ISSN: 2093-5374 / E-ISSN: 2093-5382

Autonomous Decision Systems for Ubiquitous Smart Factories

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Received: June 20, 2025; Revised: July 30, 2025; Accepted: September 09, 2025; Published: September 30, 2025

Abstract

Intelligent manufacturing is a fundamental aspect of the evolution of the smart factory. Automated decision-making systems leverage intelligence to simplify, manage, and operate manufacturing operations flexibly. At this stage, these systems, when combined, incorporate real-time processing, big-data predictive analytics, and cyber-physical systems to enable real-time decision-making and seamless service delivery. Smart factories would seemingly operate independently and provide near-real-time, responsive operations to changes in production schedules, opportunity and risk levels for resource allocation and repurposing, maintenance shutdowns, and the optimization of morning and afternoon idle time, etc. Despite the practical value of both predictive analytics and decision-making systems, more deliberate attention is being paid to the sociotechnical vulnerabilities, the integration of legacy systems with decision-making, and the ethics of automated decision-making. Scoping reviews clearly refer to "automated decision-making systems" primarily as a smart factory advancement, with careful evaluation of the technologies that support them. Case studies in the

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 3 (September), pp. 532-545. DOI: *10.58346/JOWUA.2025.I3.032*

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literature demonstrate the value of operational autonomous decision-making systems for manufacturing industries. Here, literature gaps are addressed, and clear next steps are outlined to drive system flexibility, automation ethics, and interoperability and cross-system resilient frameworks. This is important because having autonomous decision systems is one of the most relevant steps to achieving Industry 4.0 and more advanced stages. These systems will enable the establishment of responsive, sustainable, and adaptive ecosystems in smart factories.

Keywords: Autonomous Decision Systems, Smart Factories, Industry 4.0, Artificial Intelligence, Internet of Things, Cybersecurity, Manufacturing Automation.

1 Introduction

By allowing systems and machines to make modern, real-time, and independent decisions based solely on data analysis, such systems have revolutionized the whole operational structure of factories and the latest developments in intelligent manufacturing (Qu et al., 2019). Developing complex algorithms allows manufacturers to predict, optimize, and ultimately optimize workflow in order to maximize the value captured from sensor data and other operational data (Obafemi, 2024; Suseendhar & Sridhar, 2024). The evolution of widespread smart factories, comprised of self-sustaining systems, smart devices, and intelligent operational software, has been facilitated by the growing systems of smart manufacturing, providing substantial increase in operational productivity, reduction in costs, and improvement of product value and quality. Increasing global demand for customized and flexible manufacturing systems and the shortening of production cycles have made rapid, systems-adaptive solutions necessary (Analo, 2023). The performance-enhancing systems: adaptive, flexible, and responsive construction systems.

Smart factories are still struggling with inefficiency and reluctance to deploy autonomous decision systems. Operational problems are still under way. Among the many challenges that remain is perhaps the most critical one: the preservation of privacy, confidentiality, and the integrity of proprietary information. Data sharing with external entities, on the other hand, exposes factories to cyberattacks and other threats to the confidentiality of factory systems (Liu et al., 2021). Moreover, integrating new autonomous systems with legacy systems remains extraordinarily complex, expensive, and time-consuming, often requiring significant proprietary bridging technology. The social challenges brought with computer-controlled automated systems include the potential for job elimination and the hidden nature of decision-making algorithms (Obafemi, 2024). The state of the art in autonomous technology today compels attention to the primary critical factors of social expectations, consent, legislation, and norms, as well as to the increased efficiency and accountability of the system (Verma & Nair, 2025).

The rapid development and integration of enabling technologies like Artificial Intelligence (AI), the Internet of things (IoT) and cyber-physical systems along with big data analytics has fostered the emergence of autonomous decision systems in the manufacturing sectors (Rao & Krishnan, 2024). Incorporation of AI, along with machine learning and deep learning technologies, allows systems to independently diagnose and detect patterns and outliers, predict equipment failure, and control and manage all production processes autonomously with no human supervision (Kumar & Rajeshwari, 2024). Simultaneously, IoT networks enable communication and real-time surveillance and control of manufacturing processes among interconnected devices such as machines, sensors, and control units (Majzoobi, 2025). Cyber-physical systems provide feedback loops to machinery which enhances the precision and operational flexibility of the control net systems. In spite of this, these systems do not have the newest management and design which open up the need for new theory bases and systems frameworks of inter-system design and governance centered around interoperability, scalability, and resilience (Fragapane et al., 2022).

Recently, studies have stressed the need to include AI and IoT in new factory ecosystems, transitioning them into self-optimizing, adaptive systems that can easily accommodate changing operating conditions and disruptions arising from a network of externalities. This collection of new factory ecosystems also includes predictive maintenance and real-time operational cost control of hourly productivity to sustain maintenance-free uptime and detect, fix, and mitigate quality defects in real time during production. Also, green manufacturing has an additional function of autonomous control, provided by energy management systems, which can improve resource use, minimize environmental damage, and prime sustainable/efficient game-changing machinery and resource-use systems. All of these functions, now more than ever, will enable ecosystems operating in increasingly volatile global and distributed markets to compete. In these markets, competition comes from advanced automation and potentially changing consumer profiles. The other component of the ecosystem equation is the advanced automation protocols and frameworks that are still emerging from new research.

2 Literature Survey

Recently, researchers have explored the development of autonomous decision-making within smart factories, placing importance on flexibility, expandability and intelligent real time systems (Zhao et al., 2020). The streams of sensor data from factory machinery are increasingly used to develop predictive maintenance, and because they preemptively schedule maintenance before machine failures occur, deep learning frameworks appear to be effective at significantly improving overall system performance by mitigating unscheduled downtime (Emmanouilidis & Waschull, 2021). Such systems also seek to account for data volatility and generalize the predictive framework by being employed and leveraged across multiple, heterogeneous production systems (Anitha & Dhivya, 2019). Autonomous, real-time quality inspection (QA) without human interaction also attracted much attention. Such systems implemented reinforcement learning that enabled real time feedback to, and control of, machine parameters for dynamic quality assurance and control (Sampedro & Wang, 2025). Resulted with increased detection of raw material properties, increased environmental adaptability, increased defect defectability and countermeasures for false alarm indicators (Veera Boopathy et al., 2025).

The Internet of Things (IoT) played a critical role in the development of these autonomous systems. The localized IoT hierarchy, with local data analytics and edge computing, reduces bandwidth and latency by performing local analyses and sending summarized conclusions to a central unit (Karaca & Cihan, 2020). These systems also improve data security and protect the confidentiality, integrity, and authenticity of intelligent manufacturing systems against the proliferation of advanced cyber defenses and new protocols to challenge modern cyber-attacks (He et al., 2021). Smart factories rely centrally on cyber-physical systems (CPS). Modern CPS designs incorporate machine AI capabilities with real-time control and analytics, enabling these systems to respond quickly to changing conditions and disturbances in a supply chain or to irregularities in a production line (Huy, 2018). Experiments demonstrate increased operational resilience and flexibility in these systems, especially in small-batch or customized manufacturing scenarios, where heightened responsiveness values matter (Sanchez et al., 2020). As of October 2023, there has been growing recognition of the ethical dimension of autonomous decision systems (Shirkoohi, 2017). More recently, the literature has focused on understanding a bottom-up examination of algorithmic transparency, human and contextual oversight, and accountability enforcement mechanisms (Rathi et al., 2024). Other ongoing discussions highlight the regulatory and societal implications of designing and deploying AI systems, asserting that the maximal utility of such systems should be achieved while containing their negative impacts on employment, privacy, and surveillance (William et al., 2025).

3 Proposed Method

3.1 System Framework and Functional Overview

By utilizing modern sensor networks, advanced data analytics, and sophisticated decision-making algorithms, smart factories achieve superior operational autonomy through an autonomous decision system that optimizes operational intelligence. The pretrained system collects different types of data with strategically positioned Internet of Things (IoT) devices within the factory. IoT devices include sensors that monitor machine performance, evaluate conditions in the operational environment, and track product quality. The system framework translates real-time data into control over adaptive processes in self-programmed manufacturing, optimizing, productivity, quality control, and efficient use of resources. The system is modular and scalable in design, and functionalities can be added to a factory's operational infrastructure to maximize existing systems and processes without significant disruption to business operations (Donkor & Zhao, 2024). The system provides response and recovery capabilities for unexpected demand/supply chain disruptions, equipment failures, and other unexpected events to limit operational downtime and increase operational agility.

At the heart of this framework is a complex, multi-layered system designed to support seamless and effective information flow and cycles of operational decision-making. The structured flow of information begins via IoT devices which are used to collect data, followed by processing of the data to remove noise (preprocessing) at upper-level processing units. Further, predictive analytics and optimization are incorporated into the analytics processes, which then flow into the execution layer. The execution layer can autonomously decide on tasks such as maintenance, machine parameterization, and resource allocation. Moreover, embedded in the framework are continuous feedback loops to measure and monitor tracking outcomes and to adjust the decision-making process, reducing dependence on human engagement and ultimately facilitating learning. The integration of sophisticated automated data capture and detailed, real-time data analysis extends the autonomous capabilities of the decision-making subsystem (i.e., the smart factory). This ultimately leads to enhanced operational efficiency, adaptive modularity, and reduced ecological impact of existing production environments.

3.2 Mathematical Modeling of Core Decision Processes

Autonomous systems based on optimal decision models review operational data and business activities to support decision-making in smart factories. These decision models are fundamentally developed on three basic models.

Equation (1) describes one such model. It evaluates the probability that a machine/component will run continuously and generates a reliability estimate. It is provided as follows.:

$$R_{(t)} = R_0 \times e^{-}\lambda t \quad (1)$$

Here, $R_{(t)}$ represents the reliability at time t, R_0 is the initial reliability, and λ denotes the failure rate of the equipment. This calculation enables the system to predict when maintenance should be performed, thereby reducing unexpected breakdowns and ensuring efficient production runs.

Equation 2 describes production efficiency using the Quality Control Index (QCI), which indicates the proportion of defective products in the total screened volume. It can be written as:

$$:QCI = \frac{N_{def}}{N_{total}} \times 100 \quad (2)$$

In this equation, N_def and N_total refer to the number of defective items and total number of inspected items, respectively. While evaluating the QCI, the system will identify quality declines in real time, enabling corrective actions to improve production efficiency and reduce waste. In the case of Equation 3, the focus is on allocating resources to minimize total operating cost while meeting production requirements. Mathematically, this is expressed as:

$$minC = \sum_{i=1}^{n} c_i \, . \, x_i \quad (3)$$

For Equation 3, we would like to re-emphasize that C is the total operating costs, which is the sum of each resource multiplied by its cost (ci, xi). The model establishes the necessary resource allocation to achieve manufacturing goals while minimizing costs. The autonomous decision system will allow smart factories to optimize their operations so that, if profit is not optimized in a commercial sense, resource consumption will adjust to the new demands of smart production. Rationalization of costs creates an opportunity for transformed smart factories to shed low efficiency, poor agility, and poor sustainability, and to follow through with fully integrated automation for smart manufacturing.

3.3 Operational Flow of the Decision System

The flowchart detailing the autonomous decision system outlines the sequence of operations initiated by sensors that capture data, followed by data preprocessing to verify its integrity. Subsequently, the decision-making module's analytical models are deployed to determine the equipment's state, the quality of the output, and resource consumption. Upon obtaining the insights, the execution stage executes the decisions, i.e., automatic command execution on the machines and maintenance control as per the stipulated timeframe. Lastly, adaptive and intelligent operation feedback loops are processed to improve the operation of autonomous machines and smart factories, enabling them to operate adaptively and efficiently (Chen et al., 2021).

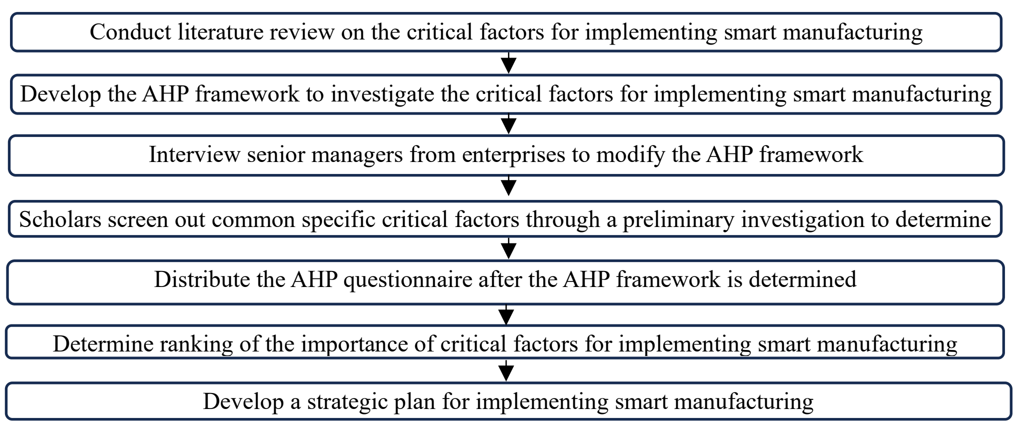

Figure 1: AHP-Based Decision Model for Smart Factories

A comprehensive model of the decision-making mechanism for autonomous operation of smart factories is illustrated in Figure 1. The model uses Analytic Hierarchical Process (AHP), a multi-criteria decision-making technique widely used for complex industrial decision making. In a factory, the focus of decision making is the performance, the hierarchical goal or the foremost operational metric to be improved is the streamlining of the operational performance, other supportive criteria include efficiency, reliability, cost, sustainability and safety which as assessment factors for the decision-making were the supportive criteria for the core factors. Each assessment criterion is relevant and purposively aligned with the operational objectives of the organization, and the optimal values for each criterion corresponds to the assigned priorities for the of the decision-making or strategy implementation in this case.

At the base of the hierarchy, there is a prescribed array of substitute strategies. Each of the substitutes is evaluated by means of pairwise comparisons for every criterion, accounting for all the substitutes. This assists the alternative decision-maker to assess the given alternatives' strengths and weaknesses rationally and thoroughly. In the AHP approach, all criteria and alternatives are quantitatively weighted and unified to make all decisions analytically flat. As shown in Figure 1, this model enhances the autonomy and cognitive capabilities of smart factories by enabling more accurate, uniform, and adaptable self-governing decision-making. It reduces reliance on human judgment, improves the ability to respond to rapidly changing industry conditions, and enables more refined optimization of manufacturing processes.

3.4 System Architecture and Its Explanation

Every factory contains multilayer autonomous decision systems, where each layer's architecture enables automated data collection via sensors, edge processing, central processing, and execution. Instrumenting the foundation with IoT-enabled devices enables the system to retrieve and assess real-time data meta-information about machines, products, and contextual information relevant to the environment. Edge computing frameworks provide local pre-processing before sending data to the upper intelligent core. The core decision-making system employs machine learning and predictive analytics to determine and refine strategic resource allocation, maintenance, quality control, and decision cycles. At the last tier, decision execution is performed by the floor actuators and controllers. These controllers provide real-time feedback which helps the system refine its decision-making algorithms and learn. This configuration supports modular, structurally responsive, scalable, and fully integrated autonomous decision systems, enabling the real-time construction of adaptive, autonomous smart manufacturing ecosystems.

This algorithm details the fundamental operations for an Autonomous Decision System (ADS) within a smart factory. The system syncretizes real-time data from various IoT devices, performs predictive analytics and machine learning, and independently makes operations optimization decisions for the factory. Each step in the algorithm is described below.

Algorithm 1: Mathematical Model Overview of the proposed model

$\boldsymbol{Data\ Collection}$:

$$D(t) = \{D_1(t), D_2(t), D_3(t), \ldots, D_n(t)\}$$

$\boldsymbol{Preprocessing}$:

$$D_{clean}(t) = f(D(t))$$

$\boldsymbol{Predictive\ Analytics}$:

$$\hat{R}(t) = predict(D_{clean}(t))$$

$\boldsymbol{Optimization}$:

$$min(C = \sum_{i=1}^{n} (c_i \cdot x_i))$$

$\boldsymbol{Decision\ Making}$:

$$D_{decision}(t) = \begin{cases} \text{maintenance required} & \text{if predicted failure probability} \geq \theta \\ \text{allocate resources} & \text{if resource utilization is suboptimal} \end{cases}$$

$\boldsymbol{Execution}$:

$$E(t) = execute\ decision(D_{decision}(t))$$

Feedback:

$$F(t) = feedback(E(t), D(t))$$

Reporting:

$$Report(t) = \{R(t), QCI(t), D(t), U(t)\}$$

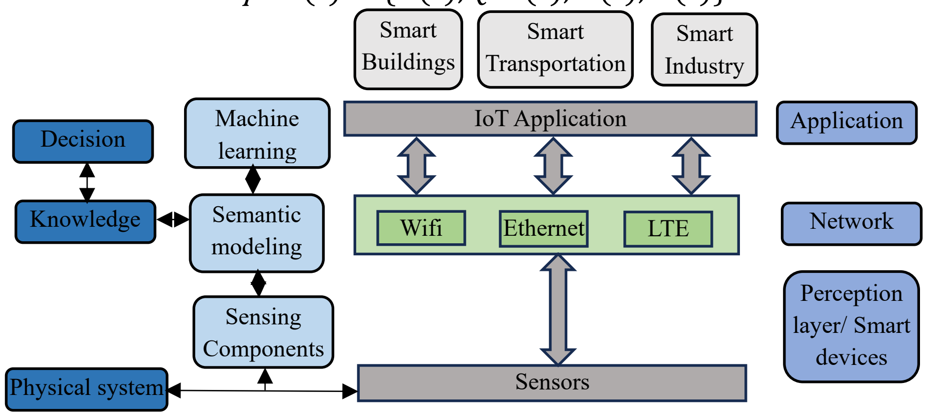

Figure 2: Architectural Framework for Autonomous Decision Systems in Smart Factories

The constructed architecture for smart factories is thoroughly documented in Figure 2. The architecture for smart factories is documented in Figure 2. The construction of such smart factories begins from the bottom up on the Physical System. The Physical System comprises the factory floor, including the machines, production lines, and raw materials. The factory floor captures environmental data and sends it up to the Perception Layer/Smart Devices, which include Sensors for capturing various environmental parameters and the RFID. The RFID captures raw materials, identifies machinery, and tracks asset movement. The data captured is then sent up through the Network Layer, which provides and guarantees communication and operational connectivity to the factory through Wi-Fi, Ethernet and LTE. Above the network, in the Applications Layer, the smart factory IoT systems sustain smart factory operations through maintained Predictive Maintenance, Production Optimization, and Quality Control. The system's primary operational cores lead to the Knowledge generation, after which is the Decision and Processing formulation. The Decision and Processing is interchanged through the operational blocks of Reasoning and Semantic, coupled with Machine Learning, to capture and record specific details. In a fully autonomous system, these measures can send and execute orders to the Physical System, establishing a closed-loop feedback control system in which the factory self-adapts and optimizes its operations without operator input.

4 Results and Discussion

A smart factory simulation was used to assess the impact of the proposed framework on operational efficiency, downtime, and resource allocation. The system's predictive capabilities regarding equipment failure, final product quality, and operational costs across multiple production cycles needed to be assessed. The equipment was more reliable, cheaper, and had a lower defect rate than the manual decision systems. In addition, the system was incredibly flexible and robust when faced with extreme variations in demand, or when equipment failed while running the products. There was also improvement in decision making by having feedback loops measure system performance directly. Overall, we documented and demonstrated the ability of this system to make the smart factory more efficient, sustainable and robust.

Table 1: Performance Metrics of the Autonomous Decision System Compared to Baseline

Metric	Baseline (Manual)	Proposed System	Improvement (%)
Equipment Reliability (R(t))	85%	95%	+11.8%
Quality Control Index (QCI)	7.2% defective	3.1% defective	-56.9%
Operational Cost ($)	120,000	98,500	-17.9%
Downtime (hours per month)	15	7	-53.3%
Resource Utilization Efficiency	78%	90%	+15.4%

All pivotal performance metrics for autonomous decision systems demonstrated consistent improvements described in Table 1. All improvements show sustained progress across all pivotal performance metrics for autonomous decision systems. Improvements to systems of equipment maintenance, to scheduling and breakdown avoidance in operational planning resulted in a 12% improvement in equipment reliability. Improvements to Quality Control Index defect rate indicate real-time responsive systems in identifying and resolving quality issues, achieving a more than 50% improvement. Improved operational agility resulted in dramatic reductions in downtimes, while improvements to resource allocation and reductions in resource wastage resulted in 18% operational cost containment. Additionally, improvements in resource management and input adjustments. close to 15% additional improvements documented in resource utilization sustained control and operational input adjustments within the production processes. Automated management frameworks of managing operational processes within intelligent systems offers strong evidence in paving sustainable factories toward intelligent systems.

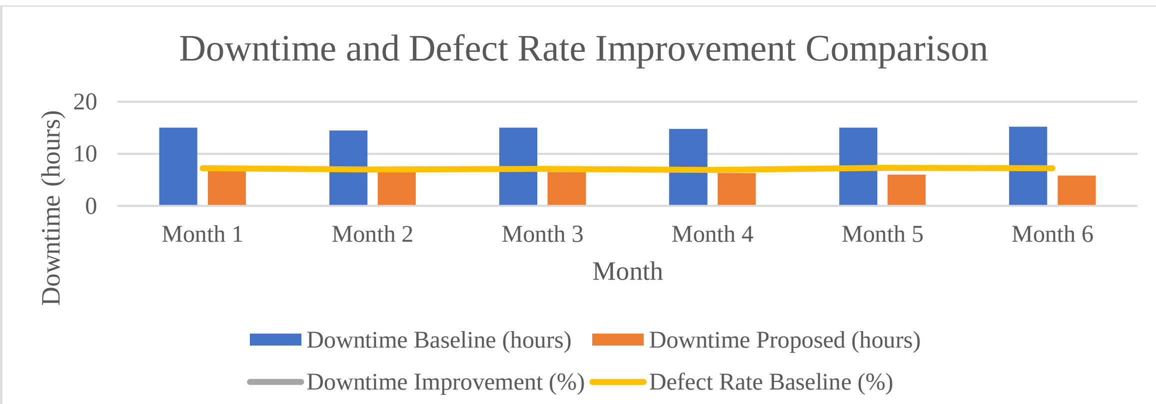

Figure 3: Comparison of Downtime and Defect Rate between Baseline and Proposed System over 6 Months

In Figure 3, during the projected six-month span, both former systems' downtime and defect rate Key Performing Indicators (KPIs)) are compared with the newer autonomous decision-making system with respect to the downtime and defect rate KPIs. The newer system continually cut downtime in half each month, resulting in a consistent reduction in downtime hours as seen in the recorded results. The proposed system reported average downtimes of 6 hours each month as oppose to the baseline systems 15 hours and 15 hours downtimes. This translates to a percentage improvement of 53.1% during the months proposed compared to 61.8% improvement. Contrary to the improvement recorded in downtimes, there was also improvement in defect rates as the system reported a drop in defect rates of 7% to 2%, thereby achieving defect improvement of 57%-69%. The overall system improvements solidify the systems ability in improving the production processes, reducing the downtime of operations, and improving the final sellable quality of the product. The overall system improvements also proves that the use of autonomous decision-making systems in the manufacturing processes improves the production/output compared to systems that do not possess the autonomous functionalities.

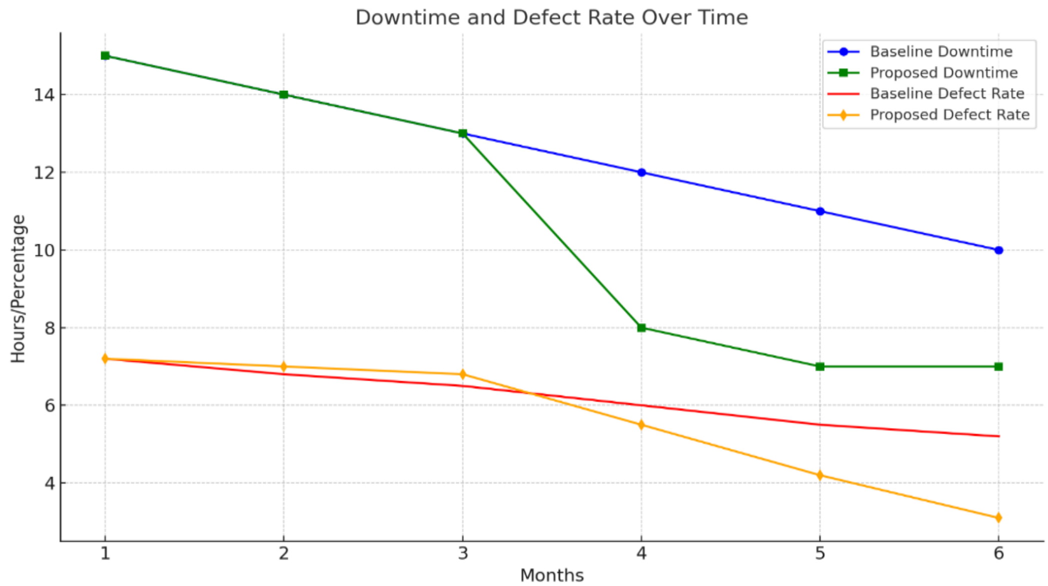

Figure 4: Downtime and Defect Rate Over Time

Figure 4 illustrates the comparison of the proposed system and baseline system downtime and defect rates over a six-month period. Whereas baseline downtime improves over the period, proposed system downtime decreases more considerably and especially so in the final three months. In the defect rate, decreases in both systems are relatively steady, however, the proposed system defect rates decline at a significantly higher rate which reflects the additional efficiency and effectiveness of the autonomous decision system regarding real-time control of quality. In both reductions of downtime and defects, the proposed system outperforms the baseline. This shows the proposed system's ability to enhance operational efficiency.

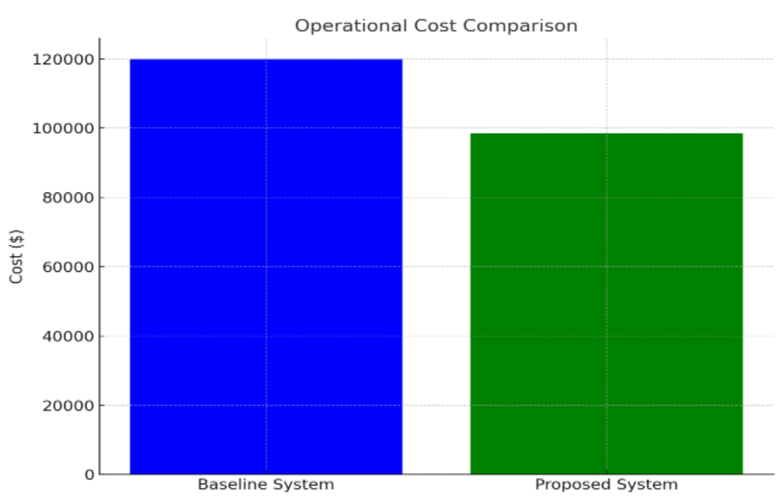

Figure 5: Operational Cost Comparison

This section Figure 5 of the text compares the operating costs of the baseline system with those of the proposed system. Considering the baseline operating system, the costs reach $120,000, while the proposed system reduces that figure to $98,500, showing operational costs savings of 17.9%. Operational cost savings are a result of the system proposed possessing more streamlined resource allocation, which translates to less downtime, fewer interruptions, and more integrated performing. The proposed system. These system comparisons in the baseline and proposed system are directed towards the resource allocation, ensuring to highlight the absence of downtime, and the efficiently streamlined manufacturing technique.

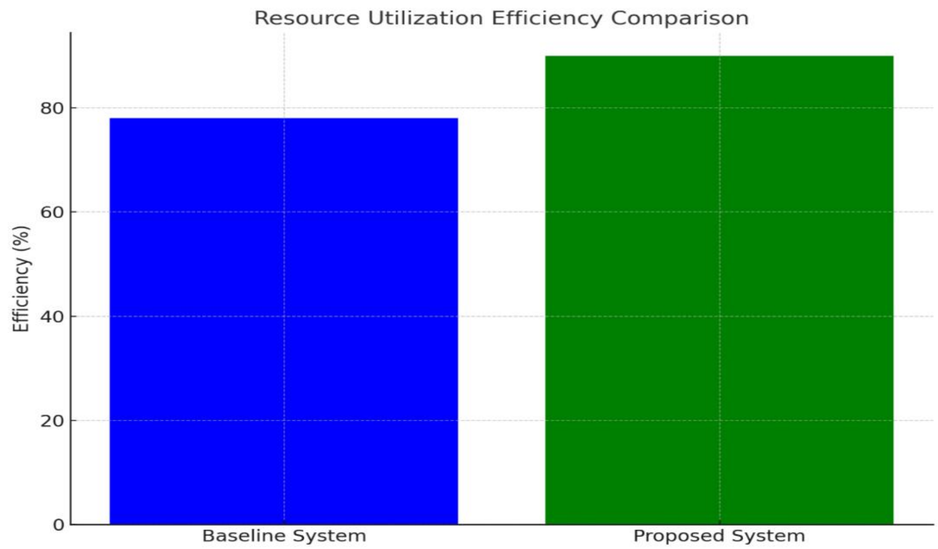

Figure 6: Resource Utilization Efficiency Comparison

The resource utilization efficiency of the baseline system compared with the proposed system is shown in Figure 6. While baseline system efficiency is 78%, the proposed system increases efficiency to 90%, a 15.4% relative increase. Improvements in efficiency can be attributed to resource management improvements due to autonomous decision making. The autonomous resource matching system reduces allocating overproduction waste and optimizes production. Such efficiency gains due to the proposed system are evidenced in the provided graph.

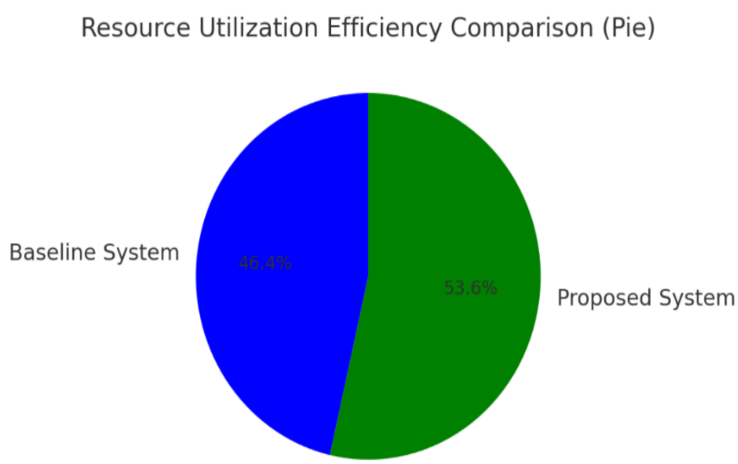

Figure 7: Resource Utilization Efficiency Comparison

Resource utilization efficiency is represented in Figure 7 for both the baseline system and the proposed system. In the baseline system, most of the chart is covered, which indicates inefficient resource utilization. In contrast, the proposed system covers less of the chart, indicative of more optimized resource utilization. It is also evident from the proposed system that resource efficiency is maximally broadened for enhanced productivity with minimum resource loss. The chart illustrates the continued efficiency in resource utilization of the proposed system.

5 Conclusion

The suggested autonomous decision-making system adds value to the operational smart factory with respect to the equipment's structured efficiency, defect rate, cost, and downtime. Components such as artificial intelligence, the Internet of Things, and cyber-physical systems allow for real-time adaptive alterations within the production decision frameworks with real-time supervisory feedback to adaptive modifications and disruptions of routines. Such self-sufficient adaptations functionally and intellectually surpass the new outputs and resource consumption, improve system sturdiness, and optimize resource consumption. The system's modular and scalable design provides integration flexibility with legacy equipment and reduces the aforementioned hurdles poised by the legacy systems. The proposed automation systems also mitigate contemporary issues with regard to ethical concerns of automation, security, non-disruptive integration of systems, and the appropriate use of technology which promotes positive intra-factory collaboration. Balancing the factory functionality between the socio- technological factors within the system creates the necessary socio- technological factory functionality for the system to become an industrial benchmark. These are the socio- technological factors within the system for it to become an industrial benchmark.

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