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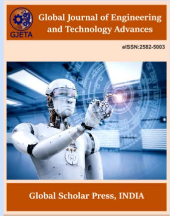

(Research Article)

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Intelligent material flow optimization using IoT sensors and RFID tracking

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Abstract

Efficient material flow management is a fundamental requirement for achieving high productivity, low operational cost, and reliable delivery performance in modern manufacturing and logistics systems. As production environments become increasingly complex and demand variability grows, traditional material handling approaches based on manual tracking, static routing, or fixed scheduling are no longer sufficient. These conventional systems often lack real-time visibility and adaptability, leading to congestion, excessive waiting times, and inefficient utilization of resources. Recent advancements in digital technologies provide new opportunities to address these challenges through intelligent and data-driven solutions. This paper proposes an intelligent material flow optimization framework that integrates Internet of Things (IoT) sensors and Radio Frequency Identification (RFID) tracking to enable continuous monitoring and adaptive decision-making. RFID technology is used to uniquely identify and track materials throughout the system, while IoT sensors collect real-time operational data related to equipment status, movement conditions, and congestion levels. The collected data is processed and analyzed using dynamic optimization algorithms that adjust material routing and scheduling decisions in real time based on current system conditions. The effectiveness of the proposed framework is evaluated through simulation-based experiments under both normal and disturbed operating scenarios. Performance is assessed using key metrics such as material waiting time, system throughput, and equipment utilization. The results demonstrate that the proposed approach significantly reduces material waiting time, improves resource balance, and enhances overall system efficiency when compared to conventional static material flow control methods. These findings highlight the potential of IoT- and RFID-enabled intelligent optimization for smart manufacturing and logistics environments.

Keywords: Material Flow Optimization; Internet of Things (IoT); RFID Tracking; Smart Manufacturing; Logistics Automation; Real-Time Monitoring

1. Introduction

Material flow efficiency is a critical determinant of performance in modern manufacturing and logistics systems. As industrial operations become more complex and customer demand grows increasingly dynamic, organizations face persistent challenges in coordinating the movement of raw materials, work-in-process items, and finished goods. Inefficient material flow often results in congestion, excessive waiting time, increased operational costs, and reduced system responsiveness. Traditional material handling approaches typically rely on static planning, predefined routes, and limited system visibility, which makes them poorly suited to handle real-time disturbances such as machine breakdowns, fluctuating workloads, and sudden priority changes. The transition toward Industry 4.0 has created new opportunities to overcome these limitations through digitalization and intelligent automation. The Internet of Things (IoT) enables continuous sensing of physical processes, while Radio Frequency Identification (RFID) provides accurate and contactless identification of materials throughout their lifecycle. Together, these technologies allow real time monitoring of material location, movement, and system conditions, transforming conventional material flow systems

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into data-rich environments. However, simply collecting real-time data does not guarantee performance improvement. Without intelligent mechanisms to analyze and act upon this data, material flow systems remain largely reactive. Effective optimization requires the integration of sensing technologies with adaptive decision-making models capable of responding dynamically to changing conditions. This paper addresses this need by focusing on intelligent material flow optimization using IoT sensors and RFID tracking, aiming to enhance operational efficiency, flexibility, and overall system performance in smart manufacturing and logistics environments.

1.1. Background and Motivation

In industrial production and logistics environments, material flow represents the backbone of operational continuity. It encompasses the transportation, storage, and handling of materials from initial input to final output. As facilities adopt automation and flexible manufacturing strategies, the complexity of material movement increases significantly. Conventional control mechanisms are often insufficient for managing such complexity, especially when system conditions change frequently. Industry 4.0 promotes the integration of cyber-physical systems, where physical processes are closely linked with digital intelligence. IoT sensors play a crucial role by enabling continuous monitoring of equipment status, location, and operational conditions. At the same time, RFID technology provides reliable and contactless identification of materials, allowing precise tracking throughout the production lifecycle. The combination of these technologies offers unprecedented visibility into material flow patterns. The motivation for this research stems from the growing gap between available sensing technologies and their effective use in optimization. While many facilities deploy IoT and RFID systems for monitoring and traceability, they often fail to translate real-time data into actionable decisions. This results in underutilized technological potential. An intelligent framework that actively uses real-time data to optimize material flow can significantly enhance productivity, reduce delays, and improve system resilience, making it a critical requirement for smart manufacturing and logistics environments.

1.2. Problem Statement

Despite the widespread adoption of digital technologies in industrial settings, material flow control remains largely static in many organizations. Routing decisions and scheduling policies are frequently predefined during system design and remain unchanged during operation. Such approaches assume stable conditions and predictable workloads, which rarely reflect real-world manufacturing environments. Unexpected disruptions, including machine breakdowns, transport delays, or sudden priority changes, can severely degrade system performance. A major limitation of traditional material flow systems is the lack of real-time awareness and adaptive coordination. Even when IoT sensors and RFID tags are deployed, the collected data is often used only for monitoring or post-process analysis. Without intelligent integration into decision-making mechanisms, real-time information fails to influence routing or scheduling adjustments. As a result, materials may accumulate in congested areas while alternative routes or idle resources remain underutilized. Furthermore, manual intervention is often required to resolve flow inefficiencies, increasing response time and operational overhead. This reactive approach limits scalability and reduces system reliability. The core problem addressed in this paper is the absence of an intelligent, automated mechanism that can continuously interpret real-time material flow data and dynamically optimize system behavior. Addressing this gap is essential for achieving truly responsive and efficient material handling systems in modern industrial environments.

1.3. Proposed Solution

To overcome the limitations of conventional material flow systems, this paper proposes an intelligent optimization framework that integrates IoT sensors and RFID tracking with real-time decision-making logic. The proposed solution transforms raw sensor data into actionable insights that directly influence material routing and handling priorities. Rather than relying on static rules, the system adapts continuously to current operational conditions. RFID technology is used to uniquely identify and track each material unit as it moves through the system. IoT sensors collect complementary data related to equipment status, congestion levels, and environmental conditions. This information is transmitted to an intelligent processing layer where data is analyzed and evaluated in real time. Based on the current system state, optimization algorithms determine the most efficient routing and scheduling decisions. A key feature of the proposed solution is its dynamic nature. When disturbances occur, such as bottlenecks or delays, the system automatically adjusts material flow paths to minimize waiting time and balance resource utilization. This enables proactive rather than reactive control. The framework is designed to be scalable and compatible with existing industrial infrastructure, making it suitable for practical deployment. By integrating sensing, communication, and optimization into a unified system, the proposed approach provides a comprehensive solution for intelligent material flow management.

1.4. Contributions

This paper makes several important contributions to the field of intelligent manufacturing and logistics systems. First, it presents a unified framework that seamlessly integrates IoT sensors and RFID technology for real-time material flow monitoring. Unlike isolated tracking systems, the proposed architecture emphasizes continuous data utilization for operational decision-making. Second, the paper introduces a dynamic optimization approach that adapts material routing and scheduling based on real-time system conditions. This approach moves beyond static planning methods and enables responsive control in the presence of disturbances. The optimization logic is designed to be computationally efficient, supporting real-time execution in industrial environments. Third, the paper provides a comprehensive performance evaluation using a simulated manufacturing scenario. Key metrics such as material waiting time, throughput, and equipment utilization are analyzed to demonstrate the effectiveness of the proposed framework. The results clearly show improvements over traditional material flow control methods. Finally, the study highlights practical implementation considerations, including scalability and system integration. These contributions collectively advance the application of IoT-driven intelligence in material flow optimization and provide a solid foundation for future research and industrial adoption.

1.5. Paper Organization

The remainder of this paper is structured to clearly present the research approach and findings. Section II reviews existing literature related to material flow optimization, IoT-based monitoring, and RFID-enabled tracking systems, identifying current limitations and research gaps. Section III details the proposed methodology, including system architecture, data acquisition, and optimization mechanisms. Section IV presents experimental results and discusses system performance under various operating conditions. Finally, Section V concludes the paper and outlines potential directions for future research.

2. Related Work

2.1. Traditional Material Flow Optimization Approaches

Early research on material flow optimization mainly focused on static scheduling, deterministic routing, and rule-based control strategies. These approaches typically rely on predefined material paths and fixed processing times to minimize transportation cost or completion time. Discrete-event simulation has been widely used to evaluate such systems under assumed operating conditions. While these methods provide valuable insights during system design, they often lack adaptability once deployed in real environments. Real-world manufacturing systems are inherently dynamic, with frequent disturbances such as machine failures, unbalanced workloads, and variable demand. Static optimization models struggle to respond effectively to these uncertainties, leading to congestion and inefficient resource utilization. As a result, researchers have increasingly recognized the need for real-time data integration and adaptive control mechanisms to improve material flow performance beyond traditional planning-based solutions.

2.2. RFID-Based Material Tracking Systems

RFID technology has been extensively studied as a solution for improving material visibility and traceability in manufacturing and logistics systems. RFID enables automatic identification and tracking of materials without line-of-sight constraints, significantly reducing manual data collection errors. Studies such as Ngai et al. demonstrated that RFID adoption improves inventory accuracy and material tracking efficiency in supply chains [1]. Other research has shown the effectiveness of RFID in warehouse management and shop-floor control. However, most RFID-based systems focus primarily on identification and monitoring rather than decision-making. Although RFID provides accurate real-time data on material location, it is often disconnected from optimization logic. Consequently, material flow decisions remain static, limiting the overall performance benefits of RFID enabled systems.

2.3. IoT-Based Monitoring in Smart Manufacturing

The emergence of IoT has enabled continuous sensing and communication across industrial systems. IoT-based monitoring frameworks collect real-time data from machines, conveyors, and transport units, enhancing situational awareness. Atzori et al. highlighted IoT's role in connecting physical and digital systems, forming the foundation of smart manufacturing environments [2]. Subsequent studies have applied IoT architectures to production monitoring, predictive maintenance, and logistics coordination. Despite these advancements, many IoT implementations emphasize data visualization and status reporting rather than control optimization. Without integration into adaptive decision-making models, IoT-based systems often fail to fully exploit their real-time data capabilities for material flow optimization.

2.4. Intelligent and Data Driven Optimization Methods

Recent research has explored combining IoT data with intelligent optimization techniques such as genetic algorithms, swarm intelligence, and reinforcement learning. Zhang et al. proposed an intelligent logistics optimization framework using real-time industrial data [3]. Similarly, Liu et al. applied reinforcement learning to dynamic scheduling problems in smart factories [4]. While these methods demonstrate promising performance improvements, they often require high computational resources or extensive training data, limiting real-time applicability. Additionally, practical deployment challenges such as system integration and scalability are not always addressed. This paper differentiates itself by proposing a lightweight, real-time optimization framework that tightly integrates IoT sensing and RFID tracking with adaptive material flow control.

3. Methodology

This section describes the proposed intelligent material flow optimization framework that integrates IoT sensors and RFID tracking to enable real-time monitoring and adaptive control. The methodology converts raw sensing data into optimized material routing and scheduling decisions through a closed-loop optimization mechanism. The framework is designed to ensure scalability, modularity, and responsiveness under dynamic operating conditions. Figure 1 presents the overall system architecture of the proposed IoT- and RFID-enabled intelligent material flow optimization framework, providing a high-level view of how the sensing, communication, and intelligence layers interact. Figure 1. Overall system architecture of the proposed IoT- and RFID-enabled intelligent material flow optimization framework, illustrating the sensing, communication, and intelligence layers with a closed-loop adaptive control mechanism.

3.1. System Architecture

The proposed system architecture follows a layered design consisting of sensing, communication, and intelligence layers. As illustrated in Fig. 1, RFID tags are attached to materials to provide unique identification, while IoT sensors monitor key operational parameters such as equipment status, queue length, and movement conditions. The communication layer ensures reliable data transmission between physical devices and processing units using wireless technologies and edge-computing infrastructure, enabling low-latency and dependable data exchange. The intelligence layer hosts data analytics and optimization modules that process incoming sensor and RFID data, evaluate system conditions, and generate adaptive routing and scheduling decisions in real time. Through this layered architecture, the proposed framework enables intelligent, responsive, and scalable material flow optimization.

Figure 1 Overall system architecture of the proposed IoT- and RFID-enabled intelligent material flow optimization framework

Figure 1. Overall system architecture of the proposed IoT- and RFID enabled intelligent material flow optimization framework, illustrating the sensing, communication, and intelligence layers with a closed-loop adaptive control mechanism RFID tags are attached to materials to provide unique identification, while IoT sensors monitor operational parameters such as equipment status, queue length, and movement conditions. The communication layer ensures reliable data transmission using wireless and edge-computing infrastructure. The intelligence layer hosts data analytics and optimization modules that evaluate system conditions and generate adaptive routing and scheduling decisions in real time.

3.2. Data Acquisition and Processing

Reliable data acquisition is essential for intelligent material flow control. Figure 2 illustrates the RFID-based material identification and localization workflow integrated with IoT data acquisition, showing how material identity, location, and time-stamped sensor data are collected and synchronized. RFID readers detect materials at checkpoints, while IoT sensors continuously update system state information.

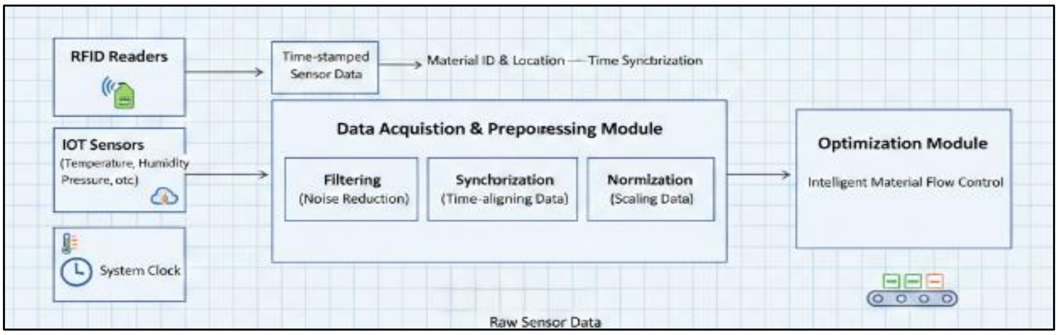

Figure 2 RFID-based material identification and localization workflow integrated with IoT data acquisition

The collected data is preprocessed to remove noise and ensure consistency. Let $D(t)$ represent raw sensor data at time t. The processed data $\hat{D}(t)$ is obtained as:

$$\hat{D}(t) = f(D(t))$$

where $f(.)$ denotes filtering, synchronization, and normalization operations. The processed data is then forwarded to the optimization module.

3.3. Optimization Model

The objective of the optimization model is to minimize total material handling time while avoiding congestion and balancing resource utilization. The optimization problem is formulated as:

$$\min \sum_{i=1}^{N} \left(T_i^{move} + T_i^{wait}\right)$$

where N is the number of material units, $T_i move$ is transportation time, and $T_i wait$ is waiting time. Capacity and route availability constraints are expressed as:

$$C_j \leq C_j^{max}, \quad \forall j$$

$$R_k(t) \in \{0,1\}, \quad \forall k$$

A dynamic priority function guides routing decisions:

$$P_i(t) = \alpha U(t) + \beta Q(t) + \gamma D_i(t)$$

where $U(t)$ represents system utilization, $Q(t)$ denotes queue length, $D_i(t)$ indicates delivery urgency, and α,β,γ are weighting coefficients.

3.4. System Workflow

The operational workflow follows a closed-loop control structure. Figure 3 illustrates the intelligent material handling workflow with real-time feedback and adaptive optimization, demonstrating how materials are identified, monitored, analyzed, and dynamically rerouted when congestion or disturbances occur.

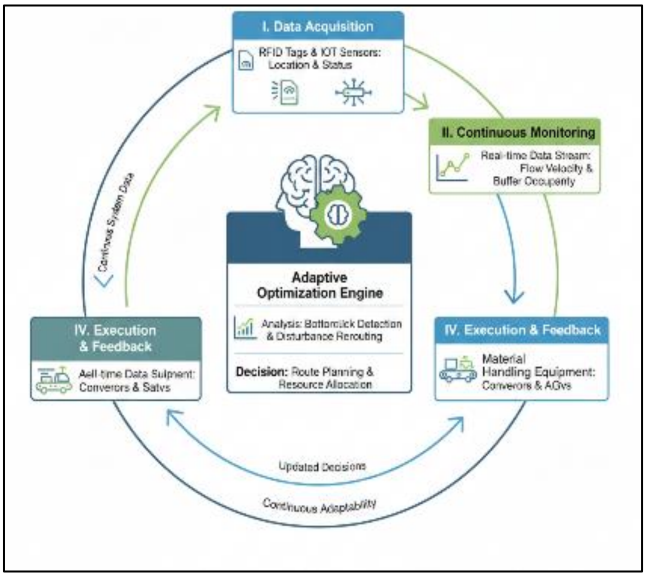

Figure 3 Intelligent material handling workflow with closed-loop adaptive control.

In this workflow, real-time system data continuously updates the optimization engine, which then communicates updated decisions to material handling equipment. This feedback loop ensures continuous adaptability and improved material flow efficiency.

3.5. System Parameters and Configuration

Key system parameters, including material priorities, routing constraints, and resource capacities, are configurable to suit different operational environments. These parameters enable the proposed framework to adapt to varying facility sizes, workload intensities, and production objectives.

4. Discussion and Results

This section presents a comprehensive evaluation of the proposed intelligent material flow optimization framework based on IoT sensors and RFID tracking. The primary objective of this analysis is to examine how real-time sensing, continuous monitoring, and adaptive decision-making influence system performance under dynamic operating conditions. The proposed framework is compared with a conventional static routing and scheduling system, which reflects common practices in traditional manufacturing and logistics environments. Performance is evaluated using quantitative indicators related to time efficiency, throughput, and resource utilization. The discussion not only highlights numerical improvements but also interprets the operational significance of integrating real-time intelligence into material flow control.

4.1. Experimental Setup

A simulated manufacturing environment was developed to evaluate the effectiveness of the proposed framework.

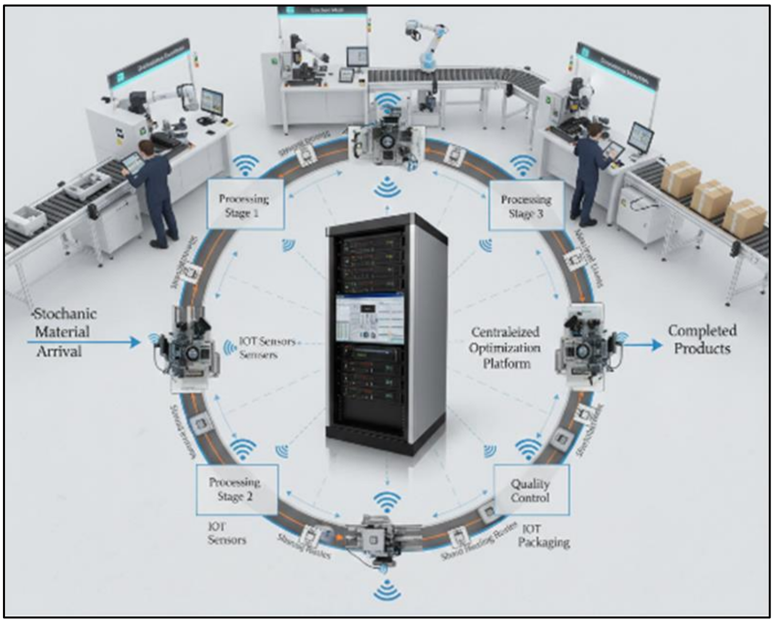

Figure 4 IoT-enabled smart job shop material flow environment

Where multiple workstations are interconnected through shared material handling routes. Materials enter the system following stochastic arrival patterns and are required to pass through several processing stages before completion. Each material unit is equipped with an RFID tag to enable continuous identification and tracking throughout the production process. IoT sensors are assumed to be deployed on conveyors, buffers, and workstations to monitor queue lengths, processing status, and resource availability.

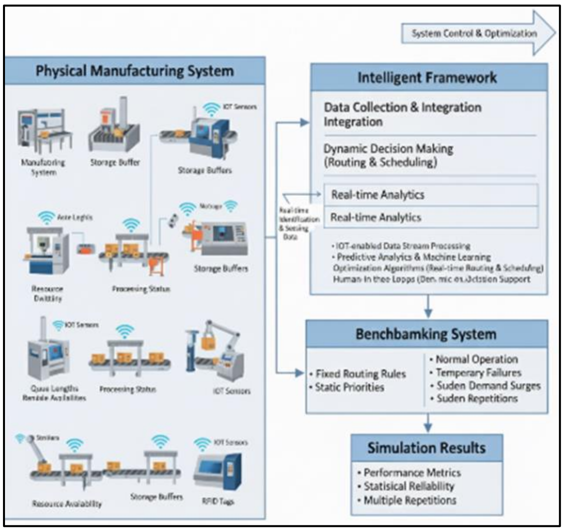

Figure 5 The simulation structure of an RFID-based manufacturing system

Demonstrating how real-time identification and sensing data are integrated into system control. The proposed intelligent framework continuously collects this data and dynamically updates routing and scheduling decisions. For benchmarking, a baseline system using fixed routing rules and static priorities was implemented. Both systems were evaluated under identical workload conditions, including normal operation and disturbance scenarios such as temporary machine failures and sudden demand surges. Each simulation scenario was repeated multiple times to ensure statistical reliability.

4.2. Performance Metrics

To assess system performance, several key performance indicators (KPIs) were selected based on material flow efficiency and operational effectiveness. The primary metric is **average material** waiting time, which reflects congestion levels and flow imbalance within the system. Lower waiting time indicates smoother material movement and reduced bottlenecks. The second metric is system throughput, defined as the number of completed material units per unit time. Throughput directly measures the productivity of the manufacturing system and its capability to meet production demand. The third metric is equipment utilization, which represents the ratio of active processing time to total available time for each resource. Balanced utilization is essential to avoid both idle capacity and excessive overloading.

The average waiting time is calculated as:

$$\overline{T}_{wait} = \frac{1}{N} \sum_{i=1}^{N} T_i^{wait}$$

where N is the total number of material units and $T_i wait$ is the waiting time of material i. These KPIs provide a comprehensive basis for comparing intelligent and conventional material flow control strategies.

4.3. Result Analysis

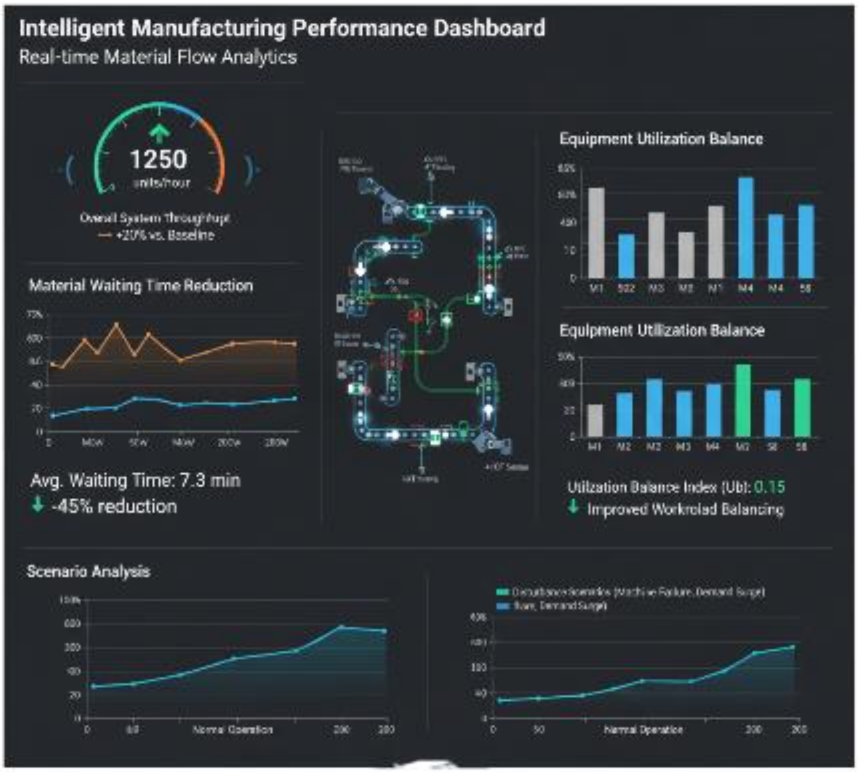

Figure 6 Smart manufacturing performance dashboard illustrating real-time material flow analytics

The simulation results clearly demonstrate the performance advantages of the proposed intelligent framework. Figure 6 presents a smart manufacturing performance dashboard illustrating real-time material flow analytics, highlighting reductions in waiting time and improvements in throughput. Average material waiting time decreased significantly across all evaluated scenarios. This reduction is primarily attributed to adaptive routing decisions that proactively divert materials away from congested paths and toward underutilized resources. System throughput showed a noticeable increase, particularly during high-load and disturbance conditions. When bottlenecks emerged, the optimization engine dynamically adjusted routing priorities, maintaining stable material flow and preventing throughput degradation. In contrast, the static system experienced sharp performance drops under similar conditions. Equipment utilization also became more evenly distributed. Resources that were previously overloaded experienced reduced congestion, while underutilized equipment received additional workload. The utilization balance index is defined as:

$$U_b = \frac{1}{M} \sum_{j=1}^{M} |U_j - \overline{U}|$$

where U_j is the utilization of resource $j, \overline{U}$ is the average utilization, and M is the number of resources. Lower values of U_b observed in the intelligent framework confirm improved workload balancing.

4.4. Comparative Performance Evaluation

Table 1 Performance Comparison Between Static and Intelligent Material Flow Systems

Metric	Static System	Proposed Intelligent System	Improvement
Average Waiting Time (min)	18.6	10.9	↓ 41.4%
Throughput (units/hour)	72	89	↑ 23.6%
Average Utilization (%)	61.3	78.5	↑ 28.0%
Utilization Balance Index	0.27	0.14	↓ 48.1%

The results summarized in Table 1 confirm that the proposed framework consistently outperforms the static system across all evaluated metrics. The reduction in waiting time indicates smoother material flow, while improvements in throughput and utilization demonstrate enhanced system productivity and operational efficiency.

4.5. Practical Implications and Discussion

From a practical standpoint, the proposed intelligent material flow optimization framework offers significant advantages for real-world manufacturing and logistics operations. The ability to respond dynamically to congestion, equipment failures, and demand fluctuations reduces reliance on manual intervention and improves operational resilience. Because the framework leverages widely adopted technologies such as IoT sensors and RFID tags, it can be integrated into existing facilities with minimal structural modification. Furthermore, the data-driven nature of the system supports scalability and future extensions, including predictive analytics and learning-based optimization. Continuous system adaptation enables smarter resource utilization, reduced operational cost, and improved service reliability. These characteristics make the proposed framework particularly suitable for smart factories, automated warehouses, and complex logistics networks operating under uncertain and dynamic conditions.

5. Conclusion

This paper presented an intelligent material flow optimization framework that integrates IoT sensors and RFID tracking to enable real-time monitoring and adaptive decision-making in manufacturing and logistics systems. By combining continuous data acquisition with dynamic routing and scheduling mechanisms, the proposed approach overcomes the limitations of traditional static material handling systems. The framework provides enhanced visibility, improved responsiveness to operational disturbances, and more balanced resource utilization. Simulation-based experimental results demonstrate that the proposed system significantly reduces material waiting time, increases throughput, and improves overall system efficiency when compared to conventional approaches. These findings confirm that intelligent, data-driven material flow control is a practical and effective solution for modern smart manufacturing environments.

Future work will focus on extending the proposed framework in several directions. First, machine learning and predictive analytics techniques will be incorporated to anticipate congestion and equipment failures before they occur, enabling proactive optimization. Second, the framework will be expanded to support multi-facility and supply chain–level coordination, addressing material flow optimization beyond a single production system. Finally, real-world industrial case studies will be conducted to validate system performance under practical constraints and to evaluate scalability, robustness, and economic impact in operational environments.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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