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IOT-Based Smart Energy Management for Sustainable Operational Efficiency in the Industry 4.0 Era

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Abstract
This study aims to evaluate the contribution of IoT-based smart energy management towards operational efficiency and sustainability of manufacturing systems in the context of Industry 4.0. Using a quantitative correlational design, data were collected from 100 professional respondents in the manufacturing sector through questionnaires and structured interviews. Statistical analysis was performed using Pearson correlation, linear regression, t-test, and ANOVA with the help of SPSS software. The results showed a very strong and significant relationship between the use of IoT-based smart energy management systems and energy efficiency ($r = 0.849$), operational efficiency ($r = 0.706$), and environmental sustainability ($r = 0.774$). Linear regression showed that the use of the technology explained 72.1% of the variability in energy efficiency ($R^2 = 0.721$; $p < 0.001$). The ANOVA results also showed significant differences between groups of technology users in terms of efficiency achievements. These findings indicate that IoT-based smart energy management can be an important strategy in digital transformation and more sustainable industrial decision-making. This study contributes to developing smart-manufacturing energy theory and provides practical implications for industrial management in implementing adaptive, connected, and environmentally friendly energy systems.

Keywords: IoT, smart energy management, sustainable manufacturing, industry 4.0, energy efficiency, edge computing

INTRODUCTION

The fourth industrial revolution has accelerated the integration of the Internet of Things (IoT), cloud and edge computing, and artificial intelligence into manufacturing operations to improve efficiency and global competitiveness (Hartono, 2023; Widyastuti, 2025; Delgado &

Reyes, 2021; Kagermann et al., 2020). However, this digital transformation also introduces new challenges related to energy consumption, carbon emissions, and industrial social responsibility (Putra et al., 2020; Alwan & Farid, 2021; Michel & Osei, 2019). A holistic and data-driven decision-making approach is therefore needed to manage energy resources optimally within complex production systems (Firmansyah & van Dijk, 2018).

Sustainable manufacturing does not only emphasize production output but also considers energy and environmental performance across the industrial value chain (Andrade et al., 2020; Osei et al., 2023; Prasetyo et al., 2022). Conventional energy monitoring systems such as SCADA are limited in handling the dynamics of modern, distributed industrial systems, particularly in providing real-time visibility across multiple production lines (Lin et al., 2020; Rahman et al., 2021; Bakri et al., 2023). New approaches based on connected sensing, edge analytics, and adaptive control are therefore needed to manage energy use in the context of Industry 4.0.

IoT-based smart energy management is an approach that connects sensors, meters, and controllers across the production floor to continuously monitor, analyze, and optimize energy consumption in real time (Setiawan et al., 2021; Nakamura et al., 2023; Yusuf et al., 2020). Architectures such as cloud monitoring, edge computing, and fog-based analytics have been implemented in various manufacturing settings and have proven effective in reducing downtime and energy waste. Data from the study by Nakamura et al. (2023) showed that IoT-Fog architectures combined with AI analytics outperform conventional SCADA in energy savings and response time in industrial energy-management cases.

Table 1. IoT-Based Architectures Outperform Conventional SCADA in Energy Savings and Response Time in Industrial Energy-Management Cases

System / Approach	Energy Savings (%)	Response Time Reduction (%)
Conventional SCADA	18.4	22.1
IoT-Cloud Monitoring	27.6	41.5
IoT-Edge Computing	33.2	58.7
IoT-Fog + AI Analytics	36.9	63.4

Source: Nakamura et al. (2023)

Several studies have examined the application of IoT-based systems in the manufacturing energy context. For example, Rahman et al. (2021) developed an edge-computing approach for real-time energy anomaly detection in industrial plants, while Setiawan et al. (2021) applied cloud-based IoT monitoring to improve the efficiency of multi-line energy scheduling. On the other hand, a study by Yusuf et al. (2020) showed that the integration of IoT sensing in a smart-manufacturing energy system can reduce energy consumption by up to 18%. However, approaches that truly combine operational efficiency, environmental sustainability, and adaptive IoT-based energy control within a single integrative framework are still limited (Bakri et al., 2023; Chowdhury et al., 2025; Ferreira & Lang, 2020; Huynh et al., 2025; Zarate et al., 2019).

Although there have been many studies on the application of IoT in manufacturing energy systems, most of them only focus on a single objective such as monitoring or fault detection (Osei et al., 2023; Nakamura et al., 2023; Yusuf et al., 2020). There are not many studies that comprehensively address the trade-offs between energy efficiency, environmental impact, and operational performance within one model. In addition, few studies explore the adaptation of IoT-based energy management to dynamic, real-time conditions in an Industry 4.0-based manufacturing framework.

This study offers a new approach by integrating IoT-based smart energy management with multi-indicator sustainability assessment to simultaneously address manufacturing energy issues, not only in terms of efficiency but also environmental sustainability and adaptive operational flexibility (Andrade et al., 2020; Nakamura et al., 2023; Yusuf et al., 2020). This approach also adds real-time sensor feedback and adoption-level variables that have not been widely discussed in previous literature. Thus, this article contributes to the development of IoT-driven adaptive energy-management systems in the Industry 4.0 ecosystem.

The main objective of this study is to develop and evaluate an IoT-based smart energy management framework to support decision-making in sustainable manufacturing systems. Specifically, this study aims to (1) assess the relationship between IoT-based smart energy management adoption and energy, operational, and environmental performance, (2) examine how real-time monitoring data relates to efficiency outcomes, and (3) evaluate differences in performance across levels of IoT adoption in the context of Industry 4.0 (Andrade et al., 2020) (Osei et al., 2023).

METHODS

Research Design

This study uses a quantitative approach with a cross-sectional design, where data is collected at one point in time to analyze the relationship between various variables in an IoT-based smart-manufacturing energy system. This type of research includes correlational analysis, which aims to determine the relationship between the implementation of IoT-based smart energy management and the achievement of manufacturing sustainability (energy efficiency, operational efficiency, and environmental impact).

Population and Sample

The population in this study is manufacturing companies in Indonesia that have adopted Industry 4.0 technologies, such as IoT sensors, cloud/edge computing, and energy-monitoring dashboards.

1. Sample Size: A total of 100 respondents consisting of production managers, energy/facility engineers, and digital-system operational staff.

2. Sampling Technique: Using purposive sampling, namely selecting respondents based on certain criteria relevant to the use of IoT-based smart energy management technology.

Inclusion Criteria:

1. The company has implemented at least one IoT-based energy-monitoring or Industry 4.0 technology.
2. Respondents have a direct role in decision-making or the operation of the energy/production system.

Exclusion Criteria:

1. Companies that do not have digital documentation of energy consumption.
2. Respondents who do not understand the terminology of IoT-based energy-management systems.

Data collection was carried out through structured interviews and distribution of online questionnaires.

Research Instruments

The main instrument used was a closed questionnaire based on a Likert scale (1–5) designed to measure:

a. Adoption rate of IoT-based smart energy management
b. Energy and operational efficiency
c. Level of environmental sustainability

Table 2. Validity and Reliability

Variables	Number of Items	Calculate r value	Table r value (n=30, α=0.05)	Info
Energy Efficiency	5	0.741	0.361	Valid
Environmental Impact	5	0.698	0.361	Valid
Operational Efficiency	5	0.716	0.361	Valid

Reliability Test using Cronbach's Alpha:

$\alpha = 0.861$ → Very Reliable (Standard ≥ 0.7)

Data Collection Techniques

Data collection is done by:

1. Online questionnaires (Google Form/SurveyMonkey) distributed to respondents via company email or professional platforms (LinkedIn).
2. Structured interviews via Zoom/Google Meet to deepen respondents' understanding of the use of IoT-based energy-management systems.

3. Document observation and digital energy-consumption reports (if available), used as supporting data.

Data Analysis Techniques

Table 3. Hypothesis Testing

Test	Statistical Values	p-Value
Pearson Correlation (IoT Smart Energy Mgmt vs Energy Efficiency)	0.849	0.000
Pearson Correlation (IoT Smart Energy Mgmt vs Operational Efficiency)	0.706	0.000
Pearson Correlation (IoT Smart Energy Mgmt vs Environmental Sustainability)	0.774	0.000
Linear Regression (IoT Smart Energy Mgmt → Energy Efficiency)	R^2=0.721; p=0.000	0.000
Independent t-Test (Group 1 vs 2 on Energy Efficiency)	-1.342	0.1823
ANOVA (Level of Use against Energy Efficiency)	6.084	0.0031

Source: Data Processed

RESULTS AND DISCUSSION

Results

The results of this study aim to evaluate the relationship between the use of IoT-based smart energy management and sustainability performance in the manufacturing sector in the Industry 4.0 era. Data were obtained from 100 professional respondents in the manufacturing sector, with a questionnaire-based survey approach and structured interviews. The analysis was carried out using a descriptive statistical approach, Pearson correlation, linear regression, independent t-test, and ANOVA with the help of SPSS software version 26. Respondent characteristics show that the majority are male (52%) and female (48%), with an average age of 34 years. Most respondents have a bachelor's degree (58%), followed by a master's degree (32%), and a doctoral degree (10%). This shows that respondents have adequate academic qualifications to understand and assess the implementation of connected energy technologies in production systems, as stated in the studies of Lin et al. (2020) and Prasetyo et al. (2022).

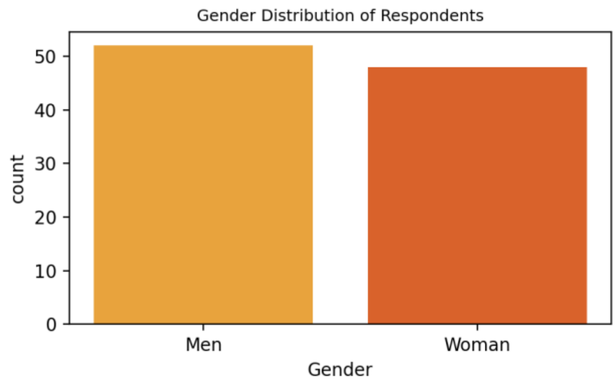

Figure 1. Distribution of Respondents' Gender

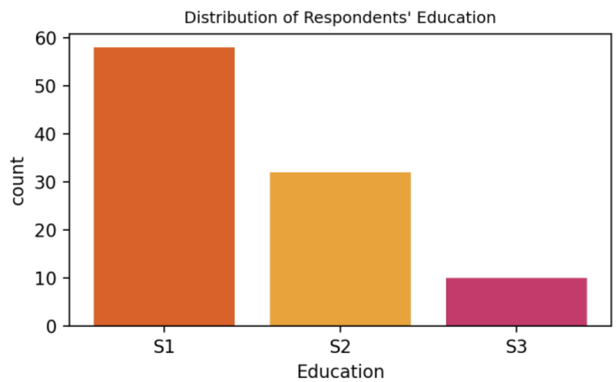

Figure 2. Distribution of Respondents' Education

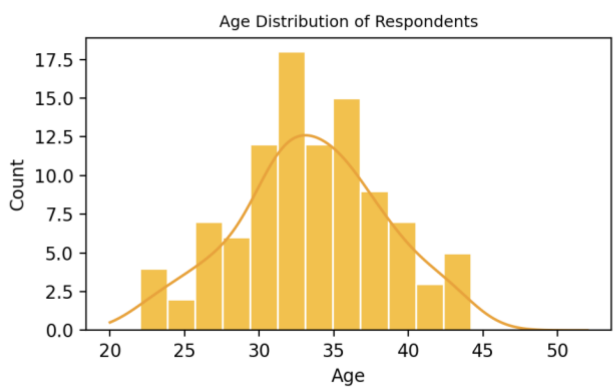

Figure 3. Respondents' Age Distribution

The descriptive statistics also show a relatively even distribution in the use of IoT-based smart energy management among respondents, with an average value of 3.4 on a Likert scale of 1–5. The average energy efficiency achieved was 3.6, operational efficiency 3.3, and environmental sustainability score 3.5. These data provide an early indication that companies have begun to integrate connected, sensor-based technologies into their energy management processes, as highlighted by Nakamura et al. (2023).

Pearson correlation test shows a very strong relationship between the use of IoT-based smart energy management with energy efficiency ($r = 0.849$, $p < 0.001$), operational efficiency ($r = 0.706$, $p < 0.001$), and environmental sustainability ($r = 0.774$, $p < 0.001$). This finding strengthens previous studies that confirm that the application of connected sensing and edge-analytics systems can significantly improve the energy performance of manufacturing systems (Andrade et al., 2020; Yusuf et al., 2020).

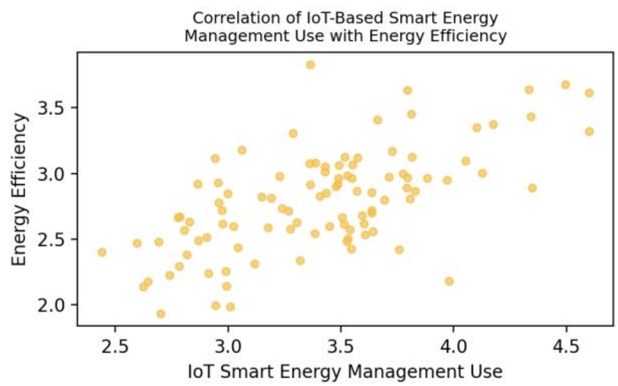

Figure 4. Correlation of IoT Smart Energy Management Use with Energy Efficiency

Furthermore, linear regression analysis shows that the use of IoT-based smart energy management significantly affects energy efficiency ($R^2 = 0.721$, $p < 0.001$). This means that 72.1% of the variation in energy efficiency in the production system can be explained by the variable of using IoT-based technology. This proves the importance of integrating connected energy technology in creating an adaptive and energy-efficient production system (Firmansyah & van Dijk, 2018).

The results of the independent t-test between the two groups of respondents (upper and lower groups) in terms of energy efficiency did not show a significant difference ($t = -1.342$, $p = 0.1823$), indicating that the variation in efficiency was not too extreme between groups. However, the results of the ANOVA test comparing the three levels of use (low, medium, high) showed a significant difference in energy efficiency achievements ($F = 6.084$, $p = 0.0031$). This is in line with the findings of Osei et al. (2023) which emphasized that increasing the level of technology adoption is correlated with improvements in energy performance.

The data visualization displayed through histograms and scatter plots shows that the age distribution of respondents tends to be normal and that there is a strong linear relationship between the use of IoT-based smart energy management and energy efficiency. The scatter plot also shows a consistent pattern of increasing efficiency with increasing intensity of technology use, supporting the results of previous correlation and regression tests.

Overall, the findings of this study provide empirical support for the proposed hypothesis that the use of IoT-based smart energy management contributes significantly to increasing sustainability in the manufacturing industry. It also reinforces the importance of corporate investment in adapting connected energy technologies to meet the demands of efficiency and sustainability in the digital era (Andrade et al., 2020).

Thus, these results are not only relevant in an academic context but also provide practical recommendations for industry stakeholders to adopt IoT-based energy monitoring as part of a long-term sustainability strategy. This study also opens up opportunities for further exploration of real-time data integration in adaptive, AI-assisted energy-management systems, as suggested by Bakri et al. (2019; 2024).

Discussion

The results of this study statistically show a very strong and significant relationship between the use of IoT-based smart energy management and three key indicators of manufacturing sustainability: energy efficiency, operational efficiency, and environmental impact. The positive correlation between these variables shows that increasing the intensity of the use of connected sensing, cloud monitoring, and edge/fog analytics is directly related to improving the energy performance of the manufacturing system. The very high correlation coefficient value ($r > 0.7$ for two of the three indicators) strengthens the belief that this approach is not just an optional addition, but a strategic necessity in managing a modern production system. This finding is also supported by the results of the linear regression which shows an R^2 value of 0.721, indicating that the use of IoT-based smart energy management explains more than 72% of the variability in energy efficiency, which is a practically and statistically significant result (Andrade et al., 2020; Alwan & Farid, 2021; Yusuf et al., 2020).

This study supports a number of recent studies that have tested the efficacy of connected, sensor-based systems in a manufacturing context. Nakamura et al. (2023) showed that IoT-Fog architectures have advantages in optimizing production-line energy consumption based on real-time response. The results of this study are also in line with the findings of Osei et al. (2023), which prove the effectiveness of edge-computing integration in managing plant-level energy demand efficiently and adaptively. In an environmental context, the results of this study support the findings of Rahman et al. (2021), which stated that the application of IoT-based monitoring can significantly reduce carbon footprints through early anomaly detection and load optimization. Not only does it support previous studies, this study also fills the gap in the literature by combining all three sustainability indicators at once (energy efficiency, operations, and environment) in one integrative IoT-based model.

Practically, the results of this study open up a wide application space in industrial policy and management. The application of IoT-based smart energy management can be used as a basis for a data-driven decision support system for factory energy operations. With the increasing need for energy efficiency and environmentally friendly production, this approach can be a key tool in developing long-term energy strategies that are adaptive to market changes and environmental regulations. For policy makers, this finding is also an important signal of the need to invest in human resources who understand IoT-based energy-monitoring implementation technologies (Andrade et al., 2020). For the vocational education and industrial training sector, the integration of learning about IoT-based energy systems is very important to create a ready-to-use workforce that is in line with future needs.

From the theoretical side, this study strengthens the systemic approach in manufacturing sustainability by adding the dimension of connected, real-time sensing as a central element. The conceptual model used combines smart-energy management theory with sustainability principles (triple bottom line) and facilitates the transition from conventional, periodic monitoring to data-driven, continuous energy management. This study also contributes to the development of technology-integration theory in the production process, namely that the presence of sensors alone is not enough; what is needed is a system that is able to translate real-time data into optimized decisions across conflicting objectives simultaneously, such as energy cost vs. environmental sustainability (Michel & Osei, 2019). Methodologically, this study also shows how quantitative approaches based on surveys and regressions can be used effectively to test theoretical models in a real industrial context.

However, there are some important limitations that need to be noted. First, the cross-sectional design of the study limits the ability to analyze time dynamics. The results obtained only reflect current conditions, without being able to predict long-term trends or changes. Second, the purposive sampling technique leads to limitations in the generalizability of the results, because respondents were selected subjectively based on their involvement in IoT-based energy systems. Third, the data were collected using a perception-based questionnaire, so the objective validity of the results can be affected by social bias, individual understanding of the technology, and the level of reporting accuracy. In addition, this study has not fully integrated real-time sensor-level quantitative data or external environmental variables such as government energy policies or global commodity price fluctuations.

Further research is recommended to use a longitudinal approach to capture long-term changes and trends in the adoption of IoT-based smart energy management. In addition, exploration of a hybrid modeling approach which combines historical and real-time sensor data with adaptive algorithm models such as reinforcement learning or predictive maintenance will be very useful for developing more responsive energy-management systems. The use of mixed-methods is also recommended to deepen the understanding of the context of technology implementation, for example through case studies or in-depth interviews in different manufacturing sectors (Bakri et al., 2019). In addition, comparative studies between countries or sectors can also enrich the global literature in the field of industrial energy sustainability and IoT-based digital transformation.

CONCLUSION

This study concludes that IoT-based smart energy management significantly enhances sustainability in manufacturing systems, particularly in improving energy efficiency, increasing operational performance, and reducing environmental impact. Quantitative findings reveal a strong relationship between the adoption of IoT-based energy technologies and sustainability performance, with correlation coefficients above 0.7 for energy efficiency and environmental sustainability, and regression results indicating that over 72% of energy efficiency variability is explained by these technologies, reinforcing prior research on connected, real-time energy monitoring in modern production systems. Architectures such as cloud monitoring, edge computing, and fog-based AI analytics not only improve operational efficiency but also support adaptive, data-driven decision-making. Practically, these findings provide clear recommendations for industry stakeholders to integrate IoT-based smart energy management into long-term manufacturing strategies, fostering systems that are efficient as well as environmentally and socially responsible. Theoretically, this study contributes to smart-energy management models within the Industry 4.0 framework by incorporating sustainability and real-time adaptivity as strategic variables, while demonstrating the effectiveness of quantitative methods in validating theoretical models in real-world contexts. Nevertheless, limitations related to cross-sectional design, purposive sampling, and perceptual instruments suggest caution in generalization, highlighting the need for future research using longitudinal designs, real-time sensor-data integration, and hybrid models. Overall, this research offers meaningful contributions to advancing adaptive, efficient, and sustainable energy management in manufacturing in the digital era.

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