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Design of a Production Efficiency Evaluation System Using an OEE Approach and IoT-Based Energy Indicators with Node-RED in the FMCG Manufacturing Industry

Hanif Wicaksono, Taufik Roni Sahroni*

Industrial Engineering Department, BINUS Graduate Program – Master of Industrial Engineering, Bina Nusantara University, Jakarta 11480, Indonesia

Corresponding Author Email: Taufik@binus.edu

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ABSTRACT

The research focuses on developing a production efficiency evaluation system using the Overall Equipment Effectiveness (OEE) method, integrating energy consumption monitoring through an Internet of Things (IoT) framework and Node-RED. The case study is conducted at a Fast-Moving Consumer Goods (FMCG) manufacturing plant. In the solid raw material transfer plant, the existing control system lacks a digital operational data recording feature, preventing real-time monitoring of machine performance and energy use. This study aims to design and implement a monitoring system utilizing current transformer (CT), pressure, and machine running-time sensors. The collected data is processed through Node-RED and visualized in real time via a FactoryTalk View-based dashboard, enabling easier machine performance tracking and data-driven decision-making. The system is expected to improve operational efficiency, reduce machine downtime, and optimize energy usage, particularly during idle periods. This research also aims to support the realization of Industry 4.0 by implementing a responsive, data-driven automation system. Results indicate that Availability increased from 92.37% to 95.53%, performance increased from 89.21% to 93.16%, and OEE increased from 82.10% to 88.89%. Energy reduced idle 12.06 kWh, equivalent to 48.36%, and emissions reduced 9.99 kg CO_2/day.

1. INTRODUCTION

The rapid evolution of automation and robotics has reshaped the foundations of modern industry, offering unprecedented improvements in efficiency, accuracy, and flexibility. As industrial processes become more complex and interconnected, the emergence of Industry 4.0 marks a pivotal shift, in which the integration of the Internet of Things (IoT) and artificial intelligence (AI) enables the development of smart factories. These advancements not only transform traditional manufacturing practices but also extend their influence into diverse fields such as healthcare, logistics, agriculture, and services. Such cross-sectoral applications significantly contribute to enhanced productivity and foster stronger industrial competitiveness in an increasingly globalized economy [1].

The manufacturing industry is facing increasingly fierce global competition, compelling companies to continuously adapt and enhance production efficiency. Modern consumers expect not only high product quality but also timely delivery and competitive pricing. Advances in Industry 4.0 technologies have accelerated automation and digital transformation, simplifying many aspects of production. Nevertheless, the overall success of manufacturing operations still depends on how effectively production equipment is utilized. In this regard, Overall Equipment Effectiveness (OEE) is a fundamental element of Total Productive Maintenance (TPM), as it enables the identification of improvement opportunities by assessing three primary dimensions: availability, performance, and quality [2]. Moreover, OEE is widely used to pinpoint sources of inefficiency and support systematic improvements in production processes [3]. The integration of IoT into industrial resource management enables real-time monitoring and regulation of energy consumption, while leveraging data-driven insights to optimize efficiency and minimize waste [4]. Node-RED plays a pivotal role in this context by facilitating seamless real-time data integration and process automation, offering straightforward connectivity between industrial systems and cloud-based services. The combined use of IoT and Node-RED within Smart Factory architectures further opens the door to predictive analytics applications [5]. In Industrial IoT (IIoT) frameworks, Node-RED has been proposed as a middleware layer responsible for processing data collected from Programmable Logic Controllers (PLCs), which can then be linked with other IoT components and remotely visualized [6].

PLCs are fundamental components in both current and future industrial development, particularly in smart manufacturing, production line automation, and machine control [7]. Designed specifically for industrial applications, PLCs offer significant advantages and reliability in managing a wide range of production processes, from assembly lines to robotic systems. These devices provide high operational dependability, flexible programming capabilities, and advanced diagnostic functions that enable rapid detection and resolution of process disruptions [8].

The product involves both liquid and solid raw materials, which require proper storage and distribution from the supply area to the processing stage, where liquids and solids are blended. At present, the control system used to handle and distribute solid raw materials still relies on technology from 1994. An outdated PLC operates this system and lacks any recording or tracking of the resources being utilized.

This study does not simply implement a conventional IoT- and Node-RED-based OEE monitoring system, as has been widely reported in previous studies. Rather, it offers several distinctive contributions. First, the proposed system integrates an interlock-based control mechanism with real-time OEE monitoring, enabling not only continuous performance observation but also the automatic reduction of idle energy consumption. Second, the conventional OEE framework is modified by excluding the quality factor and placing greater emphasis on availability, performance, and energy-related indicators, thereby making it more applicable to utility-driven systems. Third, this study establishes a direct link between operational efficiency and environmental impact by incorporating idle energy consumption (in kWh) and CO_2 emissions into the performance evaluation. Finally, the proposed approach is validated through real industrial implementation, demonstrating statistically significant improvements in both OEE and energy efficiency.

2. RELATED WORKS

2.1 Production engineering

Automation and robotics have become the backbone of modern production, driving greater efficiency, precision, and adaptability in industrial processes. In the era of Industry 4.0, the integration of IoT and artificial intelligence has paved the way for the emergence of smart factories. Beyond manufacturing, these technologies are now increasingly applied in sectors such as healthcare, logistics, agriculture, and services, thereby enhancing overall productivity and strengthening industrial competitiveness [1]. The advancement of Industry 4.0, particularly through the integration of the IoT and artificial intelligence, has accelerated the transformation of factories into smart factories. These facilities can make faster decisions, minimize waste, and optimize resource use [9]. Automation in industrial construction has introduced substantial improvements in both manufacturing and assembly stages. Technologies such as the IoT, artificial intelligence, digital twins, and robotics enhance efficiency, safety, and the consistency of production quality. Their implementation also facilitates data interoperability, production scheduling optimization, and traceability throughout the manufacturing process, thereby reducing errors, lowering costs, and accelerating project completion times [7]. To enhance performance while simultaneously reducing emissions, it is essential to optimize processes, advance electrification, adopt alternative fuels, and foster innovations in computing and automation engineering. Within the framework of Industry 4.0, digitalization has proven effective in improving energy efficiency [10]. This study emphasizes the role of automation and IoT integration in enhancing production efficiency. The research specifically focuses on energy efficiency within the Industry 4.0 framework. To achieve this, IoT utilization indicators, particularly those from Node-RED, will be used to monitor and optimize energy consumption. This focus is based on the proven potential of digitalization, automation, and data integration technologies to accelerate processes, minimize waste, and reduce production costs.

2.2 Overall Equipment Effectiveness

OEE is recognized as a key indicator within TPM, serving as a tool to identify areas for improvement through the evaluation of three essential dimensions: availability, performance, and quality [2]. In addition, OEE can also be defined as the ratio of actual productive time to the total planned production time (PPT), providing a clear measure of how effectively equipment is utilized [11]. OEE serves as a measure of equipment efficiency, helping to identify sources of loss and guiding improvements within manufacturing systems [3]. Energy consumption analysis can also be applied to estimate OEE values [12]. By leveraging OEE, companies can uncover inefficiencies and design well-structured strategies to enhance productivity [13]. The implementation of OEE provides a comprehensive overview of equipment conditions, enabling companies to prioritize improvements and enhance operational performance [14]. By applying OEE, organizations can pinpoint sources of inefficiency, monitor equipment performance, and formulate targeted improvement plans aimed at increasing overall effectiveness [15]. This study focuses on two indicators: Availability and performance. The quality indicator is excluded because the research examines transfers of existing materials between plants, during which no material is added, and no processes alter the material's quality.

2.3 Automation

Automation in manufacturing aims to reduce repetitive manual work and support rapid adaptation during system changes. In this context, integrating HMI with PLC enables centralized operation and real-time monitoring of equipment [16]. Integrated process automation connects field devices, PLC controllers, and SCADA to provide centralized access to control functions and operational data. At the same time, SCADA supports real-time monitoring through mimics, trends, and alarms [17]. PLCs are widely used as the core platform for industrial automation, executing control functions at the control layer of the automation pyramid and interfacing directly with field devices. At the same time, PLCs connect to supervisory systems such as HMI and SCADA, enabling centralized monitoring of process and equipment status as well as operator interaction at the supervisory level [18]. The control system for handling and distributing solid raw materials is based on 1994-era technology. It is run by an obsolete PLC and provides no capability to record or trace resource usage. To address these limitations, the PLC is being migrated to an Allen-Bradley platform.

2.4 Internet of Things

In the context of Industry 4.0 and the Industrial Internet of Things (IIoT), a functional architecture is required to coordinate and integrate both hardware and software, ensuring that the latest digital technologies can be fully leveraged in the industrial sector [6]. IoT plays a central role by connecting machines, sensors, and control systems to enable smarter production processes. Through such connectivity, manufacturing industries can perform real-time monitoring, implement predictive maintenance, and make data-driven decisions [19]. The application of IoT in industrial energy management also allows continuous monitoring and regulation of energy consumption, while providing data-based insights to optimize efficiency and reduce waste [4]. In the case of raw material transfer within plants, however, IoT has not yet been implemented since the existing legacy control systems are still under development and lack internet connectivity. Once adopted, IoT will enable the integration of hardware and software components and the transmission of sensor data, which in turn will support the acquisition of OEE-related information.

2.5 Node-RED

Node-RED functions as a flow-based programming platform for integrating hardware devices, communication protocols such as Modbus and MQTT, and cloud services.[4] It enables real-time data integration and process automation, providing seamless connectivity between industrial systems and cloud-based platforms. When combined with IoT, Node-RED within Smart Factory architectures also creates opportunities for predictive analytics [5]. In this context, Node-RED will serve as a bridge for the new system, allowing sensor data to be transmitted directly into the platform. This setup enables automatic collection of sensor readings, operating time, and energy usage—without human intervention—resulting in OEE values that are more accurate, consistent, and accessible at any time.

2.6 Energy efficiency and sustainability

Energy efficiency has become a key component of Industry 4.0. By integrating IoT technologies, energy usage can be monitored and controlled in real time, with sensor data processed through intelligent analytics and IoT-based monitoring systems. This allows industries to reduce energy consumption while maintaining production performance. One widely adopted approach involves energy monitoring using an open architecture integrated with OEE systems, enabling the detection of inefficiencies and the activation of automated energy-saving measures [20]. Improving energy efficiency has also emerged as a major priority in the manufacturing sector. With growing concerns over environmental sustainability, optimizing energy consumption not only reduces operational costs but also mitigates the ecological impact of production processes. By employing advanced energy monitoring technologies, industries can supervise energy usage in real time, allowing corrective actions and saving strategies to be implemented quickly to keep systems performing at their best [21]. Currently, the raw material transfer plant lacks an interlock system to detect and respond when the machine is idle, resulting in considerable energy waste. To address this issue, this study proposes installing a pressure transmitter sensor that serves as an interlock, automatically shutting down the raw material transfer system during idle periods.

Electricity demand in our plant is met through the Java–Madura–Bali (JAMALI) interconnected power system rather than by a single local generating facility. National power-sector planning indicates that supply to the DKI Jakarta load center is delivered via 500 kV extra-high-voltage and 150/70 kV high-voltage transmission corridors. Accordingly, even plants located close to the load area inject their output into the transmission network, where it becomes part of the system-wide power flows, before being routed through primary substations and stepped down for distribution to end users. Building on this grid-based arrangement, the greenhouse-gas (GHG) emissions associated with electricity consumption were estimated using the official JAMALI grid emission factors published by the Directorate General of Electricity under the Ministry of Energy and Mineral Resources (ESDM). The latest publicly available JAMALI values in that series (reference year 2019) report an Operating Margin (OM) of 0.83 tCO_2/MWh equivalent to 0.83 kg CO_2/kWh) [22], which were adopted in this study due to the absence of a newer official release. In addition, national electricity statistics show that coal remains the dominant primary energy source in PT PLN (Persero)'s generation mix (66.43% in 2024), supporting the interpretation that JAMALI's grid emission intensity is largely influenced by coal-fired generation.

Carbon dioxide (CO_2) is the primary greenhouse gas emitted from the combustion of liquid natural gas in power generation processes. Coal power plants continue to be the largest contributors to total carbon dioxide emissions in many countries, maintaining a dominant role in global greenhouse gas output over the past several decades [23]. The combustion of coal for electricity generation releases substantial amounts of carbon dioxide into the atmosphere, making it a major contributor to global warming and climate change [24]. On a global scale, carbon dioxide emissions from coal-fired power plants remain a significant driver of global warming, despite the growing efforts of many nations to implement emission reduction policies and shift toward renewable energy alternatives [25]. Carbon dioxide is a direct byproduct of the carbon combustion process in coal, with each ton of coal burned generating over two tons of CO_2 emissions released into the atmosphere [26]. The electricity supplied to our plant is generated from coal-fired power stations, which produce significant carbon emissions and are located in densely populated urban areas. In this context, we aim to improve the efficiency of our electricity consumption not only to reduce operational costs but also to support long-term sustainability objectives.

3. RESEARCH METHOD

This research aims to design a monitoring system using the OEE approach, integrated with IoT technology through the Node-RED platform, and applied to the solid raw material transfer process in the Fast-Moving Consumer Goods (FMCG) manufacturing industry. The design of this system is motivated by the industry's need to monitor machine performance in real time. With the support of integrated sensors and control systems, operational efficiency is expected to improve significantly. Figure 1 is the conceptual framework of this research.

3.1 Research stage

The overall workflow of this case begins with problem identification and the formulation of research objectives, utilizing a design thinking approach. This is followed by the design and integration of data collection sensors for an IoT- and Node-RED–based OEE system. The collected data are then utilized to calculate OEE components, analyze energy efficiency, and evaluate the performance of both the new and the existing systems. Subsequently, usability testing is conducted to assess the practicality and ease of system use, as shown in Figure 2, as the workflow framework of this research.

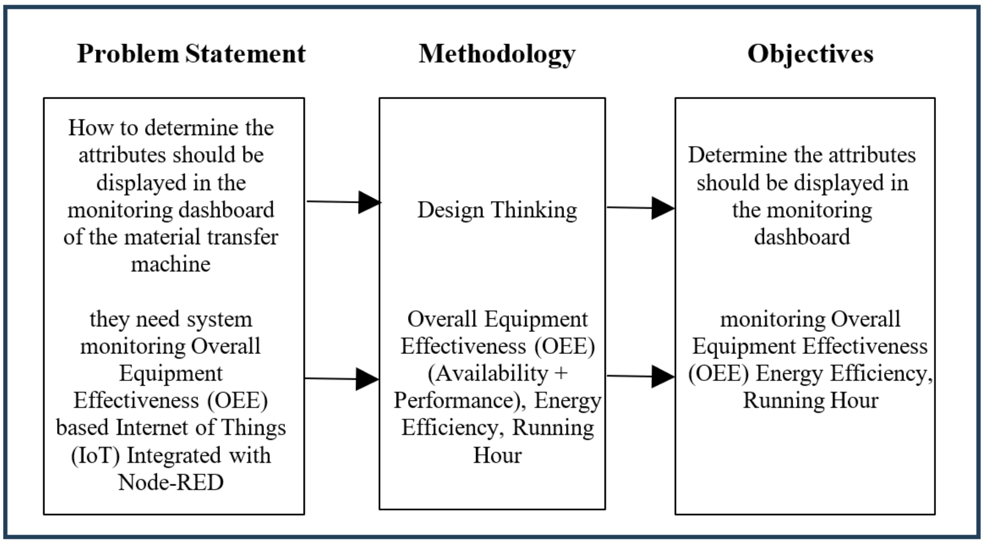

Figure 1. Conceptual framework

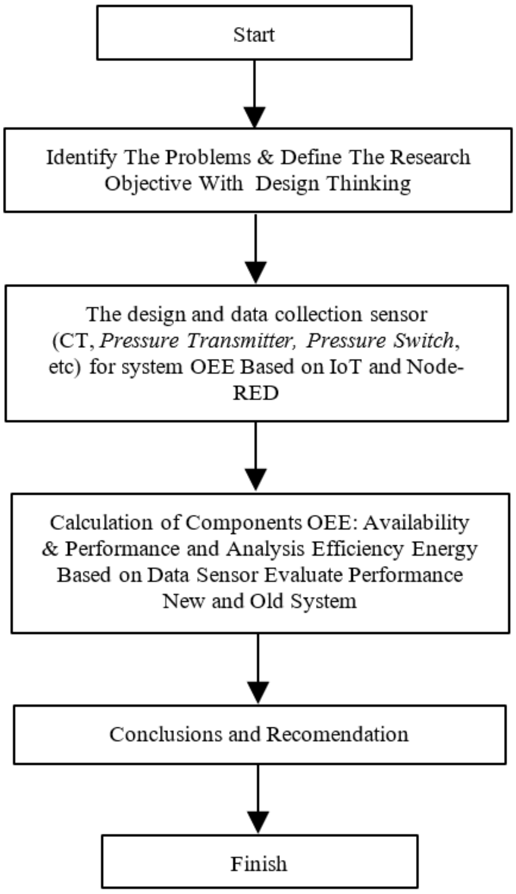

Figure 2. Overview workflow

At this stage, an IoT-based monitoring framework was developed by integrating sensors (current transformer (CT), Pressure Switch, and Pressure Transmitter) with Node-RED to PLC for data acquisition and processing. In parallel, a real-time OEE visualization dashboard was implemented to support production, maintenance, and management teams in continuous monitoring and informed decision-making.

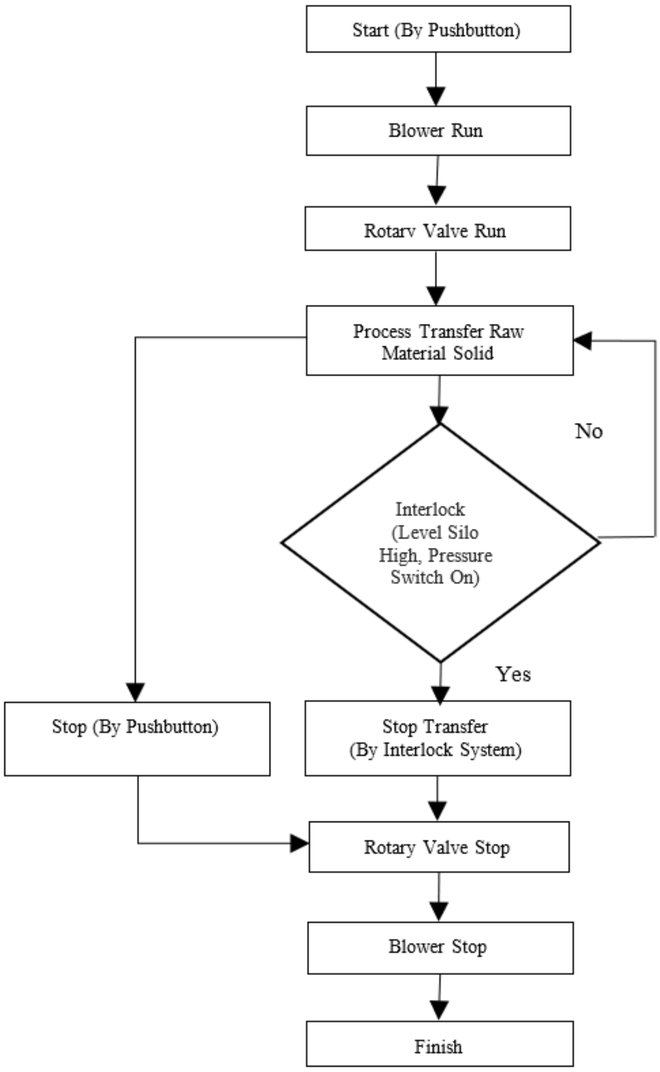

Figure 3. Flowchart existing system

This study employs a systematic research methodology consisting of six sequential stages. The first stage involves problem identification and the formulation of research objectives using the design thinking approach. This stage aims to identify the main issues in the system, define the scope of the research, and establish clear objectives for system improvement.

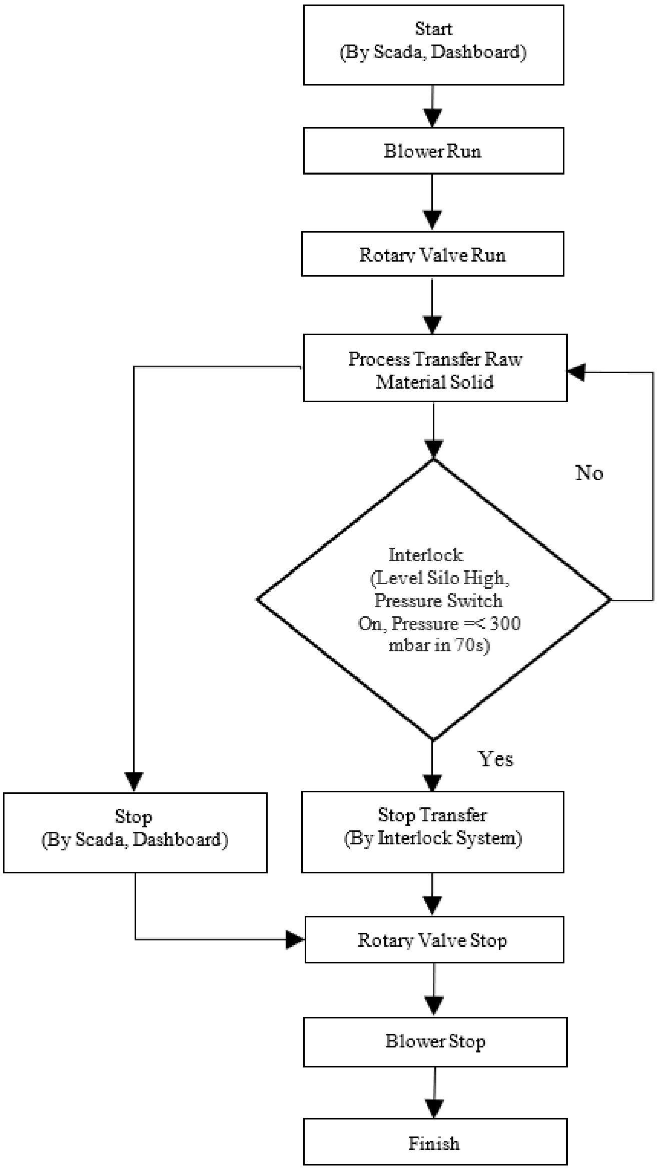

Figure 4. Flowchart new system

The second stage focuses on the design of the data acquisition system and sensor-based data collection. Several measurement devices, including CT, pressure transmitters, pressure switches, and other relevant sensors, are integrated to obtain operational data required for the OEE assessment. The collected data are processed through an IoT-based monitoring system using Node-RED.

The third stage involves the calculation of OEE components, namely availability, performance, and energy efficiency analysis. These indicators are used to evaluate the system's operational effectiveness and assess energy-efficiency performance based on sensor data.

The fourth stage consists of evaluating and comparing the performance of the proposed system with the existing system. This evaluation is conducted to determine the extent to which the developed system contributes to performance improvement and energy efficiency enhancement.

The fifth stage presents the formulation of conclusions and recommendations based on the results of data processing, OEE calculation, and system performance evaluation. Finally, the research concludes with the final stage, which marks the end of the overall research process.

The legacy system configuration is presented in the attached Figure 3, which shows an existing flowchart summarizing the control logic, signal flow, and operational sequence used in the current setup. In the proposed system, the interlock logic was revised relative to the existing configuration to mitigate unnecessary stoppages and reduce idle time during operation, thereby improving overall equipment utilization. Figure 4 describes the flowchart of the new system.

3.3 Design of the monitoring system

This work proposes an IoT-based monitoring architecture that integrates a CT, pressure switch, and pressure transmitter with Node-RED for real-time data acquisition, processing, and routing. A dedicated dashboard was designed to continuously visualize OEE indicators, assisting production and maintenance personnel, as well as management, with performance tracking and evidence-based decision-making.

Allen-Bradley 1769-L33ER CompactLogix PLC provides two Ethernet ports with Device Level Ring (DLR) support for reliable EtherNet/IP communication. It can connect up to 32 EtherNet/IP nodes, enabling integration with HMI/SCADA, sensors, and other automation devices. Figure 5 shows the PLC used in this system.

Figure 5. Allen-Bradley 1769-L33ER CompactLogix Programmable Logic Controller (PLC)

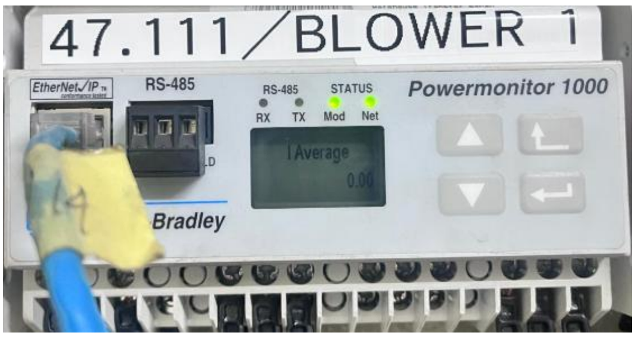

Figure 6. Allen-Bradley 1408-TS3A-ENT (PM1000)

Allen-Bradley 1408-TS3A-ENT (PM1000) power meter is used to acquire current measurements from the CT and transmit the data over an Ethernet network. The measurement range is 0–250 A. Figure 6 shows the power meter used in this system.

The IFM PA3027 pressure transmitter (4–20 mA) measures the actual pressure and transmits it as a 4–20 mA analog signal, which the PLC can read as a real-number variable. The measurement range is 0–1000 mbar. Figure 7 shows the pressure transmitter used in this study.

Figure 7. IFM PA3027

Node-RED was used to transfer data from PLC 1 to another PLC because the distance between the controllers is relatively long. Figure 8 presents the Node-RED function employed in this research.

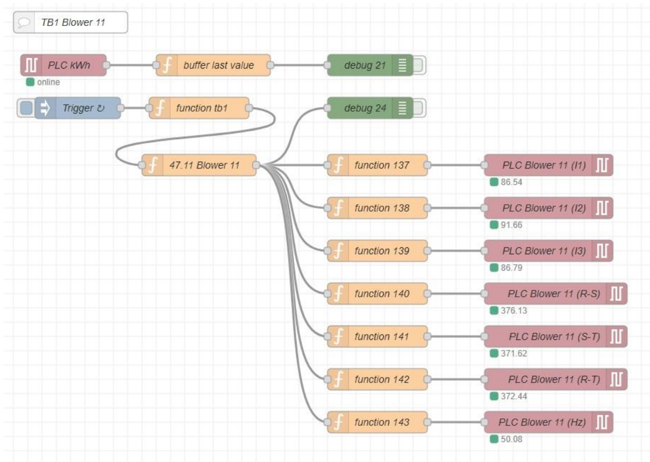

Figure 8. Flow Node-RED

Figure 8 illustrates the real-time data processing flow in Node-RED for the TB1 Blower 11 power meter monitoring system. The main data source is the PLC kWh node, which uses the Ethernet/IP protocol to read electrical energy values from the PLC/power meter. These values are then passed to the buffer's last-value node, which stores the most recently read value. This allows the system to retain and use the previous data when a reading delay occurs or when the incoming data are unstable. The data acquisition process can also be triggered manually or periodically through the Trigger node, after which the data are forwarded to the tb1 function node. This node serves as the initial data processing stage before the data are transferred to the main 47.11 Blower 11 node. In this node, data from the PLC are separated and mapped to several electrical parameters. After processing, the outputs from the 47.11 Blower 11 node are sent to several function nodes, namely function 137 to function 143. Each function node is used to retrieve, process, or format a specific parameter before the processed data is sent back to PLC Blower 11 via Ethernet/IP.

The dashboard was developed using FactoryTalk View Studio (Site Edition) version 10.00, a Rockwell Automation application commonly used for HMI implementation on Windows-based PCs. FactoryTalk View Studio was configured together with FactoryTalk ViewPoint version 9.00.241.00 to enable web-based monitoring through a browser. Figure 9 shows the FactoryTalk View Studio application used for dashboard development in this research.

Figure 9. FactoryTalk View Studio (Site Edition) version 10.00

3.4 Data analysis technique

3.4.1 Overall Equipment Effectiveness calculation

OEE measures equipment efficiency and helps identify sources of loss. We combine two levels of availability, performance, as expressed in Eq. (1) :

$$OEE_m = \text{Availability} \times \text{Performance} \tag{1}$$

Availability in OEE describes the share of scheduled production time when the equipment is actually running, as expressed in Eq. (2):

$$\text{Availability} = \frac{\text{Operating Time}}{\text{Planned Production Time}} \times 100\% \tag{2}$$

OOE's Performance reflects how efficiently the system runs versus the ideal pace during operating time, essentially the ratio of what you actually produce to what you should produce at design speed. Performance falls off during speed loss, brief stoppages, or choppy material flow. The remedy is to recalibrate speeds, address tooling/sensor issues, and stabilize the feed to bring the rate back on track as expressed in Eq. (3):

$$\text{Performance} = \frac{\text{Ideal Cycle Time} \times \text{Actual Output}}{\text{Operating Time}} \times 100\% \tag{3}$$

3.4.2 Energy efficiency and sustainability calculation

Energy use comes from two things, how much power it draws and how long it runs. So the more kilowatts, the energy is electricity power times time (hour), so the energy formula described in Eq. (4):

$$Energy\ (kWh) = ElectricPower\ (kW) \times Time\ (Hour) \tag{4}$$

Electricity cost comes from two inputs: how much energy you use and the price per unit. If we want lower costs, either by reducing kWh consumption or by switching to a cheaper energy source, as expressed in Eq. (5):

$$Cost\ of\ Electricity\ (IDR) = E\ (kWh) \times Cost\ of\ kWh\ (IDR) \tag{5}$$

Idle energy consumption refers to the electrical energy consumed by equipment while idle during production. It is determined by multiplying the idle power demand by the duration of idle time, as expressed in Eq. (6):

$$E_{Idle} = P_{idle} \times t_{idle} \tag{6}$$

Energy reduction is the percentage of energy saved after implementing the proposed method or improvement. It is determined by subtracting the energy consumption after implementation from the energy consumption before implementation, then dividing the result by the energy consumption before implementation, as expressed in Eq. (7):

$$Energy\ Reduction\ (\%) = \frac{E_{Before} - E_{After}}{E_{Before}} \times 100\% \tag{7}$$

CO_2 emissions are the amount of carbon dioxide released from electricity use in the production process. The magnitude of these emissions is calculated by multiplying energy consumption by the local grid's emission factor, expressed in Eq. (8):

$$CO_2 = E_{idle} \times EF \tag{8}$$

3.4.3 Statistical comparison

A statistical comparison was conducted to evaluate whether the differences between the before- and after-implementation conditions were statistically significant. The evaluated parameters included Availability, Actual Performance, modified OEE, idle energy consumption, and CO_2 emissions. For each parameter, the mean value was calculated to represent the average condition during the observation period, as expressed in Eq. (9):

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{9}$$

where, $\bar{x}$ is the mean value, x_i is the value of the i-th observation, and n is the number of observations.

The standard deviation was calculated to evaluate the variation of daily operational data, as expressed in Eq. (10):

$$SD = s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \tag{10}$$

The absolute change between the before- and after-implementation conditions was calculated using Eq. (11):

$$\Delta X = \bar{x}_{after} - \bar{x}_{before} \tag{11}$$

where, ΔX is the absolute change, $\bar{x}_{after}$ is the mean value after implementation, and $\bar{x}_{before}$ is the mean value before implementation.

Welch's independent t-test was used to determine whether the difference between the two observation periods was statistically significant. This test was selected because the before- and after-implementation datasets represent two different operational periods and may have unequal variances. The t-statistic is expressed in Eq. (12):

$$t = \frac{\bar{x}_{before} - \bar{x}_{after}}{\sqrt{\frac{s^2_{Before}}{n_{before}} + \frac{s^2_{after}}{n_{after}}}} \tag{12}$$

where, t is the t-statistic, $\bar{x}_{before}$ and $\bar{x}_{after}$ are the mean values before and after implementation, s^2_{Before} and s^2_{after} are the variances of the two datasets, and n_{before} and n_{after} are the numbers of observations.

The degrees of freedom for Welch's t-test are calculated using Eq. (13):

$$df = \frac{\left(\frac{s^2_{before}}{n_{before}} + \frac{s^2_{after}}{n_{after}}\right)^2}{\frac{\left(\frac{s^2_{before}}{n_{before}}\right)^2}{n_{before} - 1} + \frac{\left(\frac{s^2_{after}}{n_{after}}\right)^2}{n_{after} - 1}} \tag{13}$$

where, df represents the degrees of freedom used to determine the p-value of the t-test.

The significance level was set at $\alpha = 0.05$. Therefore, the difference was considered statistically significant when the p-value was lower than 0.05, as expressed in Eq. (14):

$$p < \alpha \tag{14}$$

where, p is the p-value and α is the significance level. Thus, $p < 0.05$ indicates that the improvement after implementation is statistically significant.

3.5 Data collection and acquisition

Data were collected directly from field instrumentation and controller-level signals to capture the equipment's operational status and performance. The IFM PA3027 pressure transmitter provided continuous pressure measurements as a 4–20 mA analog signal (0–1000 mbar), which the PLC acquired and stored as a real-valued variable. In parallel, electrical load information was obtained using a CT connected to an Allen-Bradley 1408-TS3A-ENT (PM1000) power meter. The power meter measured current within the 0–250 A range and transmitted the readings via an Ethernet network for further processing. Discrete machine conditions, including those captured from the existing interlock and status logic, to support availability and performance. Table 1 reports the baseline (before) condition, whereas Table 2 presents the after condition following the implementation. The comparison is performed using availability, performance, and OEE, together with energy consumption (kWh) and emissions as energy–environment indicators.

Table 1. Data before using the interlock system

Date	Operating Time (OT) (Minutes)	PPT (Minutes)	Availability (%)	Ideal Time Transfer/Ton (Minutes)	Actual Time Transfer/Ton (Minutes)	Actual Performance	OEE	kWh Idle	CO_2 Emissions (kg)
11/22/2025	730	665	91.10%	5.225	5.70	91.62%	83.46%	31.15	25.86
11/23/2025	635	589	92.76%	5.225	5.88	88.87%	82.43%	22.05	18.3
11/24/2025	682	645	94.57%	5.225	5.78	90.40%	85.48%	17.73	14.71
11/25/2025	807	717	88.85%	5.225	6.02	86.76%	77.09%	43.14	35.8
11/26/2025	863	791	91.66%	5.225	5.83	89.61%	82.13%	34.51	28.64
11/27/2025	714	689	96.50%	5.225	5.85	89.28%	86.16%	11.98	9.94
11/28/2025	587	508	86.54%	5.225	5.87	89.01%	77.03%	37.86	31.42
11/29/2025	645	578	89.61%	5.225	6.08	85.87%	76.95%	32.11	26.65
11/30/2025	375	365	97.33%	5.225	5.68	91.96%	89.50%	4.79	3.98
12/1/2025	662	616	93.05%	5.225	5.91	88.40%	82.25%	22.05	18.3
12/2/2025	712	677	95.08%	5.225	5.84	89.53%	85.12%	16.78	13.93
12/3/2025	788	755	95.81%	5.225	5.88	88.85%	85.11%	15.82	13.13
12/4/2025	464	422	90.95%	5.225	5.80	90.09%	81.95%	20.13	16.71
12/5/2025	672	623	92.71%	5.225	5.89	88.64%	82.18%	23.49	19.5
12/6/2025	226	192	84.96%	5.225	5.95	87.86%	74.64%	16.3	13.53

Note: planned production time (PPT); Overall Equipment Effectiveness (OEE)

Table 2. Data after using the interlock system

Date	OT (Minutes)	PPT (Minutes)	Availability (%)	Ideal Time Transfer/Ton (Minutes)	Actual Time Transfer/Ton (Minutes)	Actual Performance	OEE	kWh Idle	CO_2 Emissions (kg)
12/9/2025	603	578	95.85%	5.225	5.48	95.32%	91.36%	11.98	9.94
12/10/2025	592	572	96.62%	5.225	5.58	93.56%	90.40%	9.59	7.96
12/11/2025	584	560	95.89%	5.225	5.51	94.84%	90.95%	11.5	9.55
12/12/2025	558	528	94.62%	5.225	5.69	91.76%	86.82%	14.38	11.94
12/13/2025	507	473	93.29%	5.225	5.63	92.75%	86.51%	16.3	13.53
12/14/2025	420	396	94.29%	5.225	5.53	94.55%	89.15%	11.5	9.55
12/15/2025	460	429	93.26%	5.225	5.61	93.14%	86.86%	14.86	12.33
12/16/2025	714	694	97.20%	5.225	5.49	95.14%	92.48%	9.59	7.96
12/17/2025	557	540	96.95%	5.225	5.68	91.92%	89.11%	8.15	6.76
12/18/2025	590	571	96.78%	5.225	5.57	93.87%	90.85%	9.11	7.56
12/19/2025	553	525	94.94%	5.225	5.64	92.59%	87.91%	13.42	11.14
12/20/2025	292	273	93.49%	5.225	5.84	89.47%	83.64%	9.11	7.56
12/21/2025	288	281	97.57%	5.225	5.76	90.71%	88.51%	3.36	2.79
12/22/2025	448	425	94.87%	5.225	5.60	93.30%	88.50%	11.02	9.15
12/23/2025	730	698	95.62%	5.225	5.53	94.48%	90.35%	15.34	12.73

Note: planned production time (PPT); Overall Equipment Effectiveness (OEE)

4. RESULT AND DISCUSSION

4.1 System implementation results (IoT–Node-RED OEE & energy monitoring)

The monitoring system was deployed at the solid raw material transfer plant to overcome the main constraint of the legacy control system (installed in 1994), which provided limited digital data logging and prevented near-real-time assessment of equipment efficiency and energy behavior.

Three signals were acquired to characterize operating state and energy demand: (i) a CT measuring motor current as a proxy for electrical load, (ii) a pressure transmitter representing process condition to support idle/no-flow detection, and (iii) a run-status signal to determine machine on/off state and accumulate runtime. The combined sensing scheme enabled discrimination among running, idle, and stopped conditions, which is required for availability and performance assessment and for state-based energy analysis.

All signals were streamed to Node-RED as a middleware layer. Within Node-RED, the signals were timestamped, filtered, and converted into derived variables, including runtime accumulation, downtime duration, estimated power, energy (kWh), and event flags (running/idle/stopped). The computed indicators were published to a FactoryTalk View dashboard for near-real-time visualization, allowing operations and maintenance personnel to monitor availability, performance metrics, and energy trends without manual data entry.

Overall, the implementation delivered (a) continuous runtime and downtime records, (b) real-time computation of availability and performance (quality excluded due to transfer-only scope), and (c) energy indicators distinguishing consumption during productive running versus idle periods. These outputs provided operational transparency not achievable under the legacy arrangement and supported improvement actions.

4.2 Overall Equipment Effectiveness result (Availability and performance)

Because the studied process involves inter-plant transfer of already-produced materials, the quality factor was excluded from the OEE calculation, as the observed system is not a product-forming process with measurable good and defective units. The case study focuses on the blower-based material transfer process, in which the main performance losses arise from operating time, transfer delay, and idle energy consumption. Therefore, the evaluation emphasizes availability and performance as the most relevant indicators for assessing operational efficiency. Including a quality factor with an assumed value of 100% would not add analytical value and could create the misleading impression that product quality was directly measured in this study.

To maintain evaluation validity, the modified OEE used in this study is explicitly defined as an availability–performance-based OEE. This metric is not intended to replace the full standard OEE formulation, but to adapt the OEE concept to a utility or transfer-process context where quality loss is not directly observable. Therefore, the results should be interpreted as measures of equipment utilization and transfer performance rather than of complete manufacturing OEE. For comparison with standard OEE benchmarks, this limitation is acknowledged, and the modified OEE values are compared only in terms of availability and performance improvement, not as a full three-factor OEE including quality.

4.2.1 Availability

Availability is the proportion of planned production time during which the transfer system operates. Planned production time (PPT) is defined as the scheduled operating time within the observation window; operating time (OT) is the total accumulated runtime; and downtime (DT) is the difference between PPT and OT.

During the observation window before using the interlock system (22 November 2025 – 6 December 2025) and the observation window after the interlock system (9 November 2025 – 23 December 2025).

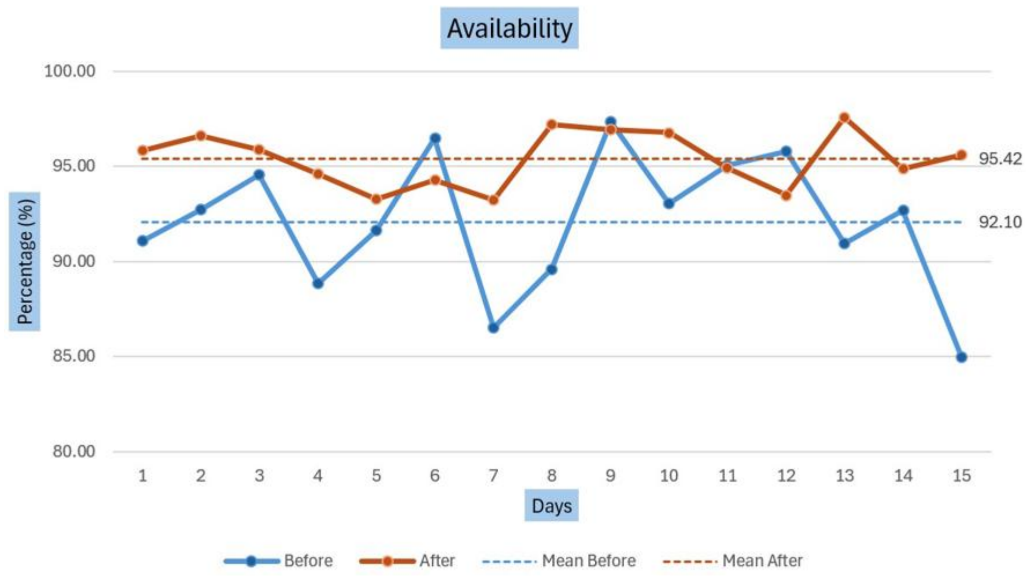

Figure 10. Availability before and after using the interlock

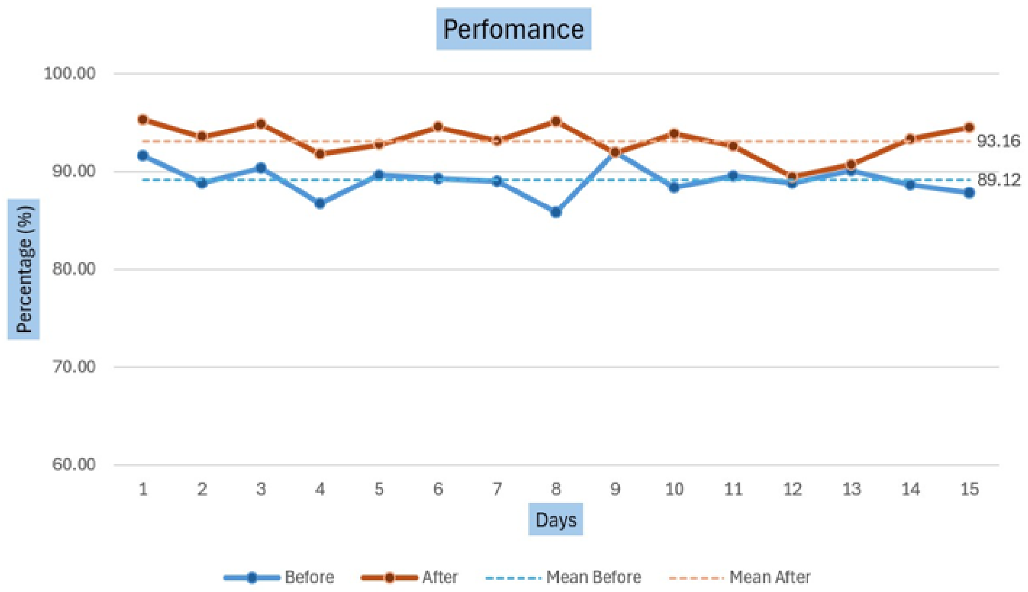

Figure 11. Performance before and after using the interlock

As shown in Figure 10, the availability before the interlock system fluctuated considerably, with several significant decreases during the observation period. The average availability before implementation was 92.10%. After the interlock system was implemented, availability became more stable and generally remained higher, averaging 95.42%.

These results indicate that the interlock system improved the operational readiness of the transfer system by reducing downtime and maintaining more consistent operation during planned production time. Thus, the implementation of the interlock system had a positive effect on system availability.

4.2.2 Performance

Performance represents how effectively the transfer system operates relative to its ideal pace during operating time (OT). To ensure methodological consistency, the Performance component of OEE was computed using a rate-based approach, comparing the ideal transfer rate with the actual average transfer rate over the observation window. Figure 11 description condition performance before and after using the interlock system.

As shown in Figure 11, the performance value before the implementation of the interlock system fluctuated during the observation period, with an average value of 89.12%. Several decreases occurred on specific days, indicating that the actual transfer rate was not consistently aligned with the ideal operating rate. After the interlock system was implemented, the performance value showed a higher, more stable trend, with an average of 93.16%.

The increase in average performance indicates that the interlock system contributed to improving the operating efficiency of the transfer system. This improvement suggests that the system operated closer to its ideal transfer rate after the interlock system was implemented. Therefore, the interlock system had a positive effect on maintaining transfer stability and improving system performance during operating time.

4.2.3 Combined effectiveness without quality the resulting value indicates that improvement leverage is concentrated in (availability/performance), with quality excluded; the OEE indicator before and after using the interlock system is shown in Figure 12.

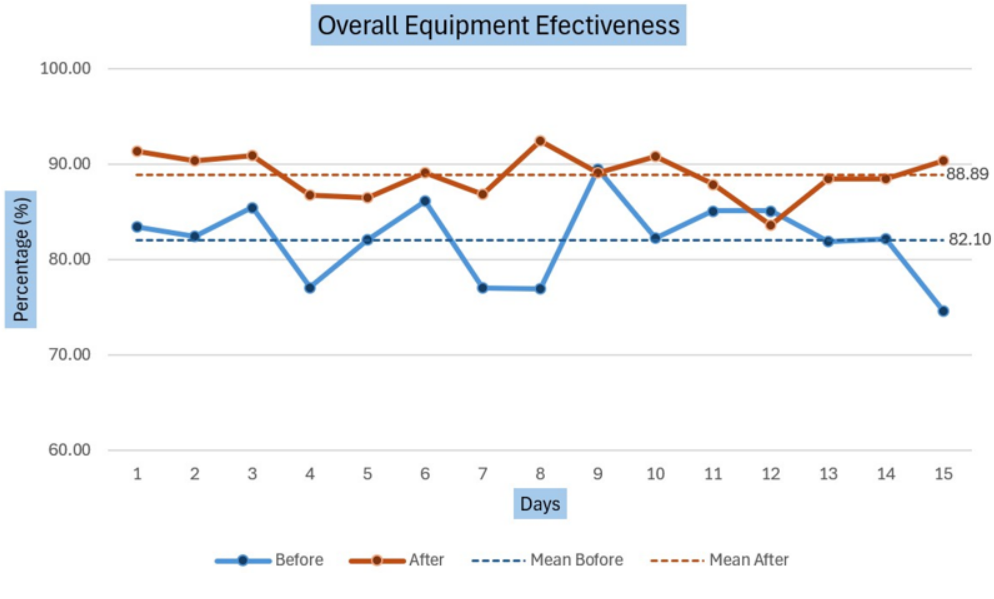

Figure 12. Overall Equipment Effectiveness (OEE) before and after using interlock

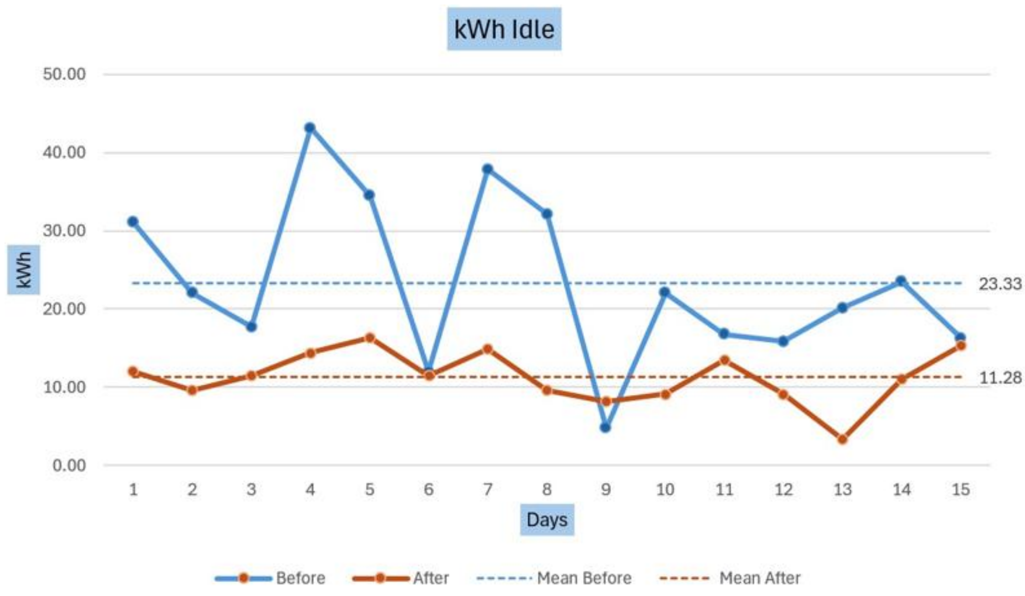

Figure 13. Energy idle consumption before and after using interlock

The OEE trend over 15 days shows a consistent improvement after the implementation of the interlock system. The average OEE increased from 82.10% to 88.89%, indicating enhanced equipment effectiveness. Despite minor fluctuations, the post-implementation values remain generally higher and more stable, suggesting that improvements are driven primarily by availability and performance rather than quality.

4.3 Energy efficiency results (Power, kWh, Cost, and CO_2)

4.3.1 Idle detection and interlock impact (pressure-based)

The pressure transmitter signal was used to determine the transfer system's operating state using a simple threshold rule. A 300 mbar cut-off was set to distinguish normal operation from idle conditions. When the pressure drops below 300 mbar and above 10 mbar, the system is considered idle (no-flow). When the pressure is 300 mbar or higher, the system is classified as running under normal transfer operation. This running/idle flag is then used by the interlock logic to trigger an automatic shutdown during idle periods, preventing the equipment from operating when no effective material transfer is occurring.

System triggers shutdown/interlock to prevent continued running without transfer. After enabling this interlock, Figure 13 shows the idle energy consumption before and after its activation.

Figure 13 compares idle energy consumption (kWh) over 15 days before and after the implementation of the interlock system. The blue line represents energy consumption before the interlock, while the orange line indicates values after implementation.

The graph shows that idle energy consumption is significantly reduced after the interlock system is applied. Before implementation, energy usage fluctuates widely, reaching higher peaks, with an average of approximately 23.33 kWh. After implementation, the consumption becomes lower and more stable, with an average reduced to about 11.28 kWh.

Although daily variations still occur, the post-interlock values consistently remain below the pre-interlock levels. This indicates that the interlock system effectively minimizes unnecessary energy consumption during idle periods by automatically shutting down when no material transfer occurs.

4.3.2 Electricity cost and CO_2 emissions

Using the tariff middle industrial consumption >200 kVA - <30.000 kVA rate of 1.035,78 IDR/kWh and the natural gas emission factor of 0.83 $kgCO_2/kWh$, after enabling this interlock, the savings were calculated as, cost saving 12.05 kWh × 1.035,78 IDR/kWh = IDR 12,476.00, and CO_2 reduction 12.05 kWh × 0.83 $kgCO_2$ = 9.99 $kgCO_2$/days.

These results show that the proposed approach improves efficiency not only in operational terms (availability/performance) but also in sustainability terms by reducing avoidable energy use associated with idle operation and thereby reducing CO_2 emissions. Figure 14 describes CO_2 emissions before and after using the interlock system.

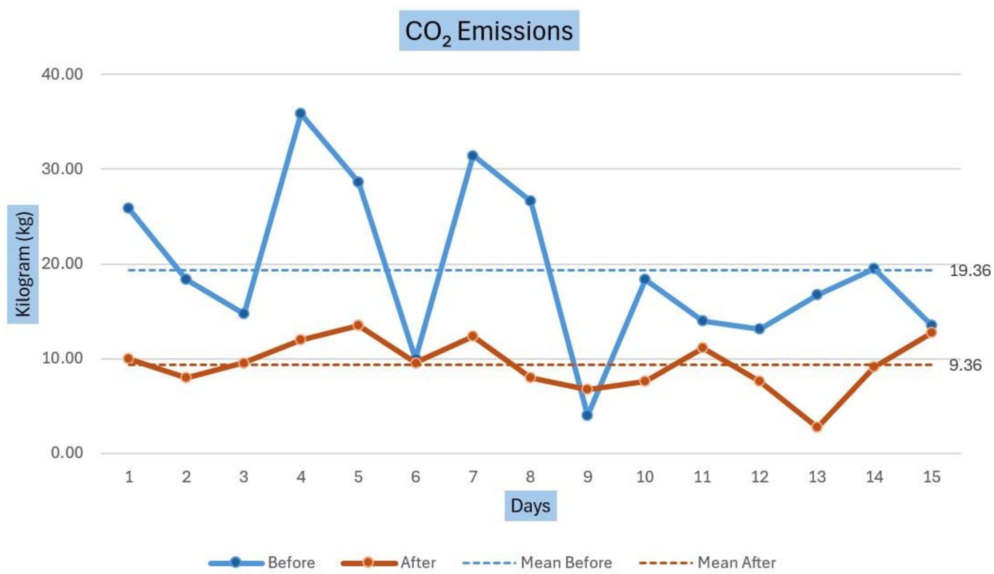

Figure 14. CO_2 emissions before using interlock

Figure 14 presents a time series comparison of daily CO_2 emissions over 15 days, under two conditions: before (blue line) and after (orange line) the implementation of the interlock system. The blue curve shows higher, more fluctuating emission levels, indicating inefficient operation with significant energy consumption during idle periods. In contrast, the orange curve is consistently lower and more stable, reflecting reduced emissions after the interlock prevents unnecessary operation.

The dashed horizontal lines represent the average emissions for each condition. The mean value before implementation is approximately 19.36 kg CO_2/day, while after implementation it decreases to around 9.36 kg CO_2/day. This clear downward shift demonstrates that the interlock system effectively reduces both variability and overall emissions, confirming its impact on improving energy efficiency and environmental performance.

4.4 Statistical review

A statistical comparison was performed to quantify and validate the operational improvement following implementation of the interlock system. The mean value in Eq. (9) was used to represent the average daily condition of each evaluated parameter during the observation period. Meanwhile, the standard deviation in Eq. (10) was calculated to assess the variation and stability of daily operational performance.

The results indicate that the interlock system improved both the average performance and operational stability. Availability increased from 92.10 ± 3.57% to 95.42 ± 1.45%, indicating not only higher equipment availability but also lower daily fluctuation. Actual Performance increased from 89.12 ± 1.60% to 93.16 ± 1.68%, while modified OEE increased from 82.10 ± 4.10% to 88.89 ± 2.31%. These improvements suggest that the interlock system enhanced process synchronization and reduced unnecessary idle time during operation.

The absolute change, calculated using Eq. (11), further confirms the magnitude of the improvement. The modified OEE increased by 6.79 percentage points, representing the combined effect of improved availability and performance. In addition, idle energy consumption decreased from 23.33 ± 10.46 kWh to 11.28 ± 3.35 kWh, while CO_2 emissions decreased from 19.36 ± 8.68 kg to 9.36 ± 2.78 kg. The reduction in both energy consumption and emissions indicates that the interlock system contributed not only to productivity improvement but also to more energy-efficient and environmentally sustainable operation.

Welch's independent t-test, expressed in Eqs. (12) and (13), was applied because the before- and after-implementation data represent two different operational periods and may have unequal variances. This approach is more appropriate than the conventional Student's t-test when operational data show different levels of variation between the two periods. The adjusted degrees of freedom were calculated using the Welch–Satterthwaite equation to ensure a more reliable significance test.

At the significance level $\alpha = 0.05$, the decision criterion in Eq. (14) was used to assess statistical significance. The results show that Availability improved significantly with $p = 0.0036$. Actual Performance and modified OEE also showed highly significant improvements ($p < 0.001$). Furthermore, idle energy consumption and CO_2 emissions were significantly reduced ($p = 0.0006$). These findings demonstrate that the observed improvements were statistically significant and were not merely descriptive differences between the two operational periods.

Overall, the implementation of the interlock system significantly improved operational effectiveness, reduced idle energy consumption, and lowered CO_2 emissions. Therefore, the proposed interlock system can be considered an effective approach to improving manufacturing process efficiency and supporting energy-saving and emission-reduction initiatives, as shown in Table 3.

Table 3. Statistical comparison of operational performance before and after interlock system implementation

Parameter	Before Mean ± SD	After Mean ± SD	Absolute Change	p-Value	Sig.
Availability (%)	92.10 ± 3.57	95.42 ± 1.45	3.32	0.0036	Yes
Performance (%)	89.12 ± 1.60	93.16 ± 1.68	4.04	<0.001	Yes
Modified OEE (%)	82.10 ± 4.10	88.89 ± 2.31	6.79	<0.001	Yes
Idle energy (kWh)	23.33 ± 10.46	11.28 ± 3.35	−12.05	0.0006	Yes
CO_2 emission (kg)	19.36 ± 8.68	9.36 ± 2.78	−9.99	0.0006	Yes

5. CONCLUSION AND RECOMMENDATION

This study confirms that implementing the interlock system improved production efficiency by reducing unnecessary idle time and enhancing process synchronization. The improvement was reflected in higher Availability, Actual Performance, and modified OEE, together with lower idle energy consumption and CO_2 emissions. Statistical analysis using Welch's independent t-test showed that all evaluated parameters changed significantly at $\alpha = 0.05$, indicating that the observed improvements were not only descriptive but also statistically validated. These findings demonstrate that a relatively simple control modification can generate measurable improvements in productivity, energy efficiency, and environmental performance without requiring major equipment replacement.

From a practical perspective, the proposed interlock system provides a simple, low-complexity, control-based solution to improve equipment utilization and reduce idle-related energy losses. Since the energy and environmental benefits have been quantified through electricity cost savings and CO_2 reduction calculations, the findings indicate that the system can support both operational efficiency and sustainable manufacturing objectives. Therefore, the interlock logic should be maintained as part of the standard control strategy, especially in production systems involving sequential equipment operation. Continuous monitoring of operational performance, idle energy consumption, and emissions is recommended to ensure that the achieved improvements remain sustainable over time.

Future research may extend the observation period and include larger datasets to evaluate the long-term consistency of the system's performance. Further studies may also assess the application of similar interlock logic across different production lines or equipment configurations. In addition, integration with real-time monitoring, predictive analytics, or Industry 4.0-based control systems could be explored to improve process reliability, proactively reduce idle losses, and strengthen sustainable manufacturing practices.

This study also has several limitations, because only availability and performance data were available in the baseline period, and quality was excluded because the machines just transfer material. Also, data emissions published by the Directorate General of Electricity from the Ministry of Energy and Mineral Resources (ESDM) were last updated in 2019.

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The authors gratefully acknowledge the Directorate General of Electricity, Ministry of Energy and Mineral Resources (ESDM), Indonesia, for providing public access to the data used in this study through the official Gatrik ESDM website. Although newer emission factors were unavailable from an official source during the study, the 2019 value remains a reasonable approximation because changes in the national electricity generation mix generally occur gradually. Nevertheless, this limitation is acknowledged, and the

emission results should be interpreted with caution. Future studies are encouraged to use updated official emission factors when newer data become available. The data source was last updated on 02 February 2026 at 9:45 PM (WIB) https://gatrik.esdm.go.id/frontend/download_index/?kode_category=emisi_pl. Data Tables 1 and 2 are available from the Zenodo Repository.

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NOMENCLATURE

CO_2	carbon dioxide emissions (kg CO_2)
E_{idle}	idle energy consumption (kWh)
EF	grid emission factor (kg CO_2/kWh)
E_{Before}	Energy consumption before implementation (kWh)
E_{After}	Energy consumption after implementation (kWh)
$\overline{x}$	mean or average value
x_i	the i-th data value
i	index of the data (e.g., 1st, 2nd, …, n-th data)
n	number of data points (sample size)
$\sum$	summation symbol (sum of all data values)
SD	standard deviation
S	sample standard deviation
Δ	change in value (before − after)
$\overline{x}_{after}$	mean after implementation of the interlock system
$\overline{x}_{before}$	mean before implementation of the interlock system
s_{before}	standard deviation before implementation
s_{after}	standard deviation after implementation
$s^2{}_{Before}$	variance before implementation
$s^2{}_{after}$	variance after implementatio
n_{before}	number of observations before implementatio
n_{after}	number of observations after implementation
df	degrees of freedom
α	significance level