Y=3.5569x+6691) to generate the predicted energy value. The difference between actual energy (from IoT) and prediction is accumulated. If the accumulation trend is positive (red), the system automatically triggers an early warning notification. To validate this logic, a simulation was conducted using historical energy consumption data from 2024. The simulation results are displayed in the following graph.

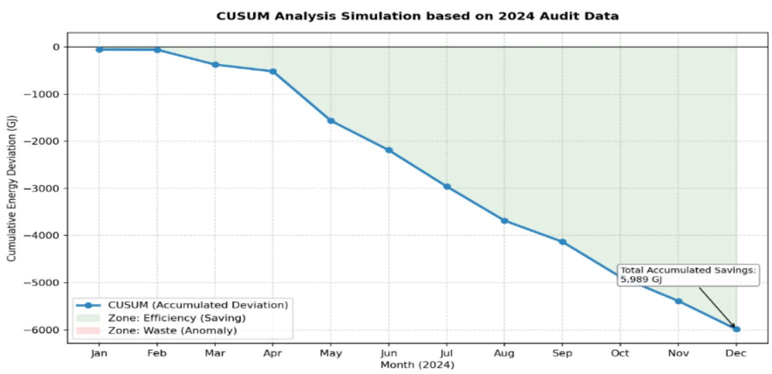


**Figure 9. Logic Flowchart of CUSUM Algorithm for Anomaly Detection in EMIS**

The CUSUM simulation on 2024 historical data proves the algorithm's proof-of-concept: the system can visualize deviations of actual energy vs. predicted baseline (e.g., September 2024, actual 7.159 GJ vs. predicted 7.608 GJ), which is impossible with manual monitoring. Without real-time EMIS, baseload energy performance cannot be detected accurately, as the CUSUM logic will automatically trigger alerts if positive trends (anomalies like 14.3 kW baseload) exceed the Upper Control Limit on real-time data.

b. Real-Time Anomaly Detection Mechanism

Unlike conventional monitoring, this system adopts a real-time anomaly detection approach as proposed by Maitra et al. (2025). The detection logic works as follows:

1. Savings Zone (Negative): If the CUSUM graph moves downward (negative values), this indicates that the company is achieving energy savings compared to the baseline (improved performance).
2. Anomaly Zone (Positive): If the graph moves upward away from zero, the system detects waste.

Referring to 2024 historical data, implementing this algorithm can visualize energy performance accumulation. For example, in September 2024, positive efficiency was detected where actual (7.159 GJ) was lower than predicted (7.608 GJ), contributing to a downward CUSUM graph. However, if a baseload spike occurs (such as the 14.3 kW case in the Admin Building), the graph will rise sharply beyond the tolerance limit (Upper Control Limit), triggering automatic notifications to the facility management team.

c. Integration with Early Warning System

Unlike manual audits which are post-mortem, this EMIS architecture integrates CUSUM logic with an automatic notification system. When the algorithm detects an anomaly (e.g., high baseload when production is low), the system automatically sends alerts via instant messaging apps or email to facility managers. This enables immediate corrective action.

This statistics-based approach validates energy performance objectively and measurably. It aligns with the "Monitoring, Measurement, and Analysis" clause requirements in the ISO 50001 standard, where organizations are required to investigate significant energy performance deviations (Tesch da Silva et al., 2020).

d. Compliance with ISO 50001

The automated CUSUM application supports compliance with ISO 50001 regarding sustainable energy performance evaluation. According to Zsebik (2018) and Pelser (2018), using automated monitoring tools like this is essential to ensure continual improvement of energy performance is not temporary but maintained long-term.

## Financial Analysis

The implementation of the IoT-based monitoring system requires an initial investment classified as 'Advanced Energy Monitoring'. This financial evaluation focuses on the trade-off between the upfront investment cost and the tangible benefits gained from real-time anomaly detection. Referring to the recommendation from the audit report, the quantitative cost-benefit breakdown is detailed in Table 4.

**Table 4. Investment Feasibility Analysis of EMIS Implementation**

| Economic Parameter | Value | Unit | Remarks |
| --- | --- | --- | --- |
| Investment Cost (CAPEX) | Rp 225.000.000 | IDR | Hardware (Sensor) & Software |
| Annual Energy Savings | Rp 44.172.687 | IDR | Estimated 5% efficiency from monitoring |
| Simple Payback Period (SPP) | 5,1 Years | Years | Category: High Cost Investment |

## Strategic Value Analysisis (Intangible Value)

Although the Payback Period > 4 years is categorized as a long-term investment, the authors argue that the strategic value of this system exceeds mere kWh savings. In line with

Naji et al.'s (2024) view in facility management transformation studies, digitalization is not just about cost but infrastructure readiness to face future risks. The EMIS system provides intangible benefits such as:

1. Budgeting Accuracy: The digital system eliminates unaccounted utility cost variances through data transparency per department.
2. Data-Based Regulatory Compliance: Facilitates ISO 50001 compliance audits and ESG reporting because all energy data is automatically and historically recorded, in accordance with the energy management framework in the Industry 4.0 era (Tesch da Silva et al., 2020).

## CLOSING

### Conclusion

Based on the design and techno-economic analysis conducted at the Study Object, several key conclusions are drawn. First, regarding business process transformation, this research successfully designed an IoT-based EMIS architecture capable of resolving information latency issues. The shift from monthly logsheets to real-time monitoring enables the early detection of baseload inefficiencies, particularly the previously undetected 14.3 kW consumption anomaly. Second, the technical validity of the system is proven through the integration of the Cumulative Sum (CUSUM) algorithm with a linear regression model ($Y=3.5569x+6691$). This model is statistically valid ($R^2=0.80$) to be used as an energy performance baseline, ensuring that the system-generated data is accountable for energy-saving verification per ISO 50001 standards. Finally, the economic feasibility analysis indicates that implementing the system requires an investment (CAPEX) of Rp 225,000,000 with a direct annual energy cost saving potential of Rp 44,172,687. Although the Simple Payback Period (SPP) is 5.1 years, positioning it as a long-term investment, the project is deemed highly feasible due to its strategic intangible values in data transparency and operational risk mitigation that cannot be achieved manually.

### Managerial Implications

This research provides strategic insights for pharmaceutical industry management in adopting Industry 4.0 technologies. The implementation of EMIS shifts the energy management paradigm from a mere cost center to a critical decision support system, where the speed to insight becomes a new competitive advantage. Furthermore, beyond kWh savings, this system functions as operational insurance through power quality early detection features, protecting critical assets from fatal damage and downtime costs that far exceed the system's investment. This digitalization also directly contributes to global sustainability targets (SDG 7, 9, and 12) by increasing energy efficiency rates, enabling industrial retrofitting via smart technologies, and reducing the pharmaceutical production carbon footprint through data-driven resource management.

### Recommendations

For further development and practical implementation, several recommendations are proposed. First, it is recommended that the company conduct a pilot project by installing IoT sensors specifically on the main LVMDP panel and Administration Building before a full-scale rollout. This phased approach aligns with the strategic risk mitigation discussed in the techno-economic analysis, allowing the management to validate system effectiveness with minimal upfront cost. Second, future research should explore advanced integration between EMIS data and production systems (SCADA) or Building Management Systems (BMS). As highlighted by Vetrivel (2024) regarding smart factory interconnectivity, this integration is crucial to enable automatic controls, such as the automatic shutdown of utilities in unoccupied areas. Lastly, given the substantial volume of data (Big Data) generated by continuous monitoring, future developments should include Machine Learning modules for predictive maintenance. This recommendation is supported by Jeevitha (2023), who emphasizes that accumulated IoT data serves as the foundation for AI-driven asset management, predicting machine failures based on current and voltage patterns to maximize long-term digital investment value.

## BIBLIOGRAPHY

Abidin, A. Z., et al. (2025). Leveraging IoT, digital twin and machine learning for smart energy audit in office building: A systematic literature review and recommendation. *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, 100124. https://doi.org/10.1016/j.prime.2025.101124

Abujiya, M. R., Riaz, M., & Lee, M. H. (2013). Increasing the sensitivity of cumulative sum charts for location. *Quality and Reliability Engineering International*, 29(6), 869-881. https://doi.org/10.1002/qre.1661

Beck, A., et al. (2025). Towards fossil-free energy supply: Cost-effective decarbonization measures in pharmaceutical energy systems. *Applied Thermal Engineering*, 236, 128213. https://doi.org/10.1016/j.applthermaleng.2025.128213

Cesarotti, V., & Spada, C. (2016). Investigating the relationship between energy consumption and overall equipment effectiveness for improving manufacturing systems. *International Journal of Productivity and Quality Management*, 17(3), 336-352. https://doi.org/10.1504/IJPQM.2016.076711

Chen, Y., et al. (2022). Optimization of key energy and performance metrics for drug product manufacturing. *International Journal of Pharmaceutics*, 618, 122487. https://doi.org/10.1016/j.ijpharm.2022.122487

Gao, Z., et al. (2019). Analysis of energy-related CO2 emissions in China's pharmaceutical industry and its driving forces. *Journal of Cleaner Production*, 223, 679-690. https://doi.org/10.1016/j.jclepro.2019.03.092

Garrido-Zafra, J., et al. (2022). IoT Cloud-Based Power Quality Extended Functionality for Grid-Interactive Appliance Controllers. *IEEE Transactions on Industry Applications*, 58(4), 1-10. https://doi.org/10.1109/TIA.2022.3160410

Jagtap, S., et al. (2021). Real-time data collection to improve energy efficiency: A case study of food manufacturer. *Journal of Food Process Engineering*, 44(2), e13600. https://doi.org/10.1111/jfpp.14338

Jeevitha, D. (2023). Energy Management in Industry 4.0 Using AI. In *Artificial Intelligence and Industry 4.0* (pp. 1-20). CRC Press. https://doi.org/10.1201/9781003432319-20

Kementerian Energi dan Sumber Daya Mineral Republik Indonesia. (2025, 18 September). Audit energi ungkap potensi penghematan puluhan juta kilo watt hour di industri. Direktorat Jenderal EBTKE. https://ebtke.esdm.go.id/artikel/berita/audit-energi-ungkap-potensi-penghematan-puluhan-juta-kilo-watt-hour-di-industri.

Mahandari, C. P., et al. (2025). Energy Baseline for Measurement and Verification on Energy Audit for an Oil and Gas Industry. *Lecture Notes in Electrical Engineering*, 1120. https://doi.org/10.1007/978-981-97-8197-3_49

Maitra, S., et al. (2025). Real-Time Anomaly Detection in Smart Energy Systems Using Statistical and Adaptive Learning Technique. *Smart Innovation, Systems and Technologies*. https://doi.org/10.1007/978-981-96-9191-3_28

Naji, K. K., et al. (2024). Unveiling Digital Transformation: Analyzing Building Facility Management's Preparedness for Transformation Using Structural Equation Modeling. *Buildings*, 14(9), 2794. https://doi.org/10.3390/buildings14092794

Pelser, W. A., et al. (2018). Results and prospects of applying an ISO 50001 based reporting system on a cement plant. *Journal of Cleaner Production*, 198, 642-653. https://doi.org/10.1016/j.jclepro.2018.07.071

Pokane, S. S., & Masota, L. (2023). Architecture Approach to Manage Electricity Utility in a Smart City. *2023 IEEE European Technology and Engineering Management Summit (E-TEMS)*, 1-6. https://doi.org/10.1109/E-TEMS57541.2023.10424593

Prudenzi, A., et al. (2019). Smart distributed energy monitoring for industrial applications. *2019 IEEE International Workshop on Metrology for Industry 4.0 and IoT*, 218-223. https://doi.org/10.1109/METROI4.2019.8792861

Reichardt, A. (2023). The use of the Internet of Things to increase energy efficiency in manufacturing industries. *International Journal of Energy Sector Management*. https://doi.org/10.1108/IJESM-12-2023-0017

Tesch da Silva, F., et al. (2020). Looking at energy through the lens of Industry 4.0: A systematic literature review of concerns and challenges. *Computers & Industrial Engineering*, 143, 106426. https://doi.org/10.1016/j.cie.2020.106426

Vetrivel, S. C. (2024). Smart factories and energy efficiency in industry 4.0. In *Industry 4.0 and Climate Change* (pp. 55-78). Wiley. https://doi.org/10.1002/9781394197798.ch4

Zsebik, A. (2018). ISO 50001—Energy Planning and Monitoring Tools and Examples. *2018 7th International Conference on Renewable Energy Research and Applications (ICRERA)*, 1205-1210. https://doi.org/10.1080/01998595.2018.12027901