

Intelligent Warehouse Automation Using PLC, IoT and Artificial Intelligence: A Novel Framework for Smart Material Handling Systems

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Abstract - The rapid growth of e-commerce, smart logistics, and Industry 4.0 has significantly increased the demand for intelligent warehouse automation systems capable of improving operational efficiency, inventory accuracy, equipment reliability, and energy management. Although conventional warehouse automation relies on Programmable Logic Controllers (PLCs), Supervisory Control and Data Acquisition (SCADA) systems, and Internet of Things (IoT) technologies, these systems primarily operate using predefined rule-based logic with limited adaptability to dynamic warehouse conditions. Moreover, existing solutions often lack seamless integration between artificial intelligence (AI), edge computing, real-time decision-making, predictive maintenance, and digital twin technologies, resulting in inefficient resource utilization, increased downtime, and higher operational costs. This research proposes a novel Intelligent Warehouse Automation Framework that integrates PLC-based industrial control, IoT-enabled sensing, edge AI analytics, cloud connectivity, and digital twin technology into a unified smart warehouse architecture. The proposed framework introduces seven original modules, including an AI-assisted PLC Decision Framework, Adaptive Conveyor Optimization Algorithm, Smart Energy Optimization Model, Edge AI-based Predictive Maintenance Engine, Hybrid PLC-IoT Communication Framework, Dynamic Warehouse Resource Allocation Algorithm, and an AI-enabled Digital Twin for real-time warehouse monitoring and intelligent operational control. These modules collaboratively optimize conveyor operations, dynamically allocate warehouse resources, predict equipment failures, reduce energy consumption, and enhance inventory visibility through continuous real-time data analysis. A mathematical performance model and algorithmic framework are developed to evaluate system throughput, equipment health, energy efficiency, communication latency, and warehouse resource utilization. The proposed architecture is validated through simulation using industrial automation platforms integrated with AI and IoT technologies, demonstrating its capability to improve operational efficiency, reduce maintenance costs, minimize downtime, and support intelligent decision-making in modern warehouses. The proposed framework contributes a scalable, modular, and future-ready automation architecture suitable for smart warehouses, distribution centers, manufacturing facilities, and logistics industries. Furthermore, the framework aligns with the principles of Industry 5.0 by enabling human-centric, intelligent, sustainable, and adaptive warehouse operations, providing a strong foundation for future research in autonomous industrial automation and smart material handling systems.

Key Words: Intelligent Warehouse Automation, Artificial Intelligence, Programmable Logic Controller (PLC), Internet of Things (IoT), Industry 5.0, Edge Computing, Digital Twin,

Predictive Maintenance, Smart Logistics, Conveyor Optimization, Industrial Automation, Smart Manufacturing.

1.INTRODUCTION

1.1 Background of Warehouse Automation

The rapid growth of e-commerce, globalization, and digital technologies has transformed warehouses from conventional storage facilities into intelligent, interconnected, and highly automated logistics environments. Modern warehouses are required to handle large volumes of inventory while maintaining high operational efficiency, order accuracy, reduced processing time, and effective resource utilization. Consequently, warehouse automation has become an important component of smart manufacturing and modern supply chain management.

Traditional warehouse operations often depend on manual activities or semi-automated equipment, leading to inventory errors, operational delays, higher labour requirements, and limited scalability. The development of Industry 4.0 has introduced technologies such as Programmable Logic Controllers (PLCs), Supervisory Control and Data Acquisition (SCADA), Industrial Internet of Things (IIoT), cloud computing, robotics, and intelligent sensing. These technologies enable continuous data acquisition, equipment monitoring, automated material handling, and real-time operational control.

Despite these developments, many warehouse automation systems still rely on predefined PLC logic and isolated control architectures. Such systems primarily execute fixed control sequences and have limited capability to adapt to changing warehouse conditions. Increasing variations in customer demand, product characteristics, inventory levels, equipment conditions, and logistics requirements therefore create a need for more adaptive and intelligent automation solutions.

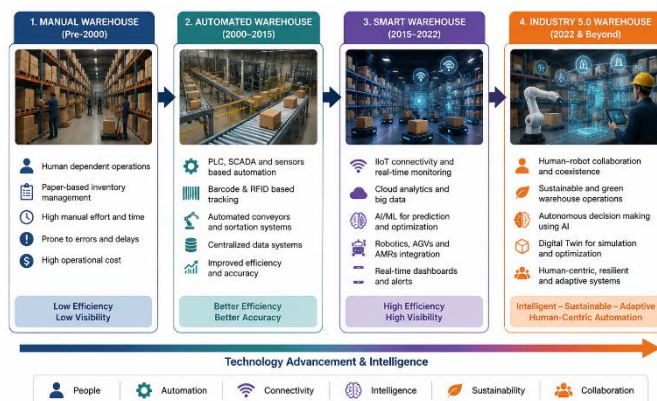


Figure 1.1 Evolution of Warehouse Automation from Manual Warehouses to Industry 5.0-enabled Intelligent Warehouses

The integration of AI, PLCs, IIoT, Edge Computing, and Digital Twin technologies can therefore establish a more adaptive warehouse automation architecture. Such an integrated system can improve inventory visibility, conveyor performance, equipment reliability, energy efficiency, resource utilization, and operational flexibility while supporting the human-centric and sustainable objectives of Industry 5.0 [16], [17], [9].

1.2 Current Challenges in Warehouse Automation

Despite significant advances in warehouse automation, several technical and operational challenges remain. Many industrial systems still rely on conventional PLC-based control with fixed logic and predefined sequences, limiting their ability to analyse operational data, adapt to changing conditions, and support intelligent decision-making.

A major challenge is the limited adaptability of conveyor and material-handling systems. Static control strategies can cause congestion, uneven workload distribution, reduced throughput, and unnecessary energy consumption. Equipment maintenance is another concern, as reactive and time-based maintenance can result in unexpected failures, downtime, and increased maintenance costs.

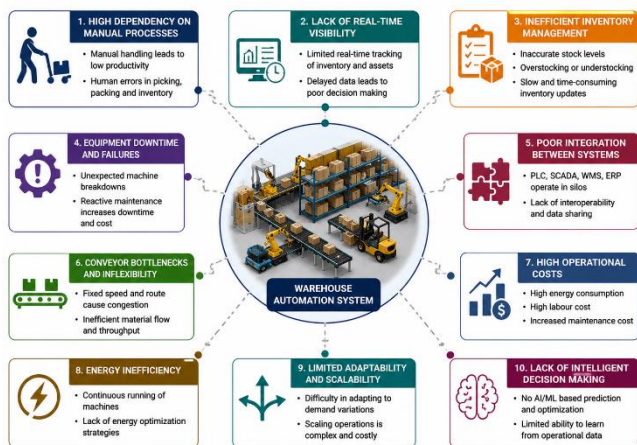


Figure 1.2 Current Challenges in Warehouse Automation

Furthermore, fragmented communication between PLCs, SCADA, IoT devices, databases, and cloud platforms can restrict real-time data sharing and system coordination. Energy-intensive equipment also requires intelligent control to reduce unnecessary power consumption. In addition, limited Digital Twin integration reduces the capability to simulate operational scenarios and evaluate optimization strategies before physical implementation. These limitations highlight the need for an integrated and adaptive warehouse automation framework [16], [17], [9].

1.3 Problem Statement

Modern warehouse automation systems integrate PLCs, SCADA, IoT devices, and industrial communication networks to automate material handling operations. However, these technologies are often implemented as separate subsystems, limiting their ability to respond effectively to dynamic warehouse conditions such as changing demand, variable material flow, equipment degradation, and energy requirements.

Therefore, this research addresses the need for an integrated Intelligent Warehouse Automation Framework that combines real-time industrial control with AI-driven analytics and digital technologies to improve operational efficiency, equipment reliability, energy performance, and sustainable warehouse operation [16], [7], [3].

1.4 Research Motivation

The rapid growth of e-commerce, advanced manufacturing, and smart logistics has increased the need for efficient, flexible, and reliable warehouse operations. Although PLCs, SCADA, WMS, and IoT have improved automation, many systems still depend on predefined control logic with limited adaptability, predictive capability, and interoperability.

The increasing complexity of warehouse operations, including fluctuating demand, diverse products, variable material flow, and equipment degradation, creates a need for intelligent systems capable of real-time monitoring, adaptive control, and data-driven decision-making. AI, IIoT, and Edge Computing provide opportunities for predictive analysis, real-time optimization, and improved equipment monitoring.

The proposed framework aims to improve adaptive decision-making, conveyor operation, equipment reliability, resource allocation, energy efficiency, and inventory management while supporting the human-centric and sustainable objectives of Industry 5.0 [16], [17], [7], [3].



Figure 1.3. Research Gap and Motivation: Existing Warehouse Automation Systems versus Proposed AI-PLC-IoT Intelligent Framework

1.5 Research Objectives

The primary objective of this research is to develop an intelligent warehouse automation framework integrating PLCs, IoT, Artificial Intelligence, Edge Computing, and Digital Twin technology to improve warehouse efficiency, reliability, adaptability, and sustainability. The specific objectives are:

- To investigate the limitations and research gaps of conventional PLC-, SCADA-, and IIoT-based warehouse automation systems.
- To develop a unified AI-PLC-IoT intelligent warehouse automation framework integrating industrial control, real-time sensing, analytics, and communication.

- To develop an AI-assisted PLC Decision Framework for adaptive control and intelligent operational decision-making.
- To propose an Adaptive Conveyor Optimization Algorithm for reducing congestion, improving material flow, and increasing throughput.
- To develop an Edge AI-based Predictive Maintenance Engine for equipment health monitoring and early failure prediction.
- To establish a Hybrid PLC–IoT Communication Framework for reliable real-time communication among industrial controllers, sensors, edge platforms, and cloud services.
- To develop a Dynamic Warehouse Resource Allocation Algorithm for intelligent task scheduling, inventory movement, and resource utilization.
- To integrate an AI-enabled Digital Twin for real-time monitoring, simulation, prediction, and operational optimization.
- To validate the proposed framework through simulation and comparative analysis using key performance indicators including throughput, energy consumption, maintenance performance, communication latency, inventory accuracy, and overall warehouse productivity.

1.6 Research Contributions

This research develops an integrated Intelligent Warehouse Automation Framework combining AI, PLCs, IoT, Edge Computing, and Digital Twin technologies. The major contributions are:

- AI-assisted PLC Decision Framework: Enables adaptive industrial control by combining real-time sensor data with AI-based decision-making.
- Adaptive Conveyor Optimization Algorithm: Dynamically optimizes conveyor speed, routing, and material flow to reduce congestion and improve throughput.
- Smart Energy Optimization Model: Monitors equipment utilization and optimizes operating parameters to reduce energy consumption while maintaining productivity.
- Edge AI-based Predictive Maintenance Engine: Uses real-time equipment data to identify degradation and predict potential failures, reducing unexpected downtime and maintenance requirements.
- Hybrid PLC–IoT Communication Framework: Enables reliable and real-time data exchange among PLCs, sensors, IoT devices, edge platforms, cloud services, and warehouse management systems.
- AI-enabled Digital Twin: Provides a synchronized virtual representation of warehouse operations for real-time monitoring, predictive analysis, simulation, and optimization.
- Integrated Intelligent Warehouse Automation Framework: Combines all proposed modules into a unified, scalable, adaptive, and Industry 5.0-ready architecture for intelligent warehouse and material-handling operations.

2.LITERATURE REVIEW

The rapid development of Industry 4.0 and digital technologies has transformed warehouses into interconnected and automated logistics environments supporting inventory management, material handling, order fulfillment, and real-time operational coordination. Recent literature identifies

smart warehousing as an important area involving information interconnection, equipment automation, process integration, and sustainability [16], [17].

A wide range of technologies, including IoT, RFID, automated vehicles, robotics, Warehouse Management Systems (WMS), and other Industry 4.0 technologies, have been adopted to improve warehouse visibility, automation, and operational flexibility [9], [11], [17]. IoT-based warehouse architectures have demonstrated the feasibility of real-time data collection and communication between warehouse devices and management systems, while research on AGVs highlights the importance of combining automated equipment, data-collection technologies, and management systems for flexible warehouse automation.

Recent research has further expanded warehouse automation through Artificial Intelligence (AI), Machine Learning (ML), and Digital Twin technologies. AI-enabled Digital Twins can provide virtual representations of warehouse assets and support simulation, monitoring, prediction, and decision-making [7], [3]. Research on logistics equipment has also demonstrated the integration of IoT sensing, Digital Twins, and ML models for equipment monitoring, anomaly detection, Remaining Useful Life prediction, and predictive maintenance.

Despite these developments, important research gaps remain. Existing studies frequently focus on individual technologies or specific warehouse functions, while information interconnection, dynamic decision-making, process integration, and sustainable operation remain areas requiring further development [16], [17]. In particular, many systems do not provide a unified architecture integrating AI-based decision-making, PLC control, IoT sensing, Edge Computing, predictive maintenance, energy optimization, resource allocation, and Digital Twin technologies.

Therefore, the existing literature establishes a strong technological foundation for intelligent warehouse automation but also indicates the need for an integrated and scalable framework. This research addresses this gap by combining multiple intelligent modules within a unified AI–PLC–IoT warehouse automation architecture, which is further developed and evaluated in the subsequent chapters.

2.1 Evolution of Warehouse Automation

Warehouse automation has evolved from labour-intensive storage and material-handling operations toward connected and intelligent systems. Early automation introduced PLCs, conveyors, barcode systems, AS/RS, and SCADA, improving material handling, inventory accuracy, and equipment monitoring. However, these systems largely depended on predefined control logic and had limited adaptability to changing operational conditions [16], [17].

The development of Industry 4.0 introduced IIoT, RFID, cloud computing, AGVs, AMRs, machine vision, and advanced WMS, enabling real-time data exchange, inventory tracking, equipment monitoring, and improved operational coordination [9], [11], [17]. IoT-based warehouse architectures demonstrated the feasibility of integrating

sensing, communication, and warehouse management for real-time operations [9].

The subsequent emergence of Industry 5.0 has expanded warehouse automation toward human-centric, sustainable, and intelligent operations. AI, Edge Computing, Digital Twin technology, and intelligent optimization can support predictive analysis, adaptive control, and operational decision-making [7], [3]. Digital Twins are particularly relevant because they provide virtual representations of physical systems and support monitoring, simulation, and decision-making in warehouse environments.

Despite this evolution, existing implementations often remain fragmented across PLC control, IoT infrastructure, warehouse software, and intelligent analytics. Research on smart warehouses identifies information interconnection, process integration, dynamic decision-making, and sustainability as continuing areas for development [16], [17].

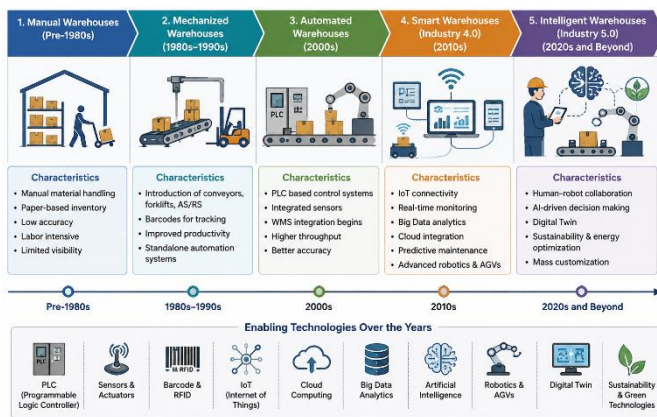


Figure 2.1. Evolution of Warehouse Automation Technologies

2.2 PLC-Based Warehouse Systems

Programmable Logic Controllers (PLCs) are fundamental to warehouse automation because of their reliability, deterministic control, real-time processing, and continuous industrial operation. They control conveyors, sorting systems, robotic equipment, AS/RS, packaging lines, and other material-handling processes. PLCs receive sensor inputs, execute programmed control logic, and generate commands for motors, drives, actuators, and sorting mechanisms.

Integration with SCADA, WMS, and industrial communication networks enables equipment monitoring, diagnostics, alarms, and real-time control. However, conventional PLC systems mainly rely on predefined logic and therefore have limited capability for adaptive decision-making, predictive analytics, and response to changing warehouse conditions. This limitation creates an opportunity for integrating AI and intelligent analytics with PLC-based control [9], [16], [17].

2.2.1 Allen-Bradley PLC Systems

Allen-Bradley PLCs is widely used for industrial control applications such as conveyors, sortation, packaging, and material handling. Their modular architecture and industrial communication capabilities support integration with sensors, drives, robots, and supervisory systems. However, their

operational behaviour remains largely dependent on programmed control logic, creating scope for AI-assisted adaptive control.

2.2.2 Siemens PLC Systems

Siemens PLC platforms provide scalable industrial control, diagnostics, and networking capabilities for applications including AS/RS, robotics, AGVs, and automated packaging. Their integration with industrial communication and automation platforms supports coordinated warehouse operation. Nevertheless, conventional applications primarily depend on deterministic control logic rather than adaptive AI-based decision-making

2.2.3 Beckhoff PLC Systems

Beckhoff systems combine PLC functionality with PC-based control and high-speed industrial communication, supporting applications such as motion control, robotics, machine vision, and intelligent conveyor systems. Their open architecture provides opportunities for integration with Edge Computing and AI-based applications, although comprehensive AI-integrated warehouse implementations remain an area for further development..

Table 2.1 Comparison of Major PLC Platforms Used in Warehouse Automation

Feature	Allen-Bradley	Siemens	Beckhoff
Manufacturer	Rockwell Automation	Siemens AG	Beckhoff Automation
Programming Software	Studio 5000	TIA Portal	TwinCAT
Communication	EtherNet/IP, DeviceNet	PROFINET, PROFIBUS, OPC UA	EtherCAT, OPC UA
Typical Applications	Conveyors, Sortation, Packaging	AS/RS, AGVs, Robotics	Motion Control, Smart Warehouses
Advantages	High Reliability, Easy Integration	Scalability, Diagnostics	High-Speed Control, Open Architecture
Major Limitation	Rule-Based Logic	Limited AI Integration	Higher Engineering Complexity

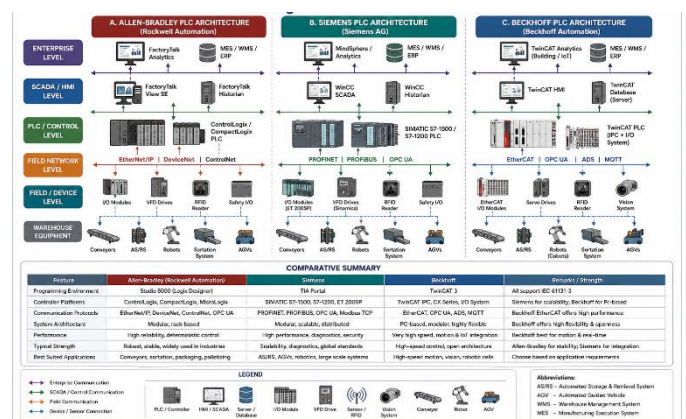


Figure 2.2. Comparative Architecture of Allen-Bradley, Siemens, and Beckhoff PLC Systems in Intelligent Warehouse Automation

2.3 IoT-Based Smart Warehouses

The Industrial Internet of Things (IIoT) enables continuous connectivity among warehouse equipment, sensors, PLCs, communication networks, and management systems. IoT-based architectures improve real-time monitoring, inventory visibility, equipment tracking, and data-driven warehouse management. Smart warehouse research identifies IoT and information interconnection as important elements of modern warehouse automation [9], [16], [17].

In IoT-enabled warehouses, data from conveyors, AS/RS, robots, RFID systems, and industrial sensors can be collected and transmitted to edge or cloud platforms for analysis. This connectivity supports inventory monitoring, equipment diagnostics, predictive maintenance, and operational optimization. IoT-based WMS implementations have also demonstrated the practical integration of real-time data collection and warehouse management functions [9].

The integration of IoT with PLCs, AI, Edge Computing, and Digital Twin technology further enables adaptive and intelligent warehouse operations. Such integration provides the data infrastructure required for predictive analysis, dynamic resource management, and real-time operational control [7], [9].

2.3.1 Industrial Sensors

Industrial sensors provide the primary data required for intelligent warehouse monitoring. Parameters such as temperature, vibration, speed, current, position, weight, and equipment condition can be continuously monitored to support equipment diagnostics, predictive maintenance, and adaptive control [9], [14].

2.3.2 Radio Frequency Identification (RFID)

RFID enables automatic identification and tracking of products, pallets, and assets without requiring direct line-of-sight scanning. Its integration with IoT-based warehouse systems improves inventory visibility and provides real-time data for warehouse management and intelligent analytics [16], [17]. Smart warehouse literature identifies RFID as one of the major IoT technologies applied to warehouse operations.

2.3.3 MQTT Communication Protocol

MQTT provides lightweight publish-subscribe communication suitable for distributed IoT environments. In warehouse automation, it can support communication between sensors, IoT gateways, edge devices, and higher-level management systems. Its use in IoT-based WMS architectures demonstrates its suitability for real-time warehouse data transmission [9].

2.3.4 OPC Unified Architecture (OPC UA)

OPC UA provides a standardized approach for communication and interoperability among heterogeneous industrial systems. Its integration with PLCs, SCADA, IoT devices, and higher-level software can support unified information exchange within intelligent warehouse architectures.

2.3.5 Edge Computing

Edge Computing enables operational data to be processed closer to warehouse equipment, reducing dependence on centralized processing and supporting low-latency decision-making. Its combination with AI and Digital Twin technologies provides opportunities for real-time monitoring, predictive analysis, and intelligent operational control [3], [7]. Research on AI-enabled warehouse Digital Twins highlights the importance of connected data and intelligent processing for warehouse monitoring and decision support.

Table 2.2 Comparison of Major IoT Technologies Used in Smart Warehouses

Technology	Primary Function	Advantages	Warehouse Applications
Industrial Sensors	Real-time data acquisition	Continuous monitoring, predictive maintenance	Conveyor monitoring, equipment health, environmental sensing
RFID	Automatic identification and tracking	High inventory accuracy, contactless operation	Inventory management, pallet tracking, asset identification
MQTT	Lightweight communication protocol	Low bandwidth, scalable publish-subscribe messaging	Sensor communication, real-time equipment monitoring
OPC UA	Secure industrial interoperability	Vendor-independent communication, cybersecurity	PLC-SCADA integration, WMS connectivity, cloud communication
Edge Computing	Local intelligent processing	Low latency, faster decision-making, reduced bandwidth	AI inference, predictive maintenance, adaptive conveyor control

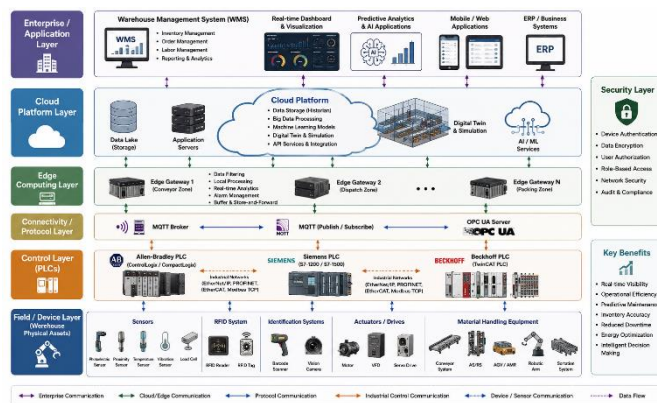


Figure 2.3. IoT-Based Smart Warehouse Architecture Integrating Sensors, RFID, PLCs, MQTT, OPC UA, Edge

Computing, Cloud Platform, and Warehouse Management System (WMS).

2.4 Artificial Intelligence in Warehouse Automation

Artificial Intelligence (AI) is transforming warehouse automation from predefined rule-based systems toward intelligent and adaptive operations. AI can analyse historical and real-time warehouse data to support prediction, optimization, and decision-making. Its integration with PLCs, IIoT, Edge Computing, and Digital Twin technologies can improve inventory management, material flow, equipment monitoring, predictive maintenance, and operational efficiency [3], [7], [12].

Modern warehouses generate large amounts of data from sensors, conveyors, AS/RS, robots, RFID systems, and WMS platforms. AI techniques convert these data into actionable information for monitoring equipment conditions, analysing workload, predicting operational requirements, and optimizing warehouse processes. Recent research also highlights the growing role of AI in warehouse Digital Twins and intelligent order-picking operations [3], [7], [12].

2.4.1 Machine Learning

Machine Learning (ML) enables systems to identify patterns from historical and real-time data and generate predictive models without relying entirely on predefined rules. In warehouse automation, ML can support demand forecasting, anomaly detection, equipment-health monitoring, predictive maintenance, inventory analysis, and operational performance prediction [3], [14].

However, ML performance depends on the quality and availability of training data and may require periodic model updating as warehouse conditions change.

2.4.2 Deep Learning

Deep Learning (DL) uses multi-layer neural networks to learn complex patterns from large datasets. In warehouse applications, DL can support image-based package recognition, object detection, inventory identification, equipment monitoring, and fault diagnosis. CNN-based models are particularly suitable for visual inspection and object recognition, while sequence-based models can support time-dependent operational prediction.

The main limitations include high computational requirements, large training datasets, and increased implementation complexity, which support the use of Edge Computing for selected real-time AI applications.

2.4.3 Reinforcement Learning

Reinforcement Learning (RL) enables an agent to learn operational decisions through interaction with its environment using reward-based feedback. In warehouse automation, RL can support dynamic routing, robot navigation, task scheduling, conveyor optimization, and resource allocation. Recent research demonstrates the application of reinforcement learning to warehouse routing and dynamic order-picking problems [5], [6].

Its main challenges include training requirements, computational complexity, and the design of appropriate reward functions for safe and stable industrial operation.

2.4.4 Computer Vision

Computer Vision enables automated interpretation of visual information from industrial cameras and imaging systems. In warehouse environments, it can support package identification, barcode recognition, sorting, inventory verification, quality inspection, robotic guidance, and safety monitoring. Recent research identifies computer vision as an important technology for warehouse management automation and inventory-related applications [1], [17].

Integration of computer vision with PLCs, IIoT, and AI-based control can provide real-time operational feedback and support automated responses to detected warehouse events.

Table 2.3 Comparison of Artificial Intelligence Techniques in Warehouse Automation

AI Technique	Primary Function	Advantages	Typical Warehouse Applications
Machine Learning	Predictive analytics and pattern recognition	Demand forecasting, anomaly detection, predictive maintenance	Inventory forecasting, equipment health monitoring
Deep Learning	Automatic feature extraction from complex data	High accuracy, image recognition, fault diagnosis	Object detection, quality inspection, inventory identification
Reinforcement Learning	Adaptive decision-making through interaction	Dynamic optimization, autonomous control	Conveyor routing, AGV navigation, task scheduling
Computer Vision	Visual inspection and object recognition	Real-time monitoring, automated inspection, safety enhancement	Barcode reading, package sorting, defect detection, worker safety

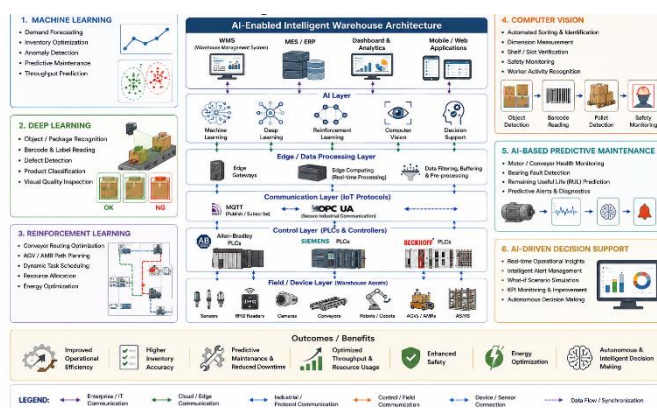


Figure 2.4. Applications of Artificial Intelligence in Intelligent Warehouse Automation

2.5 Conveyor Automation

Conveyor automation is a key component of warehouse material handling, supporting continuous product transportation between storage, sorting, packaging, and shipping areas. Conventional conveyor systems generally use PLC-based control with sensors for product detection, routing, and speed regulation. Although reliable, fixed control logic provides limited adaptability to changing workloads and material-flow conditions [16], [17].

The integration of IIoT, AI, Edge Computing, and Digital Twin technologies enables conveyors to become intelligent material-handling systems. Real-time data such as conveyor speed, motor condition, product flow, vibration, and energy consumption can be analysed to identify bottlenecks, optimize material movement, and support predictive maintenance [3], [14]. Research on logistics equipment condition monitoring further demonstrates the potential of combining Digital Twin, sensor data, and Machine Learning for equipment-health prediction [14].

Intelligent conveyor systems can also integrate barcode, RFID, and computer-vision technologies for automated product identification and routing [1], [17]. In addition, sensors installed on motors, bearings, belts, and drive mechanisms can provide continuous condition data for AI-based predictive maintenance, enabling potential failures to be identified before major equipment breakdowns [14].

However, many existing conveyor systems remain dependent on fixed PLC logic and operate independently from AI, WMS, IoT, and Digital Twin platforms. This fragmentation limits adaptive routing, real-time optimization, predictive maintenance, and intelligent energy management. Therefore, integration of conveyor control with AI, IoT, Edge Computing, and Digital Twin technologies represents an important direction for intelligent warehouse automation [3], [7], [16].

Table 2.4 Comparison of Conventional and Intelligent Conveyor Automation Systems

Feature	Conventional Conveyor System	Intelligent Conveyor System
Control Strategy	Fixed PLC Logic	AI-assisted Adaptive Control
Conveyor Speed	Constant Speed	Dynamic Speed Optimization
Product Routing	Predefined Routing	Intelligent Real-Time Routing
Monitoring	Periodic Inspection	Continuous IIoT Monitoring
Maintenance	Reactive/Preventive	AI-Based Predictive Maintenance
Energy Management	Fixed Power Consumption	Smart Energy Optimization
Decision Making	Rule-Based	Data-Driven Intelligent Decision Making
Industry Compatibility	Industry 3.0/4.0	Industry 5.0

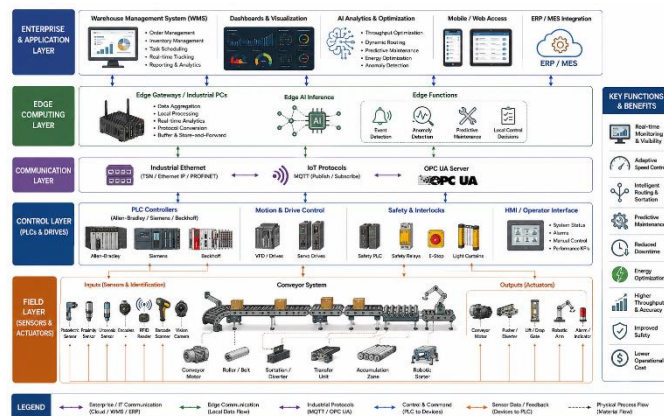


Figure 2.5. Intelligent Conveyor Automation Architecture for Smart Warehouse Systems

2.6 AGV and AMR Systems

Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs) are important technologies for automated material transportation in modern warehouses. They reduce manual handling and support flexible movement of materials between storage, picking, processing, and shipping areas. Their increasing integration with Industry 4.0 technologies has made autonomous transportation an important component of intelligent warehouse automation [11], [17].

AGVs generally operate along predefined routes using technologies such as magnetic guidance, optical markers, QR codes, or laser-based navigation. They are well suited to repetitive transportation tasks in structured warehouse environments. In contrast, AMRs use sensing, localization, mapping, and intelligent navigation to dynamically determine routes and respond to changing warehouse conditions. This provides greater flexibility for dynamic material-handling operations [11].

The integration of AGVs and AMRs with IIoT, PLCs, AI, Edge Computing, and WMS enables real-time monitoring of robot location, payload, battery condition, and operational status. AI-based algorithms can support fleet coordination, task allocation, route planning, and traffic management, while Edge Computing can provide low-latency processing for time-critical decisions [11], [17].

AI techniques, particularly Machine Learning and Reinforcement Learning, can further improve robot navigation, routing, and task scheduling. Recent research has investigated reinforcement-learning-based warehouse robot navigation and picker-routing optimization, demonstrating the potential of AI for adaptive warehouse transportation [5], [6]. AGV route optimization has also been studied using advanced optimization approaches for large-scale logistics warehouse environments [13].

Despite these advantages, AGVs and AMRs present challenges related to navigation flexibility, fleet coordination, communication reliability, battery management, sensing requirements, and integration with existing warehouse systems. Research on AGV-based Industry 4.0 warehouses highlights the need for flexible automation and improved

integration between autonomous transportation and other warehouse technologies [11].

Therefore, integration of AGV/AMR systems with AI, PLC-based control, IoT, Edge Computing, and Digital Twin technologies provides an important pathway toward adaptive and intelligent warehouse material handling. Such integration can support autonomous transportation, dynamic resource allocation, intelligent routing, and real-time operational optimization.

Table 2.5 Comparison between AGVs and AMRs

Feature	Automated Guided Vehicle (AGV)	Autonomous Mobile Robot (AMR)
Navigation	Fixed predefined routes	Dynamic autonomous navigation
Guidance Method	Magnetic tape, laser, QR code, wire guidance	LiDAR, SLAM, AI, Computer Vision
Flexibility	Limited	Very High
Obstacle Avoidance	Basic	Intelligent real-time avoidance
Route Modification	Manual reconfiguration	Automatic path planning
Artificial Intelligence	Minimal	Extensive AI integration
Typical Applications	Pallet transport, repetitive material movement	Dynamic picking, order fulfillment, inventory transport
Integration	PLC, WMS	PLC, WMS, AI, IoT, Edge Computing
Industry Readiness	Industry 4.0	Industry 5.0

Unlike conventional monitoring, which primarily provides operational status, Digital Twin systems enable simulation and evaluation of different operating scenarios before physical implementation. This capability can support bottleneck identification, material-flow analysis, equipment utilization, layout evaluation, and operational decision-making. Research on automated warehouse Digital Twins demonstrates their potential for modelling and validating warehouse operations and supporting future automation development [2], [10].

The integration of AI further enhances Digital Twin capabilities by enabling predictive analytics and intelligent decision support. AI-enabled Digital Twins can analyse operational data to support equipment-failure prediction, throughput estimation, routing optimization, and warehouse resource management [3], [7], [14]. Recent research also demonstrates the use of Digital Twin and optimization techniques for warehouse order-picking and logistics operations [15].

Edge Computing can complement Digital Twin architectures by processing time-sensitive sensor data close to physical warehouse equipment before transferring relevant information to higher-level platforms. This can support faster monitoring and decision-making while reducing unnecessary data transmission.

Digital Twins are also relevant to predictive maintenance and energy optimization. Continuous equipment data can be used to identify abnormal conditions and support condition-based maintenance, while simulation can be used to evaluate equipment utilization and energy-related operating strategies [14].

Despite these advantages, Digital Twin implementation requires reliable sensor data, communication infrastructure, data integration, model validation, and interoperability among heterogeneous industrial systems. Research therefore continues to investigate scalable Digital Twin architectures, simulation validation, AI integration, and real-time synchronization for intelligent warehouse applications [2], [7], [8], [10].

Overall, Digital Twin technology provides an important foundation for the proposed Intelligent Warehouse Automation Framework by connecting physical warehouse operations with virtual modelling, AI-based analysis, predictive maintenance, and optimization.

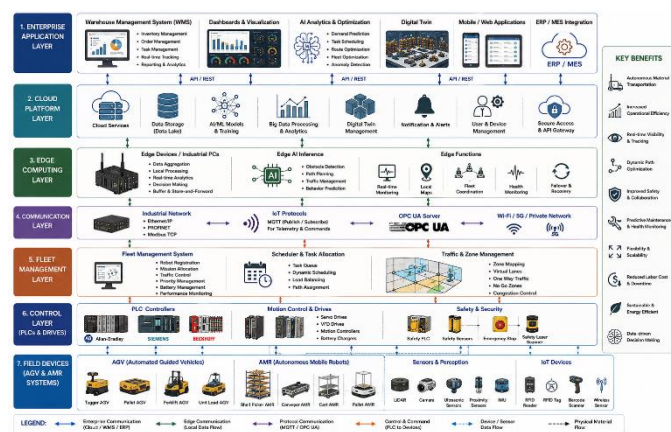


Figure 2.6. Architecture of AGV and AMR Systems for Intelligent Warehouse Automation

2.7 Warehouse Digital Twin

Digital Twin technology provides a virtual representation of physical warehouse assets and processes and enables continuous monitoring, simulation, and operational analysis. In warehouse automation, Digital Twins can integrate data from PLCs, IIoT sensors, WMS, and other industrial systems to represent equipment, material flow, inventory, and warehouse operations [2], [7].

Table 2.6 Comparison of Conventional Warehouse Monitoring and AI-Enabled Digital Twin Systems

Feature	Conventional Warehouse Monitoring	AI-Enabled Digital Twin
System Representation	Physical equipment only	Real-time virtual replica
Data Source	PLC/SCADA	PLC + IoT + AI + Cloud + Edge
Monitoring	Real-time status	Real-time synchronized visualization
Decision Support	Manual	AI-assisted predictive decision-

Feature	Conventional Warehouse Monitoring	AI-Enabled Digital Twin
		making
Maintenance Strategy	Reactive/Preventive	Predictive and condition-based
Simulation Capability	Not available	Real-time operational simulation
Resource Optimization	Limited	Dynamic AI-based optimization
Industry Compatibility	Industry 4.0	Industry 5.0

industrial equipment. This reduces communication latency and enables faster identification of abnormal conditions. The combination of Edge AI, IoT sensing, PLC control, and predictive analytics therefore provides a suitable architecture for real-time equipment-health monitoring.

Predictive maintenance can also support sustainable warehouse operation by reducing unnecessary component replacement, extending equipment service life, and minimizing downtime. However, reliable implementation requires high-quality sensor data, appropriate AI models, communication infrastructure, and integration among heterogeneous industrial systems. These challenges indicate the need for predictive maintenance to be integrated with broader warehouse automation rather than implemented as an isolated function [7], [14], [16].

Overall, the literature indicates that the combination of AI, IIoT, Edge Computing, and Digital Twin technology can provide a foundation for intelligent predictive maintenance. This research extends this concept through the proposed Edge AI-based Predictive Maintenance Engine within the integrated warehouse automation framework.

Table 2.7 Comparison of Maintenance Strategies

Maintenance Strategy	Description	Advantages	Limitations
Corrective Maintenance	Maintenance performed after equipment failure	Simple implementation	High downtime and repair cost
Preventive Maintenance	Scheduled maintenance based on time or usage	Reduces unexpected failures	May replace healthy components unnecessarily
Condition-Based Maintenance	Maintenance based on real-time equipment condition	Improved maintenance planning	Requires continuous monitoring infrastructure
AI-Based Predictive Maintenance	AI predicts failures using sensor data and analytics	Early fault detection, reduced downtime, optimized maintenance scheduling	Requires high-quality data, AI models, and IIoT infrastructure

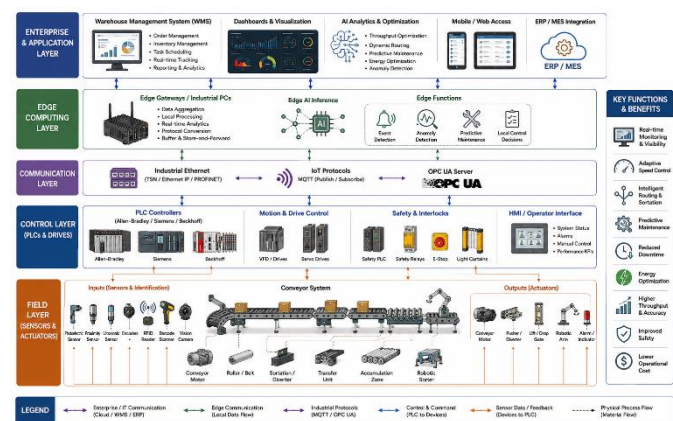


Figure 2.7. AI-Enabled Warehouse Digital Twin Architecture

2.8 Predictive Maintenance

Predictive Maintenance (PdM) is an important application of AI and IIoT in warehouse automation. Unlike corrective or fixed-schedule maintenance, PdM uses continuous equipment-condition data to identify abnormal behaviour and predict potential failures. This approach can reduce unexpected downtime, maintenance costs, and operational interruptions. Recent research demonstrates the integration of Digital Twin, sensor data, and Machine Learning for logistics equipment condition monitoring and failure prediction [14].

Modern warehouses contain critical assets such as conveyor motors, bearings, gearboxes, AGVs, AMRs, robotic systems, AS/RS, and VFDs. Monitoring parameters such as vibration, temperature, motor current, rotational speed, and energy consumption provides useful information about equipment health. IoT-enabled monitoring systems can continuously collect these parameters and transfer them to PLC, Edge, or cloud-based analytics platforms [9], [14].

AI and Machine Learning can analyse equipment-condition data to identify anomalies and predict potential failures. Models such as Random Forest, SVM, Gradient Boosting, and neural-network approaches can be applied to equipment-health classification and failure prediction. Digital Twin technology further supports predictive maintenance by maintaining a virtual representation of equipment and enabling operational behaviour and maintenance scenarios to be analysed [7], [14].

Edge Computing can improve predictive maintenance by performing data processing and AI inference close to

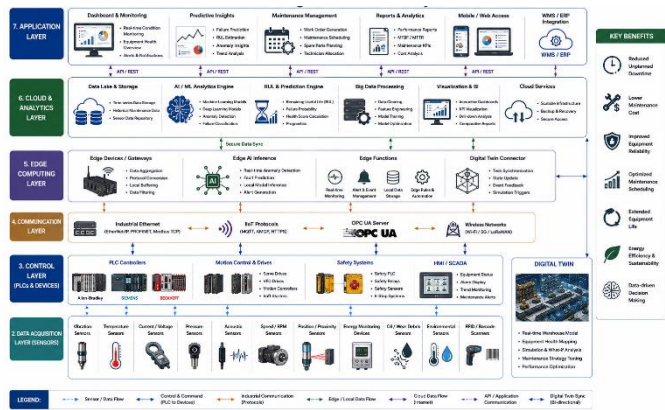


Figure 2.8. AI-Based Predictive Maintenance Architecture for Intelligent Warehouse Systems

3. PROPOSED INTELLIGENT WAREHOUSE FRAMEWORK

3.1 Introduction

The literature review indicates that existing warehouse automation systems often implement PLC control, IIoT infrastructure, AI applications, and Digital Twin technologies as separate components, limiting integrated decision-making and adaptive operational control. This research therefore proposes a Novel Intelligent Warehouse Automation Framework (IWAF) that integrates PLCs, IIoT, AI, Edge Computing, Warehouse Digital Twin, WMS, and cloud-based analytics within a unified architecture.

The proposed framework continuously acquires operational data from warehouse equipment, processes critical data at the Edge, applies AI-based analysis, synchronizes relevant information with the Digital Twin, and supports operational decisions through the WMS. This closed-loop architecture enables adaptive control, predictive maintenance, conveyor optimization, resource allocation, and real-time warehouse monitoring.

The framework is designed to improve operational efficiency, equipment reliability, energy performance, inventory visibility, and resource utilization while providing a scalable architecture for Industry 5.0-enabled warehouse operations.

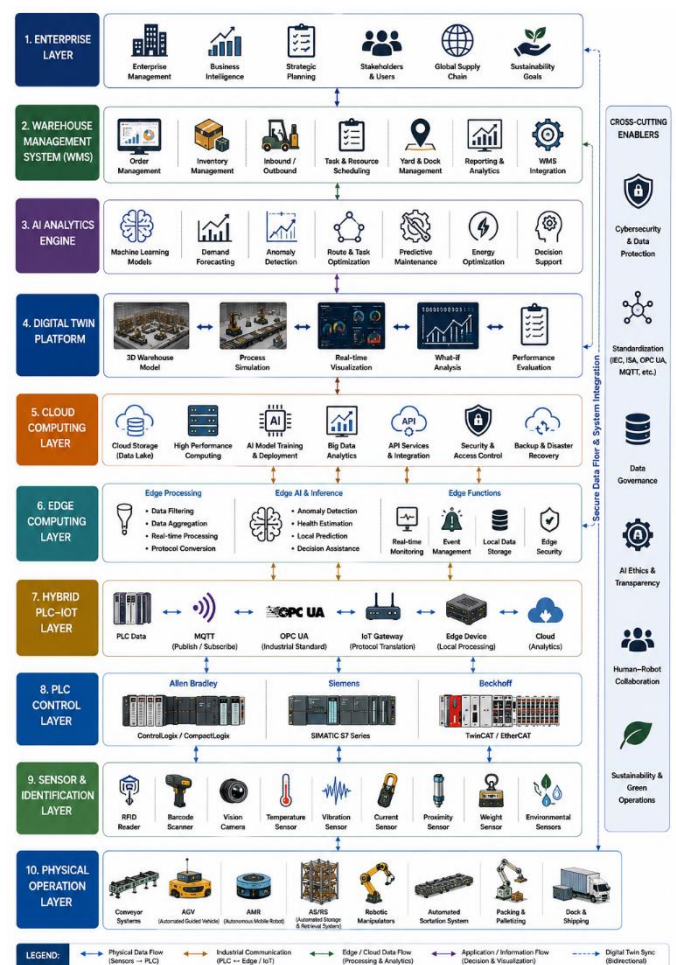


Figure 3.1 Overall Proposed Intelligent Warehouse Automation Framework

3.2 Proposed System Workflow

The proposed Intelligent Warehouse Automation Framework (IWAF) follows a multi-layer, data-driven workflow integrating PLCs, IIoT, AI, Edge Computing, Warehouse Digital Twin, WMS, and cloud analytics. The workflow is designed to support autonomous material handling, adaptive decision-making, predictive maintenance, conveyor optimization, and real-time warehouse monitoring.

The process begins when an order is received through the ERP/WMS. The WMS evaluates product information, inventory availability, priority, and delivery requirements and generates appropriate warehouse tasks. The AI Analytics Engine then analyses real-time operational data, including inventory status, conveyor workload, AGV/AMR availability, equipment condition, and warehouse traffic, to determine suitable task schedules and material-handling routes.

The resulting control instructions are transmitted through the Hybrid PLC-IIoT Communication Layer using industrial communication technologies such as MQTT, OPC UA, EtherNet/IP, and PROFINET. PLCs execute the optimized commands for conveyors, AS/RS, robotic systems, AGVs, AMRs, and other material-handling equipment.

During operation, IIoT sensors continuously collect equipment and process data, including product movement,

vibration, temperature, current, position, and visual information. Edge Computing processes these data locally for filtering, anomaly detection, equipment-health assessment, and predictive maintenance, thereby supporting low-latency operational decisions.

Processed data are simultaneously synchronized with the AI-enabled Warehouse Digital Twin, which represents the physical warehouse and its major operational components. The Digital Twin supports real-time visualization, scenario simulation, bottleneck identification, predictive maintenance planning, and performance evaluation.

Based on AI and Digital Twin analysis, the framework generates optimization decisions related to conveyor speed, AGV/AMR routing, resource allocation, inventory positioning, predictive maintenance, and energy management. These decisions are returned to the PLC control layer, creating a continuous closed-loop feedback mechanism.

Throughout operation, key performance indicators such as throughput, inventory accuracy, equipment utilization, energy consumption, order completion time, conveyor efficiency, robot productivity, and equipment health are continuously monitored through WMS/ERP dashboards. This closed-loop workflow enables continuous operational optimization and supports efficient, reliable, and sustainable warehouse automation.

real-time control, Industrial PCs perform Edge AI processing, and IoT gateways provide communication with higher-level warehouse systems.

3.3.1 Programmable Logic Controllers (PLCs)

PLCs form the primary control layer of the proposed architecture. Allen-Bradley, Siemens, and Beckhoff platforms can receive sensor inputs and control conveyors, robotic systems, AGVs, AMRs, and AS/RS equipment. Communication with Edge and IoT layers is supported through industrial protocols such as EtherNet/IP, PROFINET, Modbus TCP, OPC UA, and EtherCAT.

3.3.2 Industrial Sensors

Industrial sensors provide real-time information on equipment and warehouse conditions. Temperature, vibration, current, proximity, pressure, humidity, load, and other measurements are used for equipment monitoring, predictive maintenance, conveyor optimization, and operational analysis.

3.3.3 RFID System

RFID systems enable automatic identification and tracking of products, pallets, and assets. RFID data can be integrated with the WMS to improve inventory visibility, reduce tracking errors, and provide real-time information for warehouse analytics.

3.3.4 Industrial Vision Cameras

Vision cameras support package identification, barcode recognition, object detection, quality inspection, pallet identification, and safety monitoring. Integration with AI-based computer vision enables automated analysis and provides operational feedback to the control system.

3.3.5 Robotic Systems

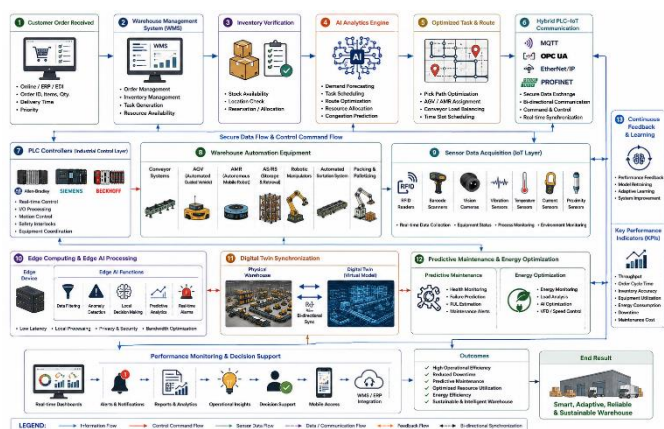
The framework incorporates AGVs, AMRs, robotic manipulators, collaborative robots, palletizing systems, and automated sorting equipment for material handling. Their coordination with PLCs, AI scheduling, and IoT communication enables flexible transportation and automated warehouse operations.

3.3.6 Industrial Personal Computer (Industrial PC)

Industrial PCs provide local computational capability for Edge AI, data processing, predictive maintenance, Digital Twin synchronization, visualization, and HMI functions. Local processing reduces dependence on cloud systems and supports low-latency operational decisions.

3.3.7 Industrial IoT Gateway

The Industrial IoT Gateway connects field devices, PLCs, Industrial PCs, cloud platforms, and WMS. It performs data aggregation, protocol conversion, buffering, filtering, and secure communication using technologies such as MQTT, OPC UA, EtherNet/IP, PROFINET, and Modbus TCP.



Overall workflow of the proposed Intelligent Warehouse Automation Framework illustrating the complete operational sequence from customer order processing, Warehouse Management System (WMS), AI-assisted decision-making, Hybrid PLC–IoT communication, industrial control, sensor data acquisition, Edge AI processing, Digital Twin synchronization, predictive maintenance, and continuous feedback-based optimization.

3.3 Hardware Architecture

The proposed Intelligent Warehouse Automation Framework (IWAF) integrates industrial controllers, sensors, RFID systems, vision cameras, robotic equipment, Industrial PCs, and IoT gateways to support real-time monitoring, intelligent control, predictive maintenance, and autonomous warehouse operation. The architecture follows a hierarchical structure in which field devices collect operational data, PLCs execute

Table 3.1 Hardware Components of the Proposed Intelligent Warehouse Framework

Hardware Component	Primary Function	Typical Devices	Role in Proposed Framework
PLC	Industrial control	Allen-Bradley, Siemens, Beckhoff	Real-time equipment control
Industrial Sensors	Data acquisition	Temperature, Vibration, Current, Proximity	Equipment monitoring
RFID System	Identification & Tracking	RFID Readers, RFID Tags	Inventory management
Vision Camera	Visual inspection	Industrial Smart Cameras	Object detection & quality inspection
Robotic Systems	Automated material handling	AGV, AMR, Robotic Arm, AS/RS	Autonomous warehouse operations
Industrial PC	Edge computing	Industrial Computer	AI inference & Digital Twin processing
IoT Gateway	Industrial communication	MQTT Gateway, OPC UA Gateway	Secure data integration & protocol conversion

PDF) addresses this limitation by integrating AI, IIoT, Edge Computing, and Digital Twin technologies with PLC-based industrial control.

The framework continuously collects data from sensors, RFID systems, barcode scanners, vision cameras, and warehouse equipment. These data are processed at the Edge for filtering, feature extraction, anomaly detection, and equipment-health assessment. AI models then analyse real-time and historical data to generate decisions related to conveyor speed, material routing, AGV/AMR scheduling, predictive maintenance, inventory priorities, and energy-efficient operation.

The resulting recommendations are transmitted through the Hybrid PLC-IoT Communication Framework to Allen-Bradley, Siemens, and Beckhoff PLCs. The PLCs maintain deterministic execution while applying the optimized control parameters to conveyors, robotic systems, AGVs, AMRs, VFDs, and AS/RS equipment. This approach combines AI-based decision intelligence with reliable PLC execution, rather than replacing conventional industrial control.

Operational feedback is continuously transferred to the Warehouse Digital Twin, where system behaviour can be monitored and alternative operating conditions evaluated. The resulting feedback is used to refine subsequent AI decisions, forming a closed-loop architecture for adaptive warehouse control.

The proposed framework therefore extends conventional PLC automation toward intelligent and adaptive operation by integrating real-time sensing, Edge AI, predictive analytics, and Digital Twin-based feedback. The concept is consistent with the broader research direction identified in the literature on AI-enabled warehouse Digital Twins and smart warehouse automation [3], [7], [16], [17].

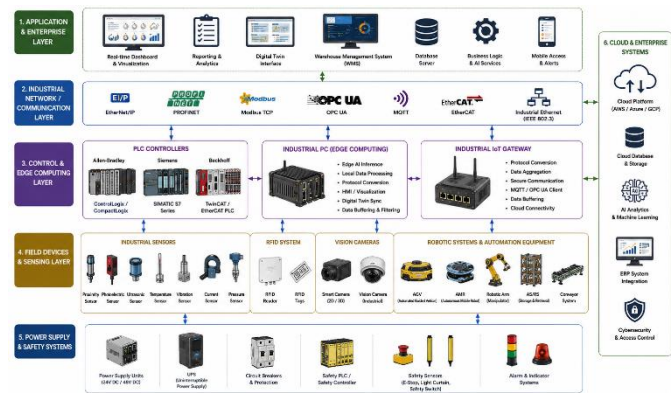


Figure 3.3. Hardware Architecture of the Proposed Intelligent Warehouse Automation Framework

The architecture illustrates the integration of PLCs, industrial sensors, RFID systems, vision cameras, robotic systems, Industrial PCs, and IoT gateways with the WMS, enabling real-time control, Edge AI processing, Digital Twin synchronization, and intelligent warehouse automation.

3.4 AI-Assisted PLC Decision Framework

Conventional PLC-based warehouse systems provide reliable and deterministic control but primarily depend on predefined logic, limiting their ability to respond to changing workload, equipment condition, congestion, and inventory requirements. The proposed AI-Assisted PLC Decision Framework (AI-

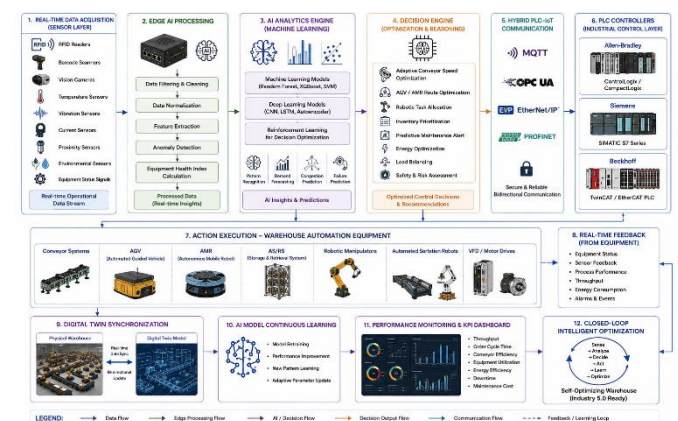


Figure 3.4. AI-Assisted PLC Decision Framework

Architecture showing real-time sensor data acquisition, Edge AI processing, AI decision generation, Hybrid PLC-IoT communication, PLC-based industrial control, warehouse equipment, Digital Twin synchronization, and feedback-based optimization.

3.5 Intelligent IoT Framework

The proposed Intelligent IoT Framework establishes continuous connectivity between warehouse equipment,

sensors, PLCs, Edge Computing devices, AI analytics, Digital Twin platforms, and the WMS. Unlike conventional IoT systems that mainly provide connectivity and monitoring, the proposed framework uses real-time data for intelligent analysis, adaptive control, and operational optimization.

The framework begins with data acquisition from industrial sensors, RFID readers, barcode systems, vision cameras, conveyors, AGVs, AMRs, robotic systems, and other warehouse equipment. These devices continuously provide information related to inventory movement, equipment condition, product identification, and warehouse operations.

An Industrial IoT Gateway collects and aggregates the field data and provides communication between operational devices and higher-level systems. Protocols such as MQTT, OPC UA, EtherNet/IP, PROFINET, and Modbus TCP can be used for data exchange. The gateway also supports data filtering, buffering, protocol conversion, and secure communication.

The collected information is processed at the Edge Computing layer, where AI-based algorithms can perform data preprocessing, anomaly detection, equipment-health assessment, and real-time inference. Local processing reduces communication latency and supports time-critical applications such as conveyor control, equipment monitoring, and predictive maintenance.

Processed information is then synchronized with cloud analytics and the AI-enabled Warehouse Digital Twin. AI models analyse operational data to support equipment-failure prediction, material-flow optimization, inventory analysis, and resource allocation. The Digital Twin provides a virtual representation of warehouse operations for monitoring, simulation, and performance evaluation [3], [7], [9].

The resulting optimization decisions are communicated back to the PLC control layer, creating a bidirectional feedback loop between physical warehouse equipment and intelligent analytics. This architecture allows the proposed system to continuously monitor operational conditions and update control decisions according to changing warehouse requirements.

Compared with conventional IoT implementations, the proposed framework integrates IoT connectivity, Edge AI, PLC control, Digital Twin, and WMS within a single architecture. This integration provides the communication and data-processing foundation required for the proposed intelligent warehouse automation system.

Table 3.2 Hardware and Communication Components of the Intelligent IoT Framework

Component	Function	Communication
Industrial Sensors	Real-time monitoring	MQTT
RFID Readers	Inventory tracking	MQTT / OPC UA
Vision Cameras	Quality inspection	GigE Vision / Ethernet
PLC Controllers	Industrial control	EtherNet/IP, PROFINET
IoT Gateway	Protocol conversion	MQTT, OPC UA
Edge	Local AI inference	OPC UA

Component	Function	Communication
Computing		
Cloud Platform	Data analytics	HTTPS / MQTT
Digital Twin	Virtual synchronization	API / OPC UA
WMS	Warehouse management	REST API

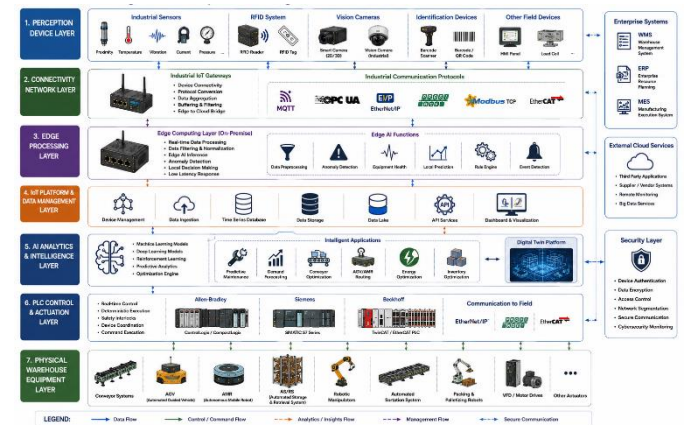


Figure 3.5. Proposed Intelligent IoT Framework for Smart Warehouse Automation

Architecture of the proposed Intelligent IoT Framework illustrating the integration of industrial sensors, RFID readers, vision cameras, PLC controllers, IoT gateways, MQTT, OPC UA, Edge Computing, Artificial Intelligence, cloud analytics, Digital Twin platform, and Warehouse Management System (WMS). The framework enables secure real-time communication, intelligent data processing, predictive maintenance, adaptive control, and continuous optimization of warehouse operations.

3.6 Adaptive Conveyor Optimization Algorithm

3.6.1 Introduction

Conveyor systems are essential for automated material transportation between receiving, storage, picking, packaging, and shipping areas. Conventional PLC-based conveyor systems generally use fixed control logic and predefined routing, which limits their ability to respond to changing workload, congestion, equipment condition, and order priorities.

To address these limitations, this research proposes an Adaptive Conveyor Optimization Algorithm (ACOA) that integrates AI, IIoT, Edge Computing, PLCs, WMS, and Digital Twin technology. The algorithm continuously evaluates real-time warehouse conditions and adjusts conveyor operation to improve throughput, reduce congestion and delays, and optimize energy consumption. The approach is consistent with research emphasizing dynamic decision-making and process integration in smart warehouse systems [16], [17].

3.6.2 Proposed Adaptive Conveyor Optimization Algorithm

The proposed ACOA operates as a closed-loop control system. IIoT sensors collect conveyor speed, motor load,

package density, equipment condition, inventory movement, and traffic information. These data are transmitted through the communication layer to Edge Computing devices, where filtering, normalization, anomaly detection, and feature extraction are performed.

The processed information is analysed by AI/ML models using parameters such as conveyor utilization, queue length, order priority, inventory demand, AGV availability, workload, and equipment health. Based on these conditions, the optimization engine determines suitable conveyor speed, routing, load distribution, diversion, and scheduling decisions.

The optimized commands are transmitted through the Hybrid PLC–IoT Communication Framework to the PLC layer. PLCs then regulate conveyor motors through VFDs, control diverters, synchronize sorting operations, and coordinate material flow. Operational feedback is continuously returned to the AI layer, enabling adaptive optimization.

The optimized warehouse state is also synchronized with the AI-enabled Digital Twin. The Digital Twin can be used to evaluate alternative routing and operating scenarios and identify potential bottlenecks before corresponding changes are applied to the physical system [7], [14].

3.6.3 Algorithm

Adaptive Conveyor Optimization Algorithm

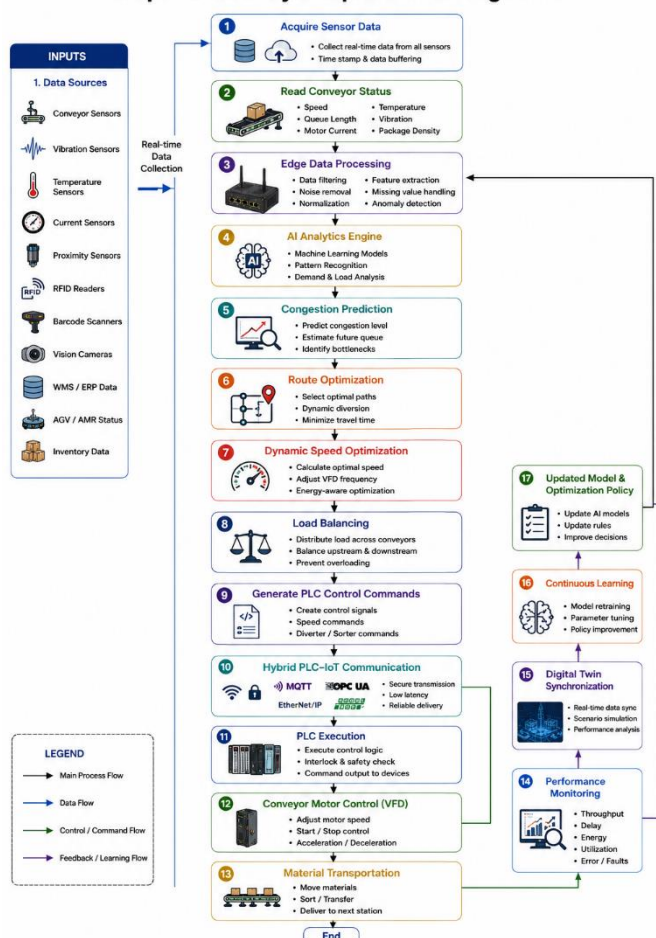


Figure 3.6. Adaptive Conveyor Optimization Algorithm

3.6.4 Mathematical Model

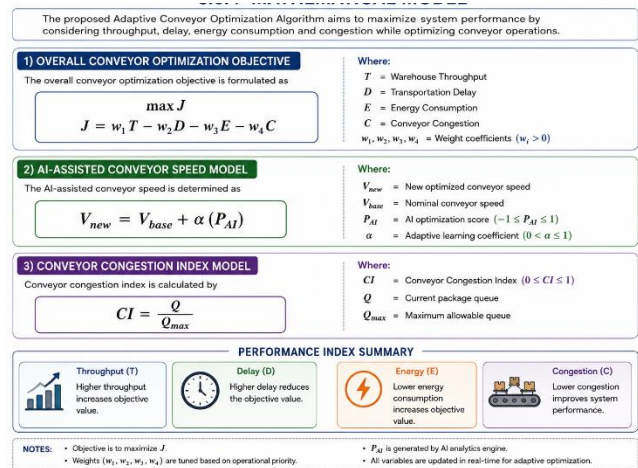


Figure 3.7. Mathematical Model

3.6.5 Novel Features

- AI-assisted adaptive conveyor speed control.
- Dynamic routing optimization.
- Intelligent congestion prediction.
- PLC–IoT integrated conveyor control.
- Edge AI-based real-time decision making.
- Digital Twin-assisted optimization.
- Intelligent load balancing.
- Energy-aware conveyor operation.
- Predictive maintenance integration.
- Industry 5.0-compatible intelligent conveyor control.

3.6.6 Advantages of the Proposed Algorithm

- Reduces conveyor congestion.
- Increases warehouse throughput.
- Minimizes operational delay.
- Improves equipment utilization.
- Optimizes energy consumption.
- Enhances predictive maintenance capability.
- Supports autonomous warehouse operation.
- Enables continuous learning through Artificial Intelligence.
- Integrates seamlessly with Digital Twin technology.
- Improves overall warehouse efficiency and sustainability.

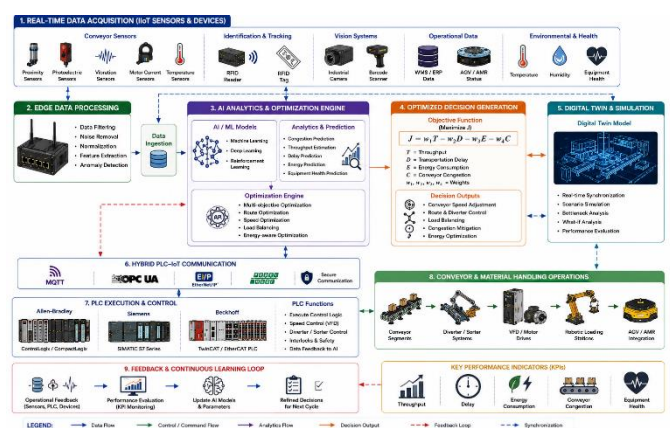


Figure 3.8. Adaptive Conveyor Optimization Framework

Framework illustrating the proposed Adaptive Conveyor Optimization Algorithm. Real-time data from conveyor sensors, RFID readers, and vision systems are processed through Edge AI and Machine Learning models to predict congestion, optimize conveyor speed, balance material flow, and generate intelligent PLC control commands. The optimized operations are synchronized with the Warehouse Digital Twin to enable continuous learning and adaptive warehouse optimization.

3.7 Smart Energy Optimization Model

3.7.1 Introduction

Energy consumption is an important challenge in automated warehouses because conveyors, robots, AGVs, AMRs, AS/RS, lighting, and HVAC systems may operate continuously. Conventional PLC-based control generally follows fixed operating schedules and may not consider real-time workload, equipment utilization, traffic, or order demand, resulting in unnecessary energy consumption.

To address this limitation, the proposed Smart Energy Optimization Model (SEOM) integrates AI, IIoT, Edge Computing, Hybrid PLC–IoT communication, VFDs, Digital Twin, and WMS technologies. The model continuously monitors energy consumption and operational conditions and adjusts equipment operation according to warehouse demand.

3.7.2 Proposed Smart Energy Optimization Model

IIoT sensors and energy meters collect information from conveyor motors, robots, AGVs, AMRs, AS/RS, HVAC systems, lighting, and electrical equipment. Parameters such as current, voltage, power, temperature, and motor load are transmitted to the Edge Computing layer.

At the Edge layer, the collected data are filtered and analysed to identify equipment utilization and energy-consumption patterns. AI/ML models then evaluate workload, traffic, order demand, and historical energy data to estimate energy requirements and identify optimization opportunities.

The optimization engine generates control decisions such as conveyor speed adjustment, VFD regulation, robot standby scheduling, AGV charging optimization, and control of idle equipment. These decisions are transmitted to PLCs through the Hybrid PLC–IoT communication layer for deterministic execution.

The optimized operating conditions are also synchronized with the Warehouse Digital Twin. Different energy-management scenarios can be evaluated virtually before applying selected strategies to the physical warehouse, supporting energy-efficient operation while maintaining required productivity [7], [16].

3.7.3 Smart Energy Optimization Algorithm

The proposed algorithm follows these steps:

- Collect real-time energy and operational data.
- Process and filter data at the Edge layer.
- Determine equipment utilization and current energy

consumption.

- Analyse historical and real-time energy patterns using AI/ML.
- Predict energy requirements based on workload and demand.
- Identify energy-saving opportunities.
- Generate optimized control parameters.
- Transmit commands to PLCs through the Hybrid PLC–IoT layer.
- Adjust conveyor speed, VFD operation, robot standby, AGV charging, and other controllable loads.
- Monitor energy consumption and operational performance.
- Synchronize results with the Digital Twin.
- Repeat the optimization cycle using updated operational data.

3.7.4 Mathematical Model

The objective of the Smart Energy Optimization Model is to minimize the total warehouse energy consumption while maintaining operational throughput and equipment performance.

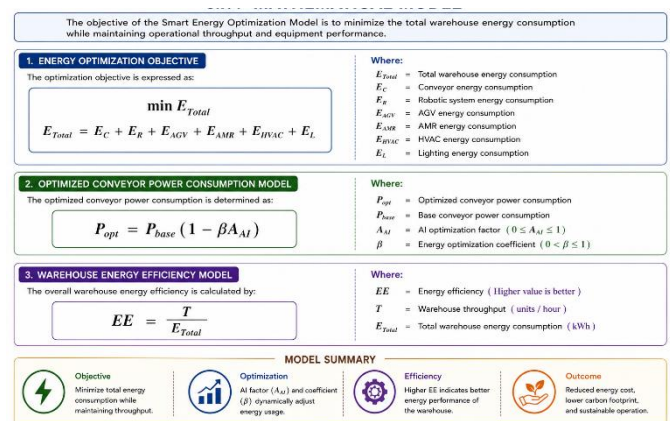


Figure 3.9. Mathematical Model

3.7.5 Novel Features of the Proposed Model

The proposed Smart Energy Optimization Model introduces several novel capabilities that distinguish it from conventional warehouse energy management systems. These include AI-assisted prediction of warehouse energy demand, adaptive conveyor speed regulation using Variable Frequency Drives, intelligent AGV battery scheduling, dynamic robot standby management, real-time HVAC and lighting optimization, Digital Twin-based energy simulation, Edge AI-enabled low-latency decision-making, Hybrid PLC–IoT communication, predictive energy analytics, and continuous learning through Artificial Intelligence. These innovations collectively improve warehouse sustainability, reduce operational costs, and support Industry 5.0-based intelligent manufacturing.

3.7.6 Advantages of the Proposed Model

The proposed Smart Energy Optimization Model significantly reduces electricity consumption across warehouse operations by dynamically controlling equipment based on real-time operational demand. It minimizes unnecessary conveyor operation, optimizes robotic activity, improves AGV battery

utilization, and intelligently manages HVAC and lighting systems. The integration of Artificial Intelligence, Digital Twin technology, and Edge Computing enhances operational efficiency while reducing carbon emissions and equipment wear. Consequently, the proposed model lowers operational costs, improves energy efficiency, extends equipment lifespan, and supports sustainable warehouse management aligned with Industry 5.0 and Net-Zero manufacturing objectives.

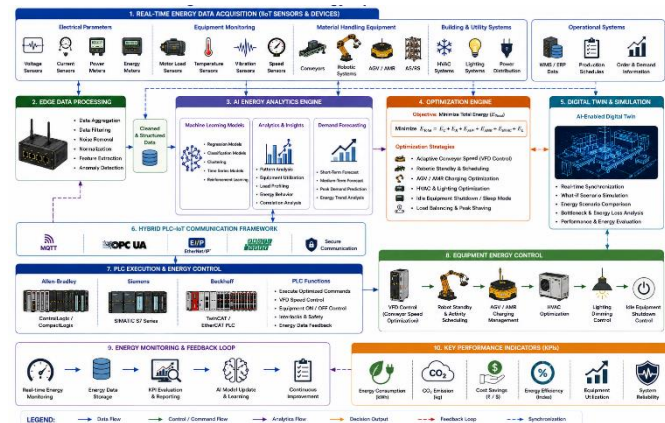


Figure 3.10. Smart Energy Optimization Framework

Architecture of the proposed Smart Energy Optimization Model illustrating real-time energy monitoring through IIoT sensors, Edge AI analytics, demand forecasting, optimization engine, Variable Frequency Drive (VFD) control, Hybrid PLC–IIoT communication, Digital Twin simulation, and continuous feedback for energy-efficient intelligent warehouse automation.

3.8 Edge AI Predictive Maintenance Engine

3.8.1 Introduction

Predictive maintenance is an important application of AI and IIoT for improving the reliability of warehouse equipment. Critical assets such as conveyor motors, bearings, gearboxes, VFDs, robots, AGVs, AMRs, and PLC-controlled systems may experience degradation during continuous operation. Unexpected failures can cause downtime, delayed order fulfilment, and increased maintenance costs.

Conventional maintenance is generally based on corrective or preventive strategies. Corrective maintenance responds after failure, while preventive maintenance follows predetermined schedules without necessarily considering actual equipment condition. Predictive maintenance instead uses equipment-condition data to identify abnormal behaviour and support maintenance before failure occurs [14].

The proposed Edge AI Predictive Maintenance Engine (EAI-PME) integrates IIoT sensing, Edge Computing, AI, Hybrid PLC–IIoT communication, and Digital Twin technology. The engine continuously evaluates equipment-health data, identifies degradation patterns, estimates potential failure conditions, and generates maintenance recommendations. Edge-based processing enables faster analysis of time-sensitive equipment data.

3.8.2 Proposed Edge AI Predictive Maintenance Engine

IIoT sensors installed on warehouse equipment collect parameters such as vibration, motor current, temperature, acoustic signals, speed, torque, power consumption, and operating hours. The measurements are transferred to Edge Computing devices through the industrial communication layer.

At the Edge layer, sensor data are filtered, normalized, and processed for feature extraction and anomaly detection. AI models then analyse the processed data to identify abnormal equipment behaviour and estimate equipment-health conditions.

When abnormal behaviour or potential failure is detected, the engine generates maintenance priorities and recommendations. These may include bearing inspection, lubrication, belt inspection, motor servicing, gearbox maintenance, or sensor calibration. Relevant maintenance information can be transferred to the WMS/maintenance system for scheduling.

Equipment-health information is simultaneously synchronized with the Warehouse Digital Twin. This enables visualization of equipment condition and evaluation of maintenance scenarios. Feedback from maintenance activities can subsequently be used to update the analytical models, supporting continuous improvement [7], [14].

3.8.3 Algorithm 3.5 Edge AI Predictive Maintenance Algorithm

The proposed algorithm follows these steps:

- Collect real-time equipment-condition data from IIoT sensors.
- Transfer data to the Edge Computing layer.
- Filter and normalize sensor measurements.
- Extract relevant health indicators and features.
- Perform real-time anomaly detection.
- Analyse equipment condition using AI/ML models.
- Estimate equipment-health status and potential failure condition.
- Compare predicted condition with predefined maintenance thresholds.
- Generate maintenance alerts and recommendations.
- Transfer maintenance information to PLC/WMS/maintenance systems.
- Synchronize equipment condition with the Digital Twin.
- Record maintenance results and update the analytical model.

3.8.4 Mathematical Model

The predictive maintenance objective is to maximize equipment reliability while minimizing maintenance cost and unexpected failures.

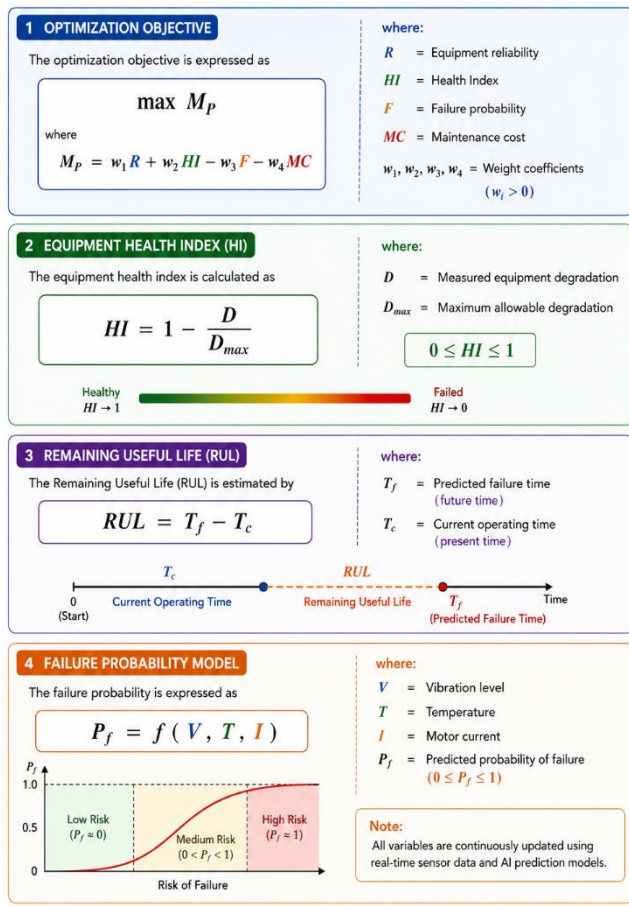


Figure 3.11. Mathematical Model

3.8.5 Novel Features

The proposed Edge AI Predictive Maintenance Engine introduces intelligent real-time equipment health monitoring using Edge AI, continuous anomaly detection, Remaining Useful Life estimation, AI-driven failure prediction, Digital Twin-assisted maintenance simulation, automated maintenance scheduling, Hybrid PLC-IoT communication, adaptive machine learning model updating, predictive maintenance dashboards, and self-learning maintenance optimization. These features significantly improve maintenance efficiency while reducing equipment downtime and operational costs.

3.8.6 Advantages

The proposed engine can reduce unexpected equipment failures by identifying abnormal operating conditions at an early stage. It supports condition-based maintenance, reduces unnecessary maintenance activities, improves equipment availability, and minimizes warehouse downtime. Integration with Digital Twin technology further supports equipment-health visualization and maintenance analysis [7], [14].

Overall, the proposed Edge AI Predictive Maintenance Engine provides an important component of the IWAF by connecting IIoT sensing → Edge AI → predictive analysis → maintenance decision → Digital Twin → feedback, thereby supporting reliable and intelligent warehouse operation..

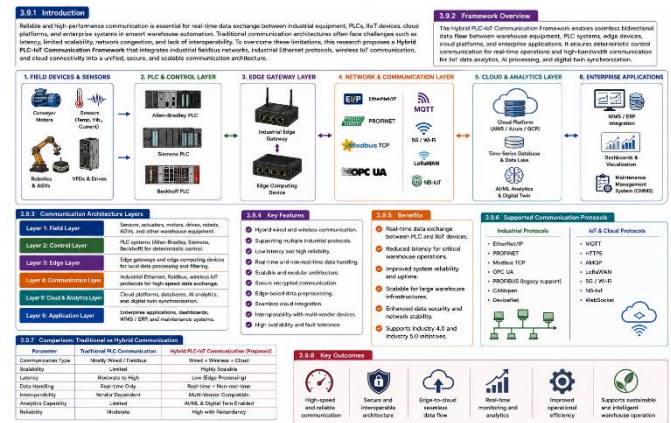


Figure 3.12. Hybrid PLC-IoT Communication Framework

3.9 Dynamic Warehouse Resource Allocation Algorithm

The proposed Dynamic Warehouse Resource Allocation Algorithm (DWRAA) integrates AI, IIoT, Edge Computing, Warehouse Digital Twin, and Hybrid PLC–IIoT communication to dynamically allocate warehouse resources according to real-time operational conditions. Resources considered by the framework include conveyors, robotic systems, AGVs, AMRs, storage locations, dock doors, and other material-handling resources.

Traditional warehouse scheduling often relies on predefined rules or static allocation strategies, which may not respond effectively to changes in customer demand, equipment availability, inventory flow, or warehouse congestion. The proposed approach addresses this limitation through continuous data-driven resource allocation.

Real-time information from IIoT sensors, WMS, ERP, PLCs, and warehouse equipment is collected and processed at the Edge layer. Relevant parameters include order status, inventory levels, conveyor utilization, robot availability, AGV location, storage occupancy, dock status, and equipment condition. AI-based analysis then evaluates current workload, resource availability, historical operational patterns, and expected demand to determine appropriate resource assignments.

Based on this analysis, the optimization engine dynamically assigns available conveyors, robots, AGVs, AMRs, storage locations, and other resources. The resulting decisions are communicated through the Hybrid PLC-IoT layer for operational execution. The Warehouse Digital Twin can simultaneously evaluate alternative allocation scenarios and provide feedback for improving resource decisions [3], [7], [16].

The proposed algorithm operates as a continuous feedback process in which warehouse throughput, equipment utilization, order completion time, congestion, and energy consumption are monitored. Updated operational information is then returned to the AI engine, allowing subsequent resource allocation decisions to reflect changing warehouse conditions.

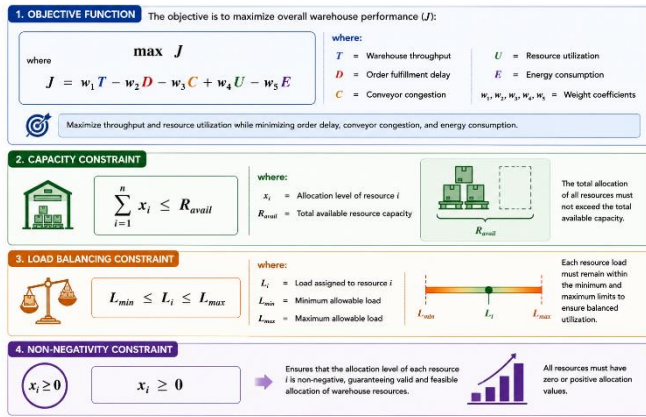


Figure 3.13. Mathematical Model

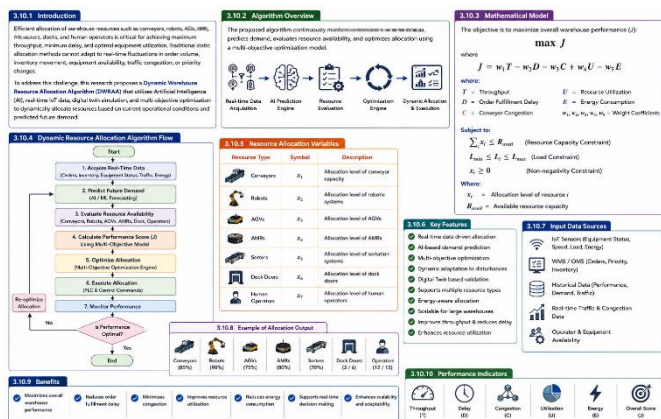


Figure 3.14. Dynamic Warehouse Resource Allocation Algorithm

3.10 AI-enabled Digital Twin

The proposed AI-enabled Digital Twin provides a dynamic virtual representation of the physical warehouse by continuously synchronizing operational data with AI-based analytics. It enables real-time monitoring, prediction, simulation, and optimization of warehouse equipment, inventory movement, conveyors, robots, AGVs, AMRs, and other operational processes. Unlike conventional monitoring systems, the Digital Twin can evaluate alternative operating scenarios before changes are implemented in the physical warehouse [2], [7].

The proposed framework integrates AI, IIoT, Edge Computing, Hybrid PLC-IoT communication, WMS, ERP, and cloud analytics. Real-time information from sensors, PLCs, conveyors, robotic systems, AGVs/AMRs, inventory systems, and energy-monitoring devices is collected through the communication layer and processed at the Edge. After preprocessing and anomaly detection, relevant information is synchronized with the Digital Twin.

The AI Analytics Engine analyses the synchronized data using Machine Learning, Deep Learning, Reinforcement Learning, and predictive models to evaluate equipment health, throughput, congestion, inventory movement, energy consumption, and operational risks. The Digital Twin therefore represents both the current warehouse state and potential future operating conditions, supporting data-driven decision-making [3], [7].

The proposed Digital Twin supports scenario simulation for predictive maintenance, resource allocation, conveyor optimization, AGV routing, robotic scheduling, energy management, and bottleneck identification. Alternative strategies can be evaluated virtually, and the selected strategy can subsequently be transferred to the physical control system through the Hybrid PLC-IoT framework. Research on warehouse Digital Twins supports their use for simulation, modelling, and operational decision support [2], [7], [15].

Continuous synchronization between the physical warehouse and Digital Twin establishes a feedback loop. Actual operational results can be compared with predicted outcomes, allowing AI models and Digital Twin parameters to be updated as warehouse conditions change. This supports continuous improvement and adaptation to equipment degradation, changing demand, and operational disturbances.

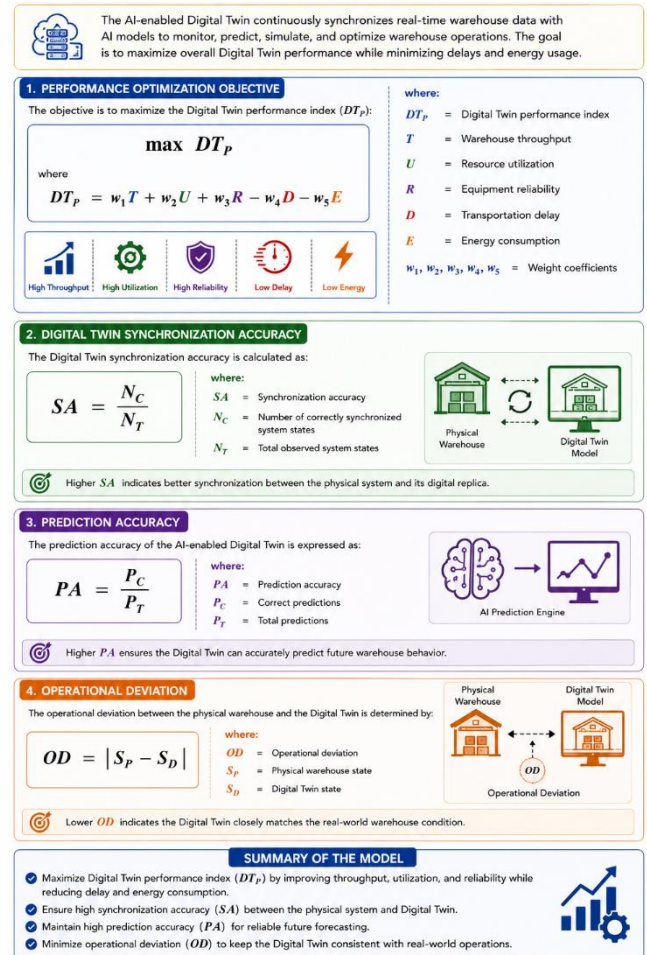


Figure 3.15. Mathematical Model

3.12 Proposed Advantages

Table 3.5 Proposed Advantages of the Intelligent Warehouse Automation Framework

S. No.	Proposed Component	Conventional Warehouse System	Proposed Intelligent Framework	Expected Benefits
1	Warehouse Decision Making	Rule-based control	AI-assisted intelligent decision making	Faster and adaptive decision making

S. No.	Proposed Component	Conventional Warehouse System	Proposed Intelligent Framework	Expected Benefits
2	PLC Control	Fixed PLC logic	AI-enabled Hybrid PLC Control	Improved operational flexibility
3	Equipment Monitoring	Periodic inspection	Real-time IIoT monitoring	Continuous equipment visibility
4	Communication	Stand-alone PLC network	Hybrid PLC–IoT Communication	High-speed and reliable data exchange
5	Conveyor Operation	Fixed conveyor speed	Adaptive AI-based conveyor optimization	Reduced congestion and higher throughput
6	Resource Allocation	Static allocation	Dynamic AI-driven allocation	Higher resource utilization
7	Predictive Maintenance	Preventive or reactive maintenance	Edge AI predictive maintenance	Reduced unexpected equipment failures
8	Energy Management	Constant energy consumption	Smart energy optimization	Lower electricity consumption
9	Digital Twin	Not available	AI-enabled Digital Twin	Real-time monitoring and simulation
10	Warehouse Optimization	Manual optimization	AI multi-objective optimization	Improved warehouse efficiency
11	AGV/AMR Management	Static routing	Intelligent dynamic routing	Reduced transportation delay
12	Robotic Operation	Fixed scheduling	AI-assisted task scheduling	Higher robotic productivity
13	Failure Prediction	Limited fault diagnosis	AI-based predictive analytics	Early fault detection
14	Warehouse Visibility	Historical reports	Real-time dashboard and Digital Twin	Better operational transparency
15	Data Processing	Cloud-only or offline analysis	Edge AI with cloud integration	Low latency and faster response
16	Equipment Utilization	Moderate	Intelligent utilization optimization	Increased equipment availability
17	Warehouse Throughput	Moderate	AI-optimized throughput	Higher order processing capacity
18	Order Fulfilment	Manual priority scheduling	Intelligent order prioritization	Reduced order completion time

S. No.	Proposed Component	Conventional Warehouse System	Proposed Intelligent Framework	Expected Benefits
19	Operational Cost	High	AI-assisted cost optimization	Reduced maintenance and operating costs
20	Sustainability	Limited energy management	Intelligent energy-efficient operation	Lower carbon emissions and Industry 5.0 readiness
21	Scalability	Limited expansion capability	Modular and scalable architecture	Easy integration with future technologies
22	Overall System Performance	Independent subsystem operation	Fully integrated intelligent warehouse ecosystem	Improved reliability, productivity, flexibility, and operational excellence

CHAPTER 4. SYSTEM ARCHITECTURE & IMPLEMENTATION

The proposed Intelligent Warehouse Automation System is implemented using a hierarchical cyber-physical architecture integrating PLCs, AI, IIoT, Edge Computing, Hybrid PLC–IoT Communication, Digital Twin, Cloud Computing, WMS, ERP, and intelligent optimization algorithms. The architecture is designed to support real-time monitoring, adaptive decision-making, predictive maintenance, resource optimization, energy management, and continuous operational improvement.

The implementation consists of interconnected functional layers that establish communication between physical warehouse equipment and intelligent software systems. At the Physical Device Layer, conveyors, robotic systems, AGVs, AMRs, AS/RS, VFDs, barcode scanners, RFID readers, industrial cameras, and environmental sensors collect operational information such as conveyor speed, inventory movement, motor current, vibration, temperature, energy consumption, equipment utilization, and warehouse traffic.

The collected information is processed through the PLC Layer, which provides deterministic industrial control. Allen-Bradley, Siemens, and Beckhoff PLC platforms execute IEC 61131-3-based control programs for conveyor synchronization, actuator operation, robot coordination, safety interlocks, diagnostics, and fault handling. This layer maintains reliable real-time equipment control while receiving optimized operating parameters from higher-level intelligence.

A Hybrid PLC–IoT Communication Framework connects the industrial control layer with Edge, AI, cloud, WMS, ERP, and Digital Twin systems. Industrial protocols such as EtherNet/IP, PROFINET, EtherCAT, Modbus TCP, and OPC

UA support equipment-level communication, while MQTT and REST-based interfaces support higher-level data exchange. This combination provides both deterministic industrial communication and scalable information connectivity.

The Edge Computing Layer performs local data preprocessing, including filtering, normalization, feature extraction, missing-data handling, and anomaly detection. Processing information close to the physical equipment reduces communication latency and supports time-sensitive applications such as conveyor control, AGV routing, equipment-health monitoring, and predictive maintenance.

The Artificial Intelligence Layer functions as the primary decision-support component. Machine Learning, Deep Learning, Reinforcement Learning, Computer Vision, and predictive analytics are used for equipment-health assessment, conveyor optimization, resource allocation, AGV routing, robotic scheduling, predictive maintenance, energy optimization, inventory forecasting, and order prioritization. AI-generated decisions are checked against operational constraints before being transferred to the PLC layer for execution.

A key component of the proposed architecture is the AI-enabled Digital Twin. It maintains a synchronized virtual representation of warehouse equipment and processes, including conveyors, robots, AGVs, AMRs, inventory flow, congestion, and energy consumption. The Digital Twin supports scenario simulation, bottleneck analysis, equipment-failure prediction, and evaluation of alternative operating strategies before their physical implementation.

The Cloud and Enterprise Integration Layer provides centralized storage, historical-data management, large-scale AI model training, analytics, and integration with WMS, ERP, MES, CMMS, and business-intelligence platforms. This layer supports long-term performance analysis, maintenance planning, inventory management, remote monitoring, and scalability for multi-warehouse applications.

5. ALGORITHMS

5.1 AI Decision Algorithm

The proposed AI Decision Algorithm functions as the central intelligence module of the Intelligent Warehouse Automation System. It integrates AI, PLCs, IIoT, Edge Computing, Digital Twin technology, and Machine Learning to support adaptive warehouse decision-making. Unlike conventional rule-based PLC systems, the algorithm evaluates real-time warehouse conditions and generates optimized decisions for conveyors, AGVs, robotic systems, inventory movement, predictive maintenance, and energy management.

The algorithm initially initializes the AI model, PLC controllers, IIoT sensor network, Edge Computing module, Digital Twin, and Hybrid PLC-IIoT Communication Framework. Once activated, real-time data are collected from sensors and PLCs, including conveyor speed, package position, motor current, vibration, temperature, energy consumption, AGV status, robot availability, inventory level, equipment utilization, and environmental conditions.

The collected data are transferred to the Edge Computing Layer, where preprocessing is performed through noise filtering, normalization, missing-value handling, feature extraction, and anomaly detection. The processed information is then supplied to the AI engine for operational analysis.

The AI engine applies Machine Learning, Deep Learning, and predictive analytics to estimate equipment health, warehouse demand, conveyor utilization, AGV availability, robot workload, congestion, inventory movement, energy consumption, and resource utilization. A multi-objective optimization process then determines suitable control actions while considering warehouse throughput, equipment utilization, transportation delay, energy consumption, maintenance requirements, and congestion.

The resulting decisions may include conveyor speed adjustment, AGV route planning, robotic task scheduling, dynamic resource allocation, inventory movement optimization, predictive maintenance scheduling, and energy-efficient operation.

Before physical execution, the proposed control decisions are evaluated through the AI-enabled Digital Twin. The Digital Twin simulates the proposed actions and verifies operational feasibility, equipment constraints, safety conditions, collision avoidance, and expected performance. If the proposed solution satisfies the defined constraints, the optimized commands are transmitted to the PLC layer through the Hybrid PLC-IIoT Communication Framework. Otherwise, the optimization process is repeated to obtain a feasible solution.

The PLC controllers then execute the validated commands for conveyors, robotic manipulators, AGVs, AS/RS, VFDs, and other warehouse equipment. During operation, real-time feedback is continuously collected and compared with the predicted system response. The resulting operational data are stored for subsequent analysis and model improvement, enabling the AI system to progressively refine its decision-making performance.

The complete algorithm therefore establishes a closed-loop process of data acquisition → Edge processing → AI prediction → optimization → Digital Twin validation → PLC execution → operational feedback. This architecture supports adaptive decision-making, intelligent equipment control, resource optimization, predictive maintenance, energy-efficient operation, and continuous warehouse improvement.

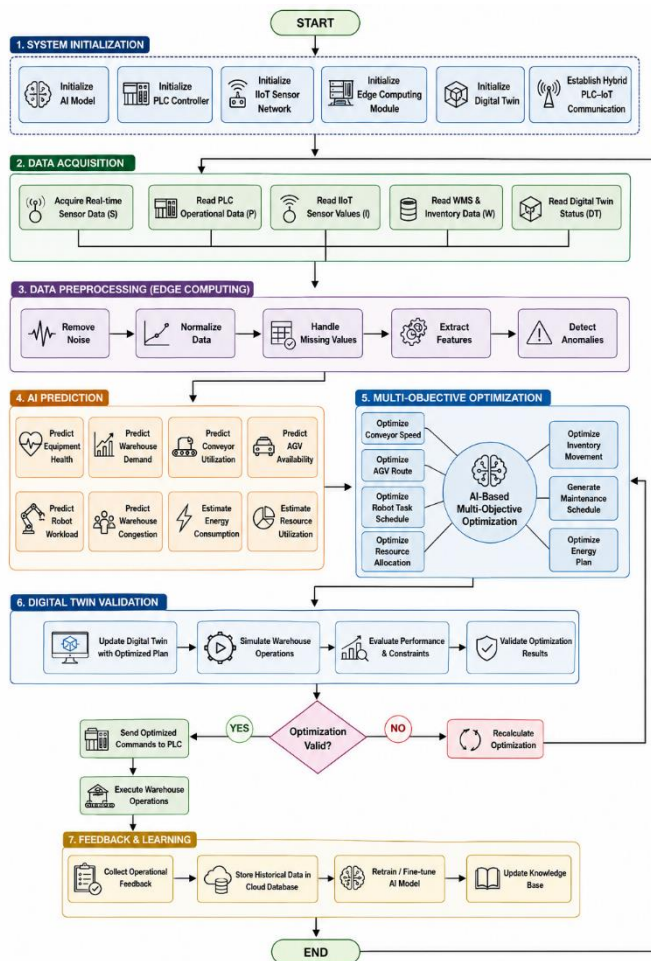


Figure 5.1. Flowchart of the Proposed AI Decision Algorithm

The flowchart illustrates the complete process from system initialization and real-time data acquisition through Edge preprocessing, AI analysis, optimization, Digital Twin validation, PLC execution, and continuous feedback-based improvement.

5.2 Conveyor Optimization Algorithm

The proposed Conveyor Optimization Algorithm is developed to improve warehouse material flow by dynamically adjusting conveyor operation according to real-time operating conditions. Conventional conveyor systems generally rely on fixed speeds and predefined routing, which can cause congestion, unnecessary energy consumption, transportation delays, and reduced throughput under changing workloads. The proposed algorithm integrates AI, PLCs, IIoT, Edge Computing, VFDs, and AI-enabled Digital Twin technology to provide adaptive conveyor control.

The algorithm continuously collects conveyor operating data such as conveyor speed, package count, motor current, belt load, vibration, package spacing, queue length, conveyor occupancy, and energy consumption through IIoT sensors. The collected information is processed at the Edge layer using filtering, normalization, feature extraction, and anomaly detection before being analysed by the AI engine.

The AI engine evaluates current and historical warehouse conditions to estimate congestion, package arrival rate, queue accumulation, equipment utilization, throughput, transportation delay, and energy consumption. Based on these parameters, a multi-objective optimization process determines suitable conveyor speed, package-release interval, routing sequence, motor frequency, and workload distribution.

Before physical implementation, the optimized control strategy is evaluated through the AI-enabled Digital Twin. The virtual simulation verifies conveyor synchronization, package flow, collision avoidance, equipment constraints, and operational feasibility. If the conditions are satisfied, optimized commands are transmitted to PLC controllers through the Hybrid PLC-IIoT Communication Framework. PLCs then regulate conveyor speed through VFDs and coordinate conveyor sections with AGVs, robots, and AS/RS systems.

During operation, feedback from conveyor sensors is continuously compared with AI predictions. The optimization parameters can therefore be updated according to changes in warehouse demand, package-arrival patterns, equipment condition, and operational performance. This creates a continuous feedback loop without requiring frequent manual modification of conventional PLC control logic.

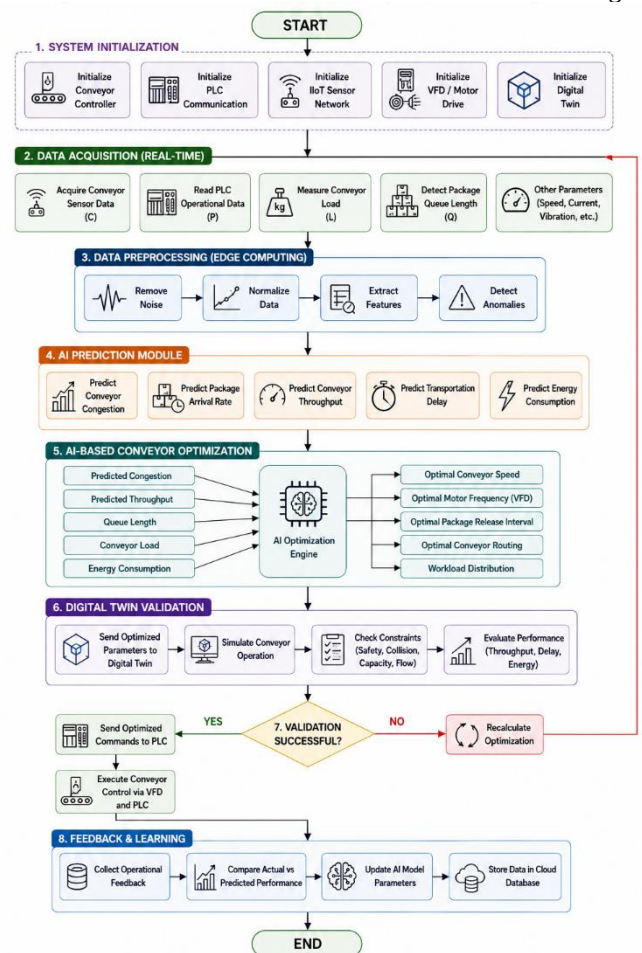


Figure 5.2. Flowchart of the Proposed Conveyor Optimization Algorithm

5.3 Predictive Maintenance Algorithm

The proposed Predictive Maintenance Algorithm continuously monitors the health of critical warehouse equipment and predicts potential failures before breakdowns occur. Unlike reactive and fixed-schedule preventive maintenance, the proposed approach integrates AI, PLCs, IIoT, Edge Computing, and Digital Twin technology to support condition-based maintenance planning. This can reduce unexpected downtime, maintenance costs, and equipment unavailability.

The algorithm initially establishes communication between PLC controllers, IIoT sensors, Edge Computing, the AI engine, Digital Twin, and the maintenance database. Sensors continuously acquire parameters such as motor current, vibration, bearing temperature, conveyor speed, lubrication condition, gearbox condition, operating hours, power consumption, and historical fault information.

The collected data are processed at the Edge layer through noise removal, normalization, missing-value handling, feature extraction, and anomaly detection. The processed information is then analysed by Machine Learning and Deep Learning models. The AI engine evaluates equipment behaviour against historical operating and maintenance patterns to estimate equipment health, failure probability, Remaining Useful Life (RUL), maintenance priority, and potential failure conditions.

Based on the predicted equipment condition, the algorithm determines an appropriate maintenance priority and schedule. Equipment with a higher predicted failure risk is assigned greater priority, whereas healthy equipment can continue operating without unnecessary maintenance intervention. The proposed maintenance strategy is subsequently evaluated through the AI-enabled Digital Twin to assess equipment availability, operational impact, maintenance timing, and system constraints.

If the proposed maintenance plan satisfies the defined constraints, the resulting recommendations are transferred to the relevant PLC/WMS/maintenance-management layer for implementation. If the conditions are not satisfied, the optimization process is repeated to generate a more suitable maintenance strategy.

After maintenance actions are completed, operational feedback is collected from the physical equipment and compared with AI predictions. The maintenance database is updated with the new information, allowing the predictive model to be periodically improved using accumulated operational data. This feedback mechanism enables the algorithm to adapt to equipment aging and changing operating

conditions.

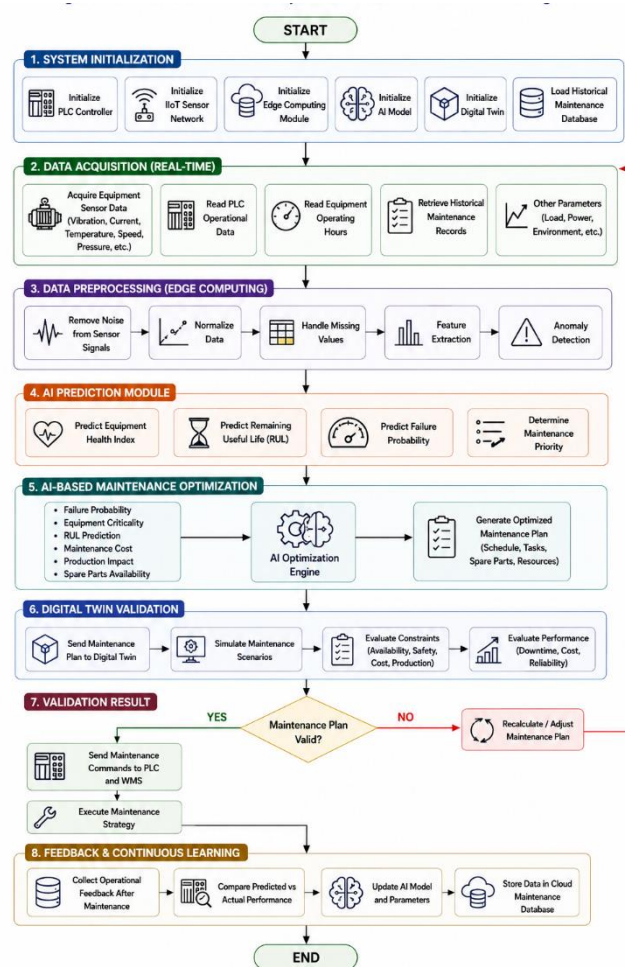


Figure 5.3. Flowchart of the Proposed Predictive Maintenance Algorithm

Figure 5.3 illustrates the workflow of the proposed Predictive Maintenance Algorithm. The algorithm continuously acquires equipment condition data through IIoT sensors and PLCs, preprocesses the data using Edge Computing, predicts equipment health and remaining useful life using AI models, optimizes maintenance schedules, validates maintenance decisions through the Digital Twin, executes approved maintenance actions via PLC controllers, and continuously updates the AI model using operational feedback for improved prediction accuracy.

5.4 Inventory Optimization Algorithm

The proposed Inventory Optimization Algorithm is designed to improve inventory management by continuously monitoring stock levels, storage utilization, material movement, and order requirements. Conventional inventory systems often rely on fixed stock thresholds and predefined replenishment rules, which can result in stock shortages, overstocking, inefficient space utilization, and delayed order fulfilment. The proposed algorithm integrates AI, PLCs, IIoT, Edge Computing, WMS, and Digital Twin technology to support adaptive inventory forecasting and optimization.

The algorithm initially establishes communication among PLC controllers, IIoT sensors, RFID readers, barcode scanners, WMS, Edge Computing, AI analytics, and the Digital Twin. Real-time information such as inventory

quantity, product identification, storage location, stock movement, customer orders, warehouse occupancy, demand, and equipment availability is continuously collected.

The collected information is processed at the Edge layer through noise filtering, normalization, missing-value handling, feature extraction, and anomaly detection. The processed data are analysed by AI/ML models to forecast customer demand, inventory turnover, replenishment requirements, storage utilization, order priority, and warehouse occupancy. Based on these predictions, the algorithm identifies potential stock shortages, excess inventory, inefficient storage allocation, and material-flow bottlenecks.

The AI optimization engine then determines suitable inventory allocation, replenishment schedules, storage locations, product priorities, and material-movement strategies. The proposed decisions are evaluated using the AI-enabled Digital Twin to verify storage capacity, equipment availability, retrieval efficiency, and operational constraints before implementation.

If the proposed strategy satisfies the defined constraints, the optimized inventory decisions are transferred through the Hybrid PLC–IoT Communication Framework to the WMS and PLC layer. PLC-controlled conveyors, AS/RS, robotic systems, AGVs, and other material-handling equipment then execute the required inventory movements and fulfilment activities. If the proposed solution does not satisfy the constraints, the optimization process is repeated.

A continuous feedback mechanism compares actual inventory transactions, demand, stock movement, and fulfilment performance with AI predictions. Updated operational data are stored for subsequent model improvement, allowing the inventory optimization process to adapt to changing demand

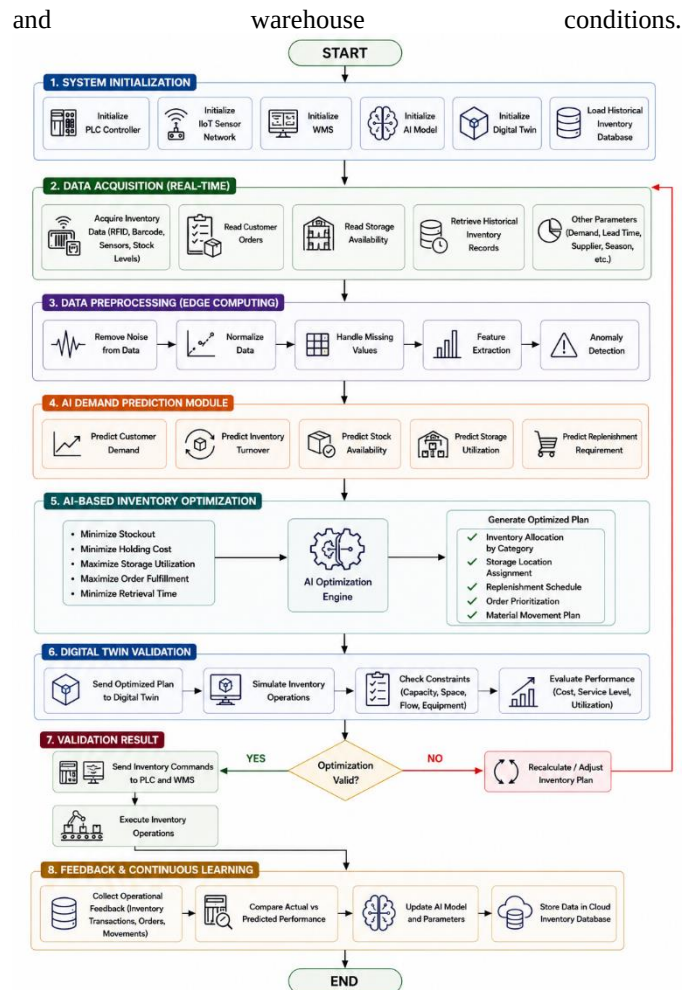


Figure 5.4. Flowchart of the Proposed Inventory Optimization Algorithm

5.5 Dynamic Routing Algorithm

The proposed Dynamic Routing Algorithm is designed to optimize the transportation routes of materials, AGVs, AMRs, robotic systems, and conveyor networks according to real-time warehouse conditions. Conventional routing systems generally depend on predefined paths and therefore have limited ability to respond to traffic congestion, blocked routes, equipment failures, urgent orders, and changing workloads. The proposed algorithm integrates AI, PLCs, IIoT, Edge Computing, WMS, Digital Twin, and Hybrid PLC–IoT communication to enable adaptive route optimization.

Initially, the algorithm initializes the AI model, PLC controllers, IIoT sensors, WMS, Edge Computing module, Digital Twin, and communication framework. Real-time information is collected from AGVs, AMRs, conveyors, RFID systems, robotic equipment, and warehouse sensors. Important parameters include vehicle/robot location, warehouse layout, traffic density, obstacles, conveyor availability, destination, order priority, battery level, equipment condition, and warehouse occupancy.

The collected data are processed at the Edge layer through filtering, normalization, feature extraction, missing-value handling, and anomaly detection. AI/ML models then analyse the processed information to estimate traffic congestion, travel

time, battery consumption, equipment availability, bottlenecks, task completion time, and route feasibility.

Based on these predictions, the optimization engine determines suitable transportation routes while considering travel distance, delay, congestion, collision risk, idle time, and energy consumption. The resulting routing decisions may include AGV routes, AMR navigation paths, conveyor routing, traffic management, task prioritization, and workload balancing.

Before implementation, the proposed routes are evaluated within the AI-enabled Digital Twin. The virtual environment verifies collision avoidance, route safety, traffic flow, equipment constraints, warehouse capacity, and transportation efficiency. If the proposed route satisfies the defined constraints, the routing commands are transferred through the Hybrid PLC-IoT Communication Framework to the PLC/WMS layer. If the solution is not feasible, the optimization process is repeated.

The PLC-controlled systems then coordinate AGVs, AMRs, conveyors, robotic manipulators, and AS/RS equipment to execute the optimized routes. During operation, travel time, energy consumption, equipment utilization, battery status, transportation delay, and route performance are continuously monitored. The feedback is compared with AI predictions and used to improve subsequent routing decisions.

The proposed Energy Optimization Algorithm is designed to minimize warehouse energy consumption while maintaining required productivity and operational performance. Conventional warehouse systems may operate equipment at fixed power levels even when workload varies, resulting in unnecessary energy consumption and increased operating costs. The proposed algorithm integrates AI, PLCs, IIoT, Edge Computing, Digital Twin, VFDs, and WMS to monitor and optimize warehouse energy usage in real time.

Initially, the algorithm initializes the AI model, PLC controllers, IIoT sensors, Edge Computing module, WMS, Digital Twin, and Hybrid PLC-IoT Communication Framework. Energy meters, current sensors, voltage sensors, and power analyzers continuously collect information from conveyors, robots, AGVs, AS/RS, and other warehouse equipment. The collected parameters include equipment status, current, voltage, power consumption, conveyor utilization, robot workload, battery condition, warehouse occupancy, environmental conditions, and operational demand.

The collected data are transferred to the Edge Computing layer for filtering, normalization, feature extraction, missing-value handling, and anomaly detection. The processed information is analysed using AI/ML models to estimate equipment energy consumption, warehouse power demand, idle time, battery utilization, peak-load conditions, and operational efficiency.

The AI optimization engine then determines suitable energy-management strategies while considering energy consumption, peak demand, operating cost, equipment utilization, throughput, and production continuity. The resulting control decisions may include adaptive conveyor speed control, VFD frequency regulation, equipment scheduling, AGV charging optimization, robot standby management, load balancing, and dynamic power allocation.

Before implementation, the proposed strategy is evaluated through the AI-enabled Digital Twin. The virtual environment assesses equipment constraints, operational schedules, throughput requirements, safety conditions, and expected energy performance. If the strategy satisfies the predefined constraints, the optimized commands are transferred through the Hybrid PLC-IoT Communication Framework to the PLC/WMS layer. Otherwise, the optimization process is repeated.

The PLC controllers execute the approved energy-management commands for conveyors, robots, AGVs, AS/RS, and other controllable warehouse equipment. During operation, energy consumption, equipment utilization, production rate, and operational performance are continuously monitored. Actual results are compared with AI predictions, and the resulting information is stored for subsequent model improvement.

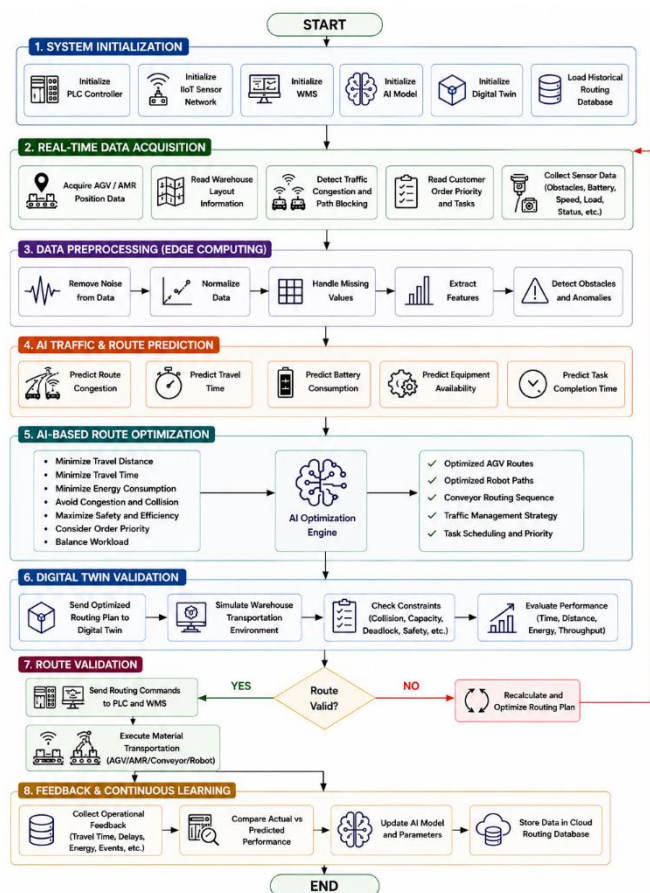


Figure 5.5. Flowchart of the Proposed Dynamic Routing Algorithm

5.6 Energy Optimization Algorithm

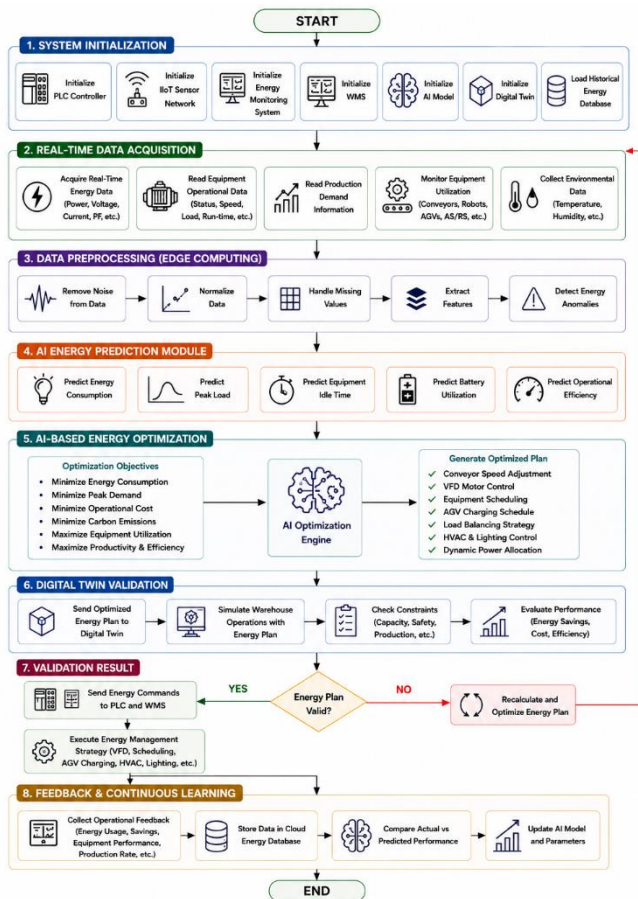


Figure 5.6. Flowchart of the Proposed Energy Optimization Algorithm

5.7 Digital Twin Synchronization Algorithm

The proposed Digital Twin Synchronization Algorithm maintains continuous synchronization between the physical warehouse and its virtual Digital Twin to support real-time monitoring, predictive simulation, operational planning, and adaptive optimization. Conventional monitoring systems mainly provide equipment status and historical information, whereas the proposed approach enables the virtual warehouse model to continuously reflect the current physical operating state.

The algorithm integrates AI, PLCs, IIoT, Edge Computing, WMS, Cloud Computing, and Digital Twin technology within a unified cyber-physical architecture. Initially, the Digital Twin platform, AI model, PLC controllers, IIoT network, Edge Computing module, WMS, cloud database, and Hybrid PLC–IIoT communication framework are initialized.

During operation, real-time data are collected from conveyors, AGVs, AMRs, robotic systems, AS/RS, RFID readers, barcode scanners, environmental sensors, energy-monitoring devices, and PLCs. Parameters such as equipment status, inventory level, material movement, robot position, conveyor speed, equipment utilization, energy consumption, and production status are continuously monitored.

The collected data are transferred to the Edge Computing layer for filtering, normalization, missing-value handling, feature extraction, and anomaly detection. The processed

information is then analysed by AI models to estimate equipment health, warehouse performance, transportation efficiency, inventory conditions, operational bottlenecks, energy consumption, and potential future operating conditions.

The processed operational state is used to update the Digital Twin so that the virtual warehouse remains synchronized with the physical system. The Digital Twin can then simulate alternative scenarios involving equipment operation, routing, resource allocation, predictive maintenance, and energy optimization. The simulation results support selection of suitable operational strategies while considering throughput, equipment utilization, delay, congestion, maintenance requirements, and energy consumption.

Before implementation, the selected strategy is checked against safety requirements, equipment capacity, warehouse policies, and operational constraints. If the strategy satisfies these requirements, the corresponding commands are transmitted through the Hybrid PLC–IIoT Communication Framework to the PLC/WMS layer. If the strategy is not feasible, the optimization process is repeated.

During operation, actual warehouse performance is continuously compared with Digital Twin predictions. The resulting feedback is used to evaluate synchronization accuracy and improve subsequent predictions. Operational data can also be stored in the cloud database for further AI model development and Digital Twin refinement.

6. MATHEMATICAL MODEL

6.1 Conveyor Efficiency Equation

The Conveyor Efficiency Equation is proposed to quantitatively evaluate the operational performance of the intelligent conveyor system within the AI-enabled warehouse automation framework. Conveyor efficiency is one of the most important performance indicators because it directly influences material throughput, transportation delay, energy consumption, equipment utilization, and overall warehouse productivity. Unlike conventional warehouse systems that measure conveyor performance only by conveyor speed or throughput, the proposed mathematical model integrates multiple operational parameters to provide a comprehensive efficiency evaluation suitable for real-time optimization.

The proposed model considers the combined effects of material throughput, transportation delay, conveyor energy consumption, equipment utilization, and system reliability. Artificial Intelligence continuously acquires these parameters from Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT) sensors, and the Digital Twin platform. The calculated conveyor efficiency is subsequently utilized by the AI optimization engine to regulate conveyor speed, redistribute warehouse workload, minimize congestion, and improve operational performance.

The overall conveyor efficiency is expressed as:

$$CE = \frac{T \times U \times R}{D \times E}$$

Where,

CE = Conveyor Efficiency Index
T = Material Throughput (packages/hour)
U = Equipment Utilization Factor
R = Conveyor Reliability
D = Transportation Delay (minutes)
E = Energy Consumption (kW)

The throughput is determined by,

$$T = \frac{N}{t}$$

Where,

N = Number of transported packages
t = Processing time

The equipment utilization is calculated as,

$$U = \frac{T_0}{T_a}$$

Where,

T₀ = Actual operating time
T_a = Total available operating time

The conveyor reliability is estimated by,

$$R = 1 - \frac{F}{F_{max}}$$

Where,

F = Number of equipment failures
F_{max} = Maximum allowable failures

Transportation delay is expressed as,

$$D = T_c - T_s$$

Where,

T_c = Completion time
T_s = Scheduled transportation time

The total energy consumption of the conveyor system is

$$E = P \times t$$

Where,

P = Conveyor power consumption (kW)
t = Operating time (hours)

The Artificial Intelligence engine continuously computes the Conveyor Efficiency Index using real-time sensor information obtained from PLC controllers and IIoT devices. Higher values of the Conveyor Efficiency Index indicate improved warehouse performance characterized by increased throughput, higher equipment utilization, greater reliability, reduced transportation delay, and lower energy consumption. The calculated efficiency value is further transmitted to the AI optimization module and the Digital Twin, where it is used for adaptive conveyor speed control, congestion reduction, predictive maintenance planning, and dynamic warehouse resource allocation.

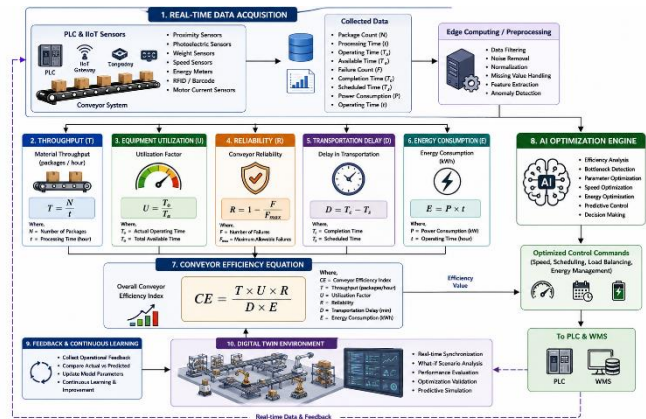


Figure 6.1. Mathematical Model of the Proposed Conveyor Efficiency Equation

6.2 Throughput Equation

The Throughput Equation is proposed to evaluate the material handling capacity of the intelligent warehouse automation system by measuring the number of packages successfully transported within a specified operating time. Throughput is one of the most critical Key Performance Indicators (KPIs) because it directly reflects warehouse productivity, conveyor performance, AGV utilization, robotic efficiency, and order fulfillment capability. Unlike conventional warehouse systems that measure throughput solely based on conveyor output, the proposed model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, and Digital Twin technology to continuously monitor and optimize throughput under dynamic operating conditions.

The proposed throughput model considers package transportation rate, equipment utilization, operational availability, and processing efficiency. Real-time operational data are continuously collected from conveyor sensors, RFID readers, barcode scanners, PLC controllers, AGVs, robotic systems, and IIoT devices. Artificial Intelligence analyses these data to identify operational bottlenecks, predict workload variations, and dynamically optimize warehouse operations to maximize throughput while maintaining operational safety and energy efficiency.

The overall warehouse throughput is expressed as:

$$TP = \frac{N}{t}$$

Where,

TP = Warehouse Throughput (packages/hour)
N = Total number of successfully transported packages
t = Total processing time (hours)

The package processing rate is calculated as,

$$PR = \frac{N}{T_p}$$

Where,

PR = Package Processing Rate (packages/minute)

T_p = Package processing time

The conveyor productivity factor is defined as,

$$CP = \frac{N_s}{N_p}$$

Where,

CP = Conveyor Productivity

N_s = Successfully transported packages

N_t = Total assigned packages

The equipment utilization factor is,

$$EU = \frac{T_o}{T_a}$$

Where,

EU = Equipment Utilization

T_o = Actual operating time

T_a = Available operating time

The optimized throughput considering operational efficiency is expressed as,

$$TP_{opt} = TP \times EU \times CP$$

where

TP_{opt} = Optimized Warehouse Throughput

Artificial Intelligence continuously computes the throughput using real-time warehouse data obtained from PLC controllers, IIoT sensors, RFID systems, and warehouse management software. The calculated throughput is compared with historical warehouse performance and Digital Twin simulations to identify productivity losses and operational bottlenecks. The optimized throughput value is then utilized by the AI optimization engine to regulate conveyor speed, coordinate AGV movement, schedule robotic operations, balance warehouse workload, and improve material flow. Consequently, the proposed Throughput Equation enables intelligent warehouse systems to maximize operational productivity while minimizing transportation delay, congestion, and equipment idle time.

The Warehouse Utilization Equation is proposed to quantitatively evaluate the effective utilization of warehouse resources, storage capacity, equipment, and operational infrastructure within the intelligent warehouse automation system. Warehouse utilization is a critical performance indicator because it directly influences storage efficiency, order fulfillment capability, equipment productivity, warehouse congestion, and operational cost. Conventional warehouse systems generally measure utilization only by occupied storage space, which does not accurately represent the overall operational performance. The proposed mathematical model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Warehouse Management Systems (WMS), and Digital Twin technology to continuously monitor and optimize warehouse utilization under dynamic operating conditions.

The proposed model considers storage occupancy, equipment utilization, inventory movement, and warehouse operational efficiency. Real-time operational information is continuously acquired from PLC controllers, RFID readers, barcode scanners, IIoT sensors, Automated Guided Vehicles (AGVs), robotic systems, Automated Storage and Retrieval Systems (AS/RS), and warehouse management software. The Artificial Intelligence engine analyses these data to identify underutilized storage locations, equipment idle time, warehouse congestion, and resource imbalance before generating optimized warehouse allocation strategies.

The overall warehouse utilization is expressed as

$$WU = \frac{S_u}{S_t}$$

Where,

WU = Warehouse Utilization Index

S_u = Utilized Storage Capacity

S_t = Total Available Storage Capacity

The storage occupancy ratio is calculated as

$$SO = \frac{N_s}{N_c}$$

Where,

SO = Storage Occupancy Ratio

N_s = Number of Occupied Storage Locations

N_c = Total Storage Locations

The equipment utilization factor is

$$EU = \frac{T_o}{T_a}$$

The inventory movement efficiency is expressed as

$$IME = \frac{M_s}{M_t}$$

Where,

IME = Inventory Movement Efficiency

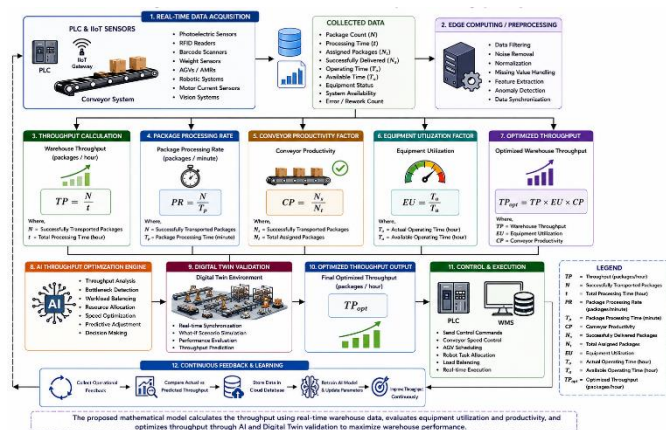


Figure 6.2. Mathematical Model of the Proposed Throughput Equation

6.3 Warehouse Utilization Equation

M_s = Successful Material Movements
 M_t = Total Material Movement Requests

The optimized warehouse utilization is calculated as

$$WU_{opt} = WU \times EU \times IME$$

Where,

WU_{opt} = Optimized Warehouse Utilization

Artificial Intelligence continuously computes the Warehouse Utilization Index using real-time warehouse information obtained from PLC controllers, IIoT sensors, RFID systems, AGVs, robotic equipment, and the Warehouse Management System. The calculated utilization values are compared with historical warehouse performance and Digital Twin simulations to detect inefficient storage allocation, equipment underutilization, and warehouse bottlenecks. The optimized utilization value is then employed by the AI optimization engine to improve storage allocation, task scheduling, inventory placement, equipment utilization, and warehouse resource management. Consequently, the proposed Warehouse Utilization Equation enhances storage efficiency, minimizes idle resources, improves warehouse productivity, and supports autonomous decision-making within Industry 5.0 intelligent warehouse environments.

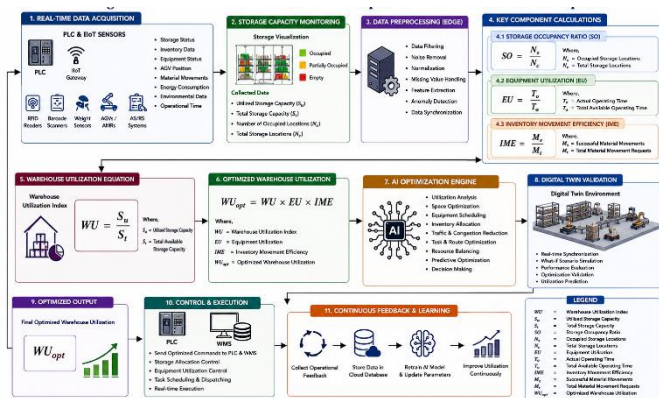


Figure 6.3. Mathematical Model of the Proposed Warehouse Utilization Equation

6.4 Energy Consumption Model

The Energy Consumption Model is proposed to quantitatively evaluate the energy utilization of the intelligent warehouse automation system by integrating equipment power consumption, operational time, equipment utilization, and Artificial Intelligence-based energy optimization. Energy consumption is one of the most important Key Performance Indicators (KPIs) in modern warehouse automation because it directly affects operational cost, equipment efficiency, carbon emissions, and overall system sustainability. Conventional warehouse systems generally monitor only total electricity usage without considering real-time operational conditions or intelligent energy optimization. The proposed mathematical model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Variable Frequency Drives (VFDs), Digital Twin technology, and Warehouse Management Systems (WMS) to continuously monitor, predict, and optimize warehouse energy consumption.

Real-time operational information is continuously collected from smart energy meters, PLC controllers, IIoT sensors, conveyor systems, Automated Guided Vehicles (AGVs), robotic manipulators, Automated Storage and Retrieval Systems (AS/RS), HVAC systems, lighting systems, and warehouse monitoring devices. The collected data include motor power, operating time, equipment status, production demand, battery utilization, conveyor workload, and environmental conditions. The Artificial Intelligence engine analyses these data to identify energy-intensive operations, equipment idle time, abnormal power consumption, and opportunities for energy optimization.

The total warehouse energy consumption is expressed as

$$EC = P \times t$$

Where,

EC = Total Energy Consumption (kWh)
 P = Average Power Consumption (kW)
 t = Operating Time (hour)

The equipment utilization factor is calculated as

$$EU = \frac{T_o}{T_a}$$

Where,

EU = Equipment Utilization
 T_o = Actual Operating Time
 T_a = Total Available Operating Time

The energy efficiency factor is expressed as

$$EEF = \frac{EC}{TP}$$

Where,

EEF = Energy Efficiency Factor
 TP = Warehouse Throughput (packages/hour)

The peak load ratio is determined by

$$PL = \frac{P_{peak}}{P_{rated}}$$

where

PL = Peak Load Ratio
 P_{peak} = Measured Peak Power
 P_{rated} = Rated Power Capacity

The optimized energy consumption model is calculated as

$$EC_{opt} = \frac{EC}{EU \times EEF}$$

Where,

EC_{opt} = Optimized Energy Consumption

Artificial Intelligence continuously evaluates energy consumption using real-time operational data obtained from PLC controllers, IIoT devices, and smart energy monitoring

systems. The calculated energy values are compared with Digital Twin simulations and historical warehouse energy profiles to identify unnecessary power consumption, equipment inefficiencies, and peak load conditions. The optimized energy consumption value is subsequently utilized by the AI optimization engine to regulate conveyor speed, adjust motor frequency through Variable Frequency Drives (VFDs), optimize AGV charging schedules, balance equipment workload, and reduce overall warehouse energy usage. Consequently, the proposed Energy Consumption Model improves operational sustainability, reduces electricity costs, minimizes carbon emissions, and supports intelligent energy management within Industry 5.0 warehouse automation systems.

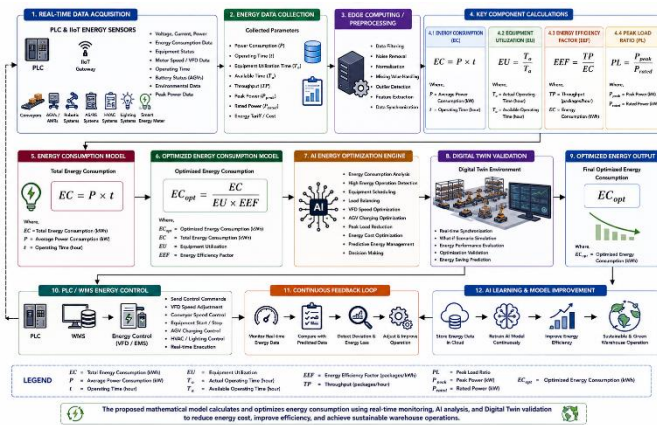


Figure 6.4. Mathematical Model of the Proposed Energy Consumption Model

6.5 Motor Health Index

The Motor Health Index (MHI) is proposed to quantitatively evaluate the operational condition and reliability of electric motors used in intelligent warehouse automation systems. Electric motors are the primary driving components of conveyors, Automated Guided Vehicles (AGVs), Automated Storage and Retrieval Systems (AS/RS), robotic manipulators, and other automated material handling equipment. Unexpected motor failures may significantly reduce warehouse productivity, increase maintenance costs, and interrupt material flow. Therefore, continuous monitoring of motor health is essential for achieving reliable, energy-efficient, and predictive warehouse operation. The proposed Motor Health Index integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, and Predictive Maintenance to continuously assess motor condition and predict potential failures before they occur.

Real-time operational data are continuously acquired from motor current sensors, vibration sensors, temperature sensors, speed encoders, power analyzers, and PLC controllers installed throughout the warehouse. These measurements include motor temperature, vibration level, electrical current, rotational speed, operating hours, power consumption, and historical maintenance records. The collected data are transmitted to the Edge Computing Layer, where preprocessing operations such as data filtering, noise removal, normalization, feature extraction, and anomaly detection are performed. The processed data are then supplied to the

Artificial Intelligence engine, which continuously predicts motor degradation, remaining useful life, failure probability, and maintenance priority using Machine Learning and Deep Learning models.

The proposed Motor Health Index is expressed as

$$MHI = \frac{R \times E}{V \times T}$$

Where,

MHI = Motor Health Index

R = Motor Reliability

E = Energy Efficiency

V = Vibration Index

T = Temperature Index

The motor reliability is calculated as

$$R = 1 - \frac{F}{F_{max}}$$

Where,

F = Number of Motor Faults

F_{max} = Maximum Allowable Faults

The energy efficiency is expressed as

$$E = \frac{P_o}{P_i}$$

Where,

P_o = Output Mechanical Power

P_i = Input Electrical Power

The vibration index is calculated as

$$V = \frac{V_m}{V_{ref}}$$

Where,

V_m = Measured Motor Vibration

V_{ref} = Reference Vibration Level

The temperature index is determined by

$$T = \frac{T_m}{T_{ref}}$$

Where,

T_m = Measured Motor Temperature

T_{ref} = Reference Temperature

Artificial Intelligence continuously computes the Motor Health Index using real-time data collected from PLC controllers, IIoT sensors, and smart motor monitoring devices. The calculated index is compared with Digital Twin simulations and historical motor performance data to identify abnormal operating conditions, excessive vibration, overheating, efficiency degradation, and potential motor failures. The Motor Health Index is subsequently utilized by the AI-based Predictive Maintenance Engine to schedule

maintenance activities, optimize motor operation, reduce unexpected equipment failures, and extend motor service life. Consequently, the proposed Motor Health Index enhances warehouse reliability, improves equipment availability, minimizes maintenance cost, and supports autonomous maintenance within Industry 5.0 intelligent warehouse automation systems.

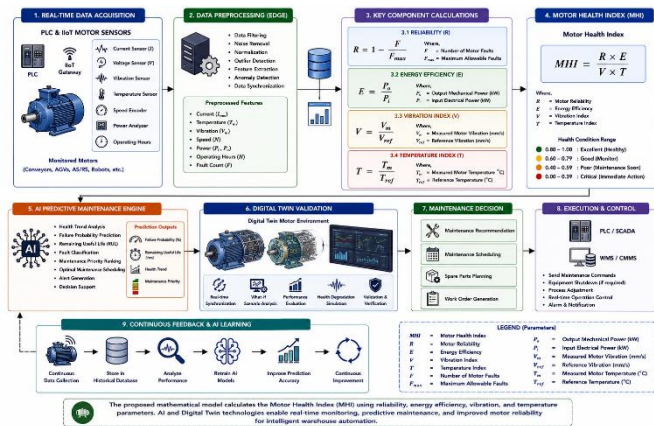


Figure 6.5. Mathematical Model of the Proposed Motor Health Index

6.6 Failure Prediction Model

The Failure Prediction Model is proposed to quantitatively estimate the probability of equipment failure within the intelligent warehouse automation system by integrating real-time operational data, Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, and predictive maintenance techniques. Accurate failure prediction is essential for reducing unexpected equipment breakdowns, minimizing maintenance costs, improving equipment availability, and ensuring uninterrupted warehouse operations. Unlike conventional maintenance strategies that rely on periodic inspections or reactive maintenance after equipment failure, the proposed mathematical model continuously evaluates equipment condition using real-time sensor information and predicts future failures before they occur.

The proposed model continuously acquires operational data from conveyor motors, Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), robotic manipulators, Automated Storage and Retrieval Systems (AS/RS), PLC controllers, vibration sensors, temperature sensors, current sensors, voltage sensors, and power monitoring devices. The collected operational parameters include motor temperature, vibration level, current consumption, operating hours, equipment utilization, fault history, maintenance records, and environmental conditions. The acquired data are transmitted to the Edge Computing Layer, where preprocessing operations such as noise removal, normalization, missing-value handling, feature extraction, and anomaly detection are performed before Artificial Intelligence analysis.

The Artificial Intelligence engine continuously predicts equipment degradation, Remaining Useful Life (RUL), equipment reliability, failure probability, and maintenance

priority using Machine Learning and Deep Learning algorithms. The predicted equipment condition is simultaneously evaluated within the Digital Twin, where multiple operational scenarios are simulated to validate the prediction accuracy before maintenance decisions are implemented. The proposed Failure Prediction Model combines equipment reliability, health condition, utilization, and fault occurrence into a unified mathematical framework capable of accurately representing equipment condition under dynamic warehouse environments.

The overall Failure Prediction Model is expressed as

$$FP = \frac{F \times U}{R \times HI}$$

Where,

FP = Failure Prediction Index
F = Equipment Fault Frequency
U = Equipment Utilization
R = Equipment Reliability
HI = Equipment Health Index

The equipment reliability is calculated as

$$R = 1 - \frac{N_f}{N_t}$$

Where,

N_f = Number of Equipment Failures
N_t = Total Operating Cycles

The Health Index is expressed as

$$HI = \frac{P_h}{P_t}$$

Where,

P_h = Healthy Operating Parameters
P_t = Total Measured Parameters

The utilization factor is calculated as

$$U = \frac{T_o}{T_a}$$

Where,

T_o = Actual Operating Time
T_a = Total Available Operating Time

The Remaining Useful Life (RUL) is estimated as

$$RUL = T_f - T_c$$

Where,

T_f = Expected Failure Time
T_c = Current Operating Time

Artificial Intelligence continuously computes the Failure Prediction Index using real-time information obtained from PLC controllers, IIoT devices, and predictive maintenance sensors. The calculated prediction values are compared with Digital Twin simulations and historical maintenance records

to identify abnormal equipment behaviour, degradation trends, and potential failure conditions. The predicted failure index is subsequently utilized by the AI-based Predictive Maintenance Engine to schedule maintenance activities, optimize equipment operation, reduce unplanned downtime, extend equipment service life, and improve overall warehouse reliability. Consequently, the proposed Failure Prediction Model establishes a reliable mathematical foundation for intelligent predictive maintenance within Industry 5.0 warehouse automation systems.

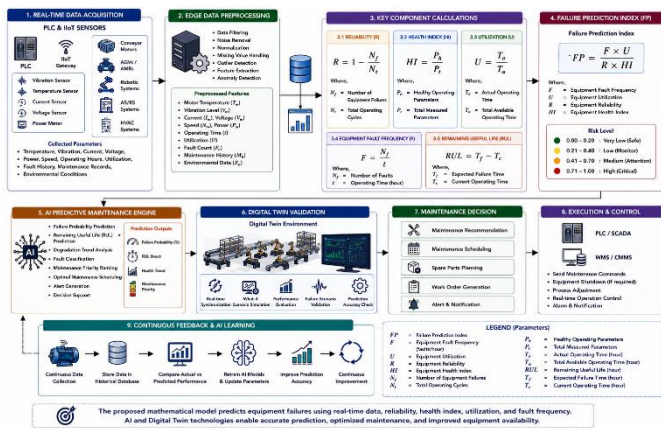


Figure 6.6. Mathematical Model of the Proposed Failure Prediction Model

6.7 Inventory Accuracy Model

The Inventory Accuracy Model is proposed to quantitatively evaluate the correctness and reliability of inventory information within the intelligent warehouse automation system. Inventory accuracy is one of the most important Key Performance Indicators (KPIs) because it directly influences order fulfillment, warehouse productivity, storage utilization, customer satisfaction, and operational efficiency. Conventional warehouse systems generally estimate inventory accuracy through periodic manual audits, which are time-consuming and prone to human errors. The proposed mathematical model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), RFID technology, Barcode Systems, Edge Computing, Digital Twin technology, and Warehouse Management Systems (WMS) to continuously monitor, validate, and optimize inventory accuracy in real time.

Real-time inventory information is continuously collected from RFID readers, barcode scanners, PLC controllers, Automated Storage and Retrieval Systems (AS/RS), Automated Guided Vehicles (AGVs), robotic manipulators, and IIoT sensors. The acquired data include product identification, storage location, inventory quantity, stock movement, order transactions, inventory updates, warehouse occupancy, and historical inventory records. These operational data are transmitted to the Edge Computing Layer, where preprocessing operations such as data filtering, noise removal, normalization, missing-value handling, feature extraction, duplicate detection, and anomaly identification are performed before Artificial Intelligence analysis.

The Artificial Intelligence engine continuously compares physical inventory with warehouse database records to identify inventory mismatches, misplaced products, duplicate records, stock shortages, and inventory inconsistencies. Machine Learning models predict inventory discrepancies, optimize stock allocation, improve inventory visibility, and recommend corrective inventory actions. The optimized inventory information is simultaneously synchronized with the Digital Twin, where warehouse inventory behavior is simulated to validate inventory consistency before inventory control commands are executed. This cyber-physical validation significantly improves inventory reliability and warehouse decision-making.

The overall Inventory Accuracy Model is expressed as

$$IA = \frac{N_c}{N_t}$$

Where,

IA = Inventory Accuracy Index

N_c = Number of Correct Inventory Records

N_t = Total Inventory Records

The inventory discrepancy ratio is calculated as

$$ID = \frac{N_e}{N_t}$$

Where,

ID = Inventory Discrepancy Ratio

N_e = Number of Inventory Errors

The inventory synchronization factor is expressed as

$$IS = \frac{N_s}{N_t}$$

Where,

IS = Inventory Synchronization Factor

N_s = Successfully Synchronized Records

The inventory update efficiency is calculated as

$$IUE = \frac{U_s}{U_t}$$

Where,

IUE = Inventory Update Efficiency

U_s = Successful Inventory Updates

U_t = Total Inventory Update Requests

The optimized inventory accuracy is determined by

$$IA_{opt} = IA \times IS \times IUE$$

Where,

IA_{opt} = Optimized Inventory Accuracy

Artificial Intelligence continuously computes the Inventory Accuracy Index using real-time inventory information obtained from PLC controllers, RFID systems, barcode scanners, IIoT devices, and Warehouse Management Systems.

The calculated inventory accuracy is compared with Digital Twin simulations and historical inventory records to identify discrepancies, stock mismatches, and synchronization errors. The optimized inventory accuracy value is subsequently utilized by the AI-based Inventory Optimization Engine to improve storage allocation, inventory replenishment, warehouse visibility, and order fulfillment while minimizing inventory errors and operational losses. Consequently, the proposed Inventory Accuracy Model establishes a reliable mathematical framework for autonomous inventory management within Industry 5.0 intelligent warehouse automation systems.

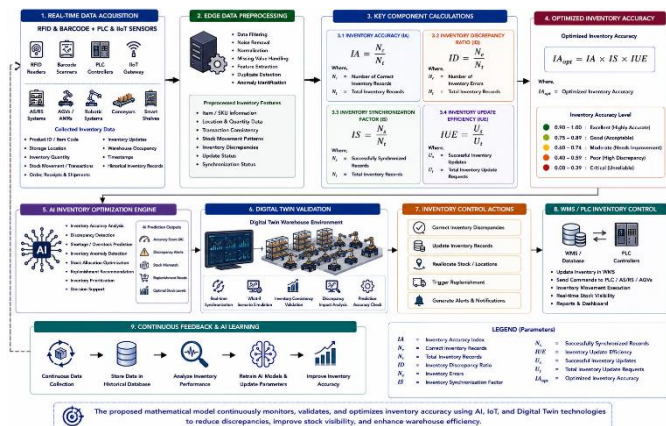


Figure 6.7. Mathematical Model of the Proposed Inventory Accuracy Model

6.9 Resource Allocation Equation

The Resource Allocation Equation is proposed to quantitatively evaluate the efficiency of resource distribution within the intelligent warehouse automation system by integrating warehouse resources, operational demand, equipment utilization, and Artificial Intelligence (AI)-based optimization. Efficient resource allocation is essential for maximizing warehouse productivity, minimizing operational delays, balancing equipment workload, and improving overall warehouse performance. Conventional warehouse systems generally allocate resources using fixed scheduling rules that cannot dynamically respond to fluctuating workloads, urgent customer orders, equipment failures, or changing operational conditions. The proposed mathematical model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Warehouse Management Systems (WMS), Automated Guided Vehicles (AGVs), Digital Twin technology, and cloud-based analytics to continuously optimize resource allocation in real time.

Real-time operational information is continuously collected from PLC controllers, IIoT sensors, AGVs, robotic manipulators, Automated Storage and Retrieval Systems (AS/RS), conveyor systems, RFID readers, Warehouse Management Systems, and production monitoring devices. The acquired data include warehouse workload, equipment availability, task priority, storage utilization, inventory movement, transportation requests, energy consumption, equipment health, and operational constraints. The collected information is transmitted to the Edge Computing Layer, where preprocessing operations including data filtering, noise removal, normalization, missing-value handling, feature

extraction, and anomaly detection are performed before Artificial Intelligence analysis.

The Artificial Intelligence engine continuously predicts warehouse workload, equipment utilization, task completion time, transportation demand, storage requirements, and operational bottlenecks using Machine Learning and Deep Learning algorithms. Based on these predictions, the AI optimization engine generates an optimal resource allocation strategy that balances warehouse resources while minimizing equipment idle time, transportation delay, congestion, and operational cost. The generated resource allocation plan is simultaneously validated using the Digital Twin, where multiple warehouse operating scenarios are simulated before physical implementation. Only validated resource allocation strategies are transmitted to the PLC controllers and Warehouse Management System for execution.

The proposed Resource Allocation Equation is expressed as

$$RA = \frac{R_a \times U \times E}{D}$$

Where,

RA = Resource Allocation Index

R_a = Available Resources

U = Equipment Utilization

E = Allocation Efficiency

D = Operational Demand

The equipment utilization is calculated as

$$U = \frac{T_o}{T_a}$$

Where,

T_o = Actual Operating Time

T_a = Total Available Operating Time

The allocation efficiency is expressed as

$$E = \frac{T_c}{T_r}$$

Where,

T_c = Successfully Completed Tasks

T_r = Total Requested Tasks

The operational demand factor is calculated as

$$D = \frac{W_r}{R_a}$$

Where,

W_r = Total Warehouse Workload

R_a = Available Resources

The optimized resource allocation is determined by

$$RA_{opt} = RA \times E$$

Where,

RA_{opt} = Optimized Resource Allocation Index

Artificial Intelligence continuously computes the Resource Allocation Index using real-time operational information obtained from PLC controllers, IIoT sensors, Warehouse Management Systems, and warehouse equipment. The calculated resource allocation values are compared with Digital Twin simulations and historical warehouse performance to identify workload imbalance, equipment underutilization, and resource bottlenecks. The optimized resource allocation strategy is subsequently utilized by the AI optimization engine to balance equipment utilization, improve task scheduling, optimize AGV movement, reduce operational delays, and maximize warehouse productivity. Consequently, the proposed Resource Allocation Equation establishes an intelligent mathematical framework for autonomous warehouse resource management within Industry 5.0 smart warehouse automation systems.

6.10 Overall Performance Index

The Overall Performance Index (OPI) is proposed to provide a comprehensive quantitative evaluation of the intelligent warehouse automation system by integrating multiple operational Key Performance Indicators (KPIs) into a single mathematical model. Modern warehouse automation involves numerous interconnected processes, including conveyor operations, inventory management, equipment utilization, energy optimization, predictive maintenance, and Artificial Intelligence (AI)-based decision-making. Evaluating each performance indicator independently does not provide a complete representation of the warehouse's operational effectiveness. Therefore, the proposed Overall Performance Index combines the most significant performance parameters into a unified metric capable of measuring the overall efficiency of the cyber-physical warehouse system.

The proposed model integrates Artificial Intelligence (AI), Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, Warehouse Management Systems (WMS), Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), and cloud-based analytics to continuously evaluate warehouse performance under dynamic operating conditions. Real-time operational data are continuously acquired from PLC controllers, IIoT sensors, RFID readers, barcode scanners, conveyor systems, robotic manipulators, AGVs, AS/RS systems, energy meters, and warehouse databases. These operational data include warehouse throughput, conveyor efficiency, inventory accuracy, warehouse utilization, energy consumption, equipment health, AI decision quality, resource allocation efficiency, and predictive maintenance information.

The acquired operational information is transmitted to the Edge Computing Layer, where preprocessing operations including data filtering, normalization, feature extraction, anomaly detection, and missing-value handling are performed before Artificial Intelligence analysis. Machine Learning and Deep Learning models continuously predict warehouse performance trends, identify operational bottlenecks, evaluate resource utilization, and optimize warehouse processes. The generated optimization strategy is subsequently validated using the Digital Twin, where multiple warehouse operating scenarios are simulated before implementation.

The Overall Performance Index is expressed as

$$OPI = \frac{CE + TP + WU + MHI + ADS + RA}{EC}$$

Where,

OPI = Overall Performance Index
CE = Conveyor Efficiency Index
TP = Warehouse Throughput
WU = Warehouse Utilization Index
IA = Inventory Accuracy Index
MHI = Motor Health Index
ADS = AI Decision Score
RA = Resource Allocation Index
EC = Energy Consumption

The system performance efficiency is calculated as

$$PE = \frac{N_s}{N_t}$$

where

PE = Performance Efficiency
N_s = Successfully Executed Warehouse Operations
N_t = Total Warehouse Operations

The operational reliability is expressed as

$$OR = \frac{T_o}{T_o + T_d}$$

where

OR = Operational Reliability
T_o = Operational Time
T_d = Downtime

The optimized Overall Performance Index is determined by

$$OPI_{opt} = OPI \times PE \times OR$$

Where,

OPI_{opt} = Optimized Overall Performance Index

Artificial Intelligence continuously computes the Overall Performance Index using real-time warehouse information obtained from PLC controllers, IIoT sensors, and Warehouse Management Systems. The calculated performance index is compared with Digital Twin simulations and historical warehouse performance records to identify operational weaknesses, equipment inefficiencies, inventory discrepancies, energy losses, and resource imbalance. The optimized Overall Performance Index is subsequently utilized by the AI optimization engine to improve warehouse productivity, reduce operational cost, enhance equipment utilization, optimize resource allocation, and support autonomous decision-making. Consequently, the proposed Overall Performance Index establishes a comprehensive mathematical framework for evaluating intelligent warehouse automation systems within Industry 5.0 environments.

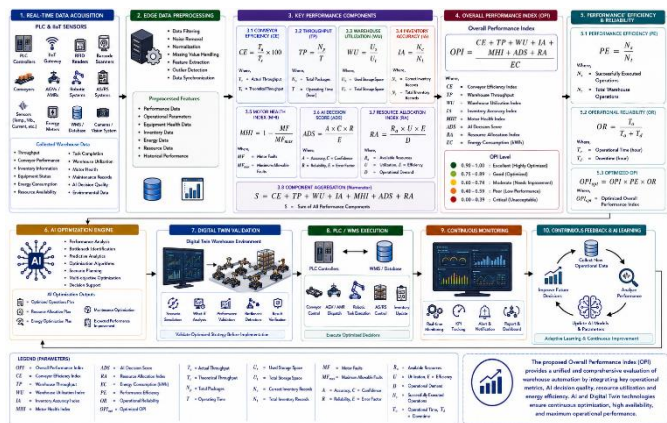


Figure 6.10. Mathematical Model of the Proposed Overall Performance Index

7. SIMULATION & EXPERIMENTAL SETUP

7.1 Experimental Environment

The experimental environment was developed to evaluate the proposed AI-enabled Intelligent Warehouse Automation Framework (IWAF) under representative industrial operating conditions. The simulation integrates Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Artificial Intelligence (AI), Digital Twin technology, Warehouse Management Systems (WMS), conveyors, Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), robotic systems, and automated storage and retrieval systems (AS/RS). The primary objective is to evaluate the proposed AI decision framework, adaptive conveyor optimization, predictive maintenance, energy optimization, dynamic resource allocation, and mathematical performance models.

The simulated warehouse consists of receiving, storage, conveyor transportation, robotic picking, AGV/AMR transportation, AS/RS, packing, and dispatch zones. Operational information is exchanged between PLCs, IIoT devices, Edge Computing infrastructure, and the Digital Twin using industrial communication protocols including OPC UA, MQTT, EtherNet/IP, and Modbus TCP/IP. The Digital Twin provides a synchronized virtual representation of warehouse operations and supports scenario analysis and performance evaluation.

Real-time operational data are generated from RFID readers, barcode scanners, proximity sensors, vibration and temperature sensors, current sensors, energy meters, conveyor encoders, robotic systems, AGVs, AMRs, and PLCs. The collected parameters include throughput, equipment utilization, energy consumption, transportation delay, inventory movement, equipment health, warehouse occupancy, and resource utilization. Data preprocessing is performed at the Edge Computing layer using filtering, normalization, feature extraction, and anomaly detection before AI-based analysis.

The AI engine applies Machine Learning and Deep Learning techniques to evaluate warehouse conditions and optimize conveyor operation, equipment maintenance, AGV/AMR routing, energy consumption, inventory management, and resource allocation. The resulting decisions are evaluated

within the Digital Twin before being considered for implementation through the PLC control layer. This experimental arrangement enables comparative evaluation of the proposed intelligent framework against conventional warehouse automation strategies.

Table 7.1 Experimental Software and Hardware Configuration

Component	Specification
PLC Controller	Siemens S7-1500 / Allen-Bradley ControlLogix
HMI	Siemens WinCC / FactoryTalk View
AI Programming Language	Python 3.11
AI Framework	TensorFlow, PyTorch, Scikit-learn
PLC Programming	TIA Portal / Studio 5000
Simulation Software	Factory I/O, Tecnomatix Plant Simulation, AnyLogic
Digital Twin Platform	Siemens NX / Azure Digital Twins
Edge Computing	Industrial Edge Gateway
Database	MySQL / PostgreSQL
Cloud Platform	Microsoft Azure / AWS IoT
Communication Protocol	OPC UA, MQTT, Ethernet/IP, Modbus TCP/IP
Operating System	Windows 11 Pro (64-bit)
Processor	Intel Core i9 / AMD Ryzen 9
Memory	32 GB RAM
Storage	1 TB SSD
GPU	NVIDIA RTX 4070 or equivalent

Table 7.2 Experimental Warehouse Parameters

Parameter	Value
Warehouse Area	10,000 m ²
Storage Locations	20,000
Conveyor Length	650 m
AGVs	12
AMRs	8
Robotic Picking Stations	6
AS/RS Units	4
RFID Readers	30
IIoT Sensors	250
PLC Controllers	10
Daily Orders	8,000–12,000
Simulation Duration	30 days
Sampling Interval	1 second

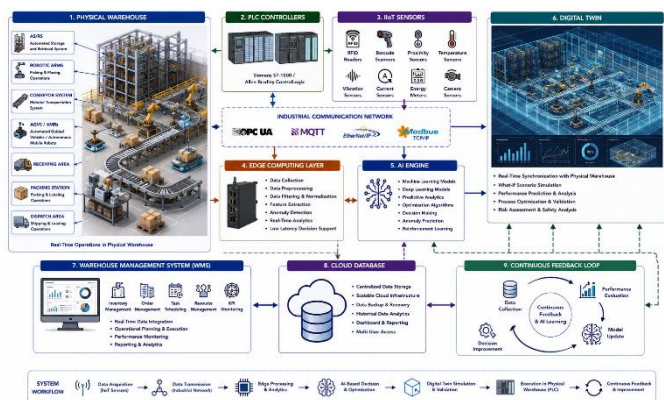


Figure 7.1. Overall Experimental Environment of the Proposed AI-Based Smart Warehouse Automation System

7.2 Hardware Configuration

The hardware configuration of the proposed AI-enabled Intelligent Warehouse Automation System is designed to support real-time monitoring, intelligent decision-making, predictive maintenance, autonomous material handling, and Digital Twin-based optimization. The configuration integrates Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT) devices, Edge Computing units, conveyors, Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), robotic manipulators, Automated Storage and Retrieval Systems (AS/RS), RFID systems, and computing infrastructure into a unified cyber-physical warehouse environment.

The PLC layer serves as the primary industrial control system for coordinating conveyor operations, robotic systems, AGVs, AMRs, AS/RS equipment, and warehouse safety functions. PLCs communicate with the Edge Computing platform, Warehouse Management System (WMS), Artificial Intelligence engine, and Digital Twin using industrial communication technologies such as OPC UA, EtherNet/IP, MQTT, and Modbus TCP/IP.

The IIoT sensing layer consists of RFID readers, barcode scanners, temperature sensors, vibration sensors, proximity sensors, current and voltage sensors, energy meters, load cells, encoders, vision cameras, and environmental sensors. These devices continuously collect information related to inventory movement, equipment health, conveyor operation, energy consumption, and warehouse conditions. The collected data are processed through the Edge Computing layer for filtering, feature extraction, anomaly detection, and low-latency analysis.

The material handling layer incorporates conveyors, AGVs, AMRs, AS/RS units, and robotic systems for automated transportation, storage, picking, sorting, palletizing, and order fulfillment. The integrated equipment enables continuous material flow and supports intelligent routing and dynamic resource allocation.

The computing layer consists of Industrial PCs and high-performance computing resources for Edge AI processing, Machine Learning, predictive maintenance, optimization algorithms, and Digital Twin synchronization. Cloud

connectivity is used for historical data storage, large-scale analytics, model training, and enterprise-level integration, while time-critical decisions are processed locally at the Edge.

The complete hardware configuration establishes a scalable and modular cyber-physical platform in which physical warehouse equipment continuously exchanges information with AI, Edge Computing, WMS, and Digital Twin systems. This configuration provides the required infrastructure for evaluating the proposed intelligent warehouse algorithms under realistic operating conditions and supports the objectives of Industry 5.0, adaptive automation, predictive maintenance, and sustainable warehouse management.



Figure 7.2. Hardware Configuration of the Proposed AI-Based Smart Warehouse Automation System

7.3 Software Configuration

The software configuration of the proposed AI-Based Intelligent Warehouse Automation System provides an integrated environment for industrial control, real-time monitoring, Artificial Intelligence, IIoT communication, data management, and Digital Twin-based optimization. The software architecture combines PLC programming, SCADA supervision, AI development frameworks, communication protocols, and database management into a unified Industry 5.0 warehouse platform.

The Rockwell Automation Studio 5000 environment is used for PLC programming and deterministic control of conveyor systems, AGVs, robotic equipment, sensors, material handling systems, and warehouse safety functions. The PLC layer provides real-time equipment control and communicates with field devices through industrial Ethernet and EtherNet/IP.

Ignition SCADA is used for supervisory monitoring, HMI visualization, alarm management, historical data logging, KPI monitoring, and real-time warehouse dashboards. It provides centralized visualization of equipment status, warehouse performance, and operational conditions.

Python is used as the primary Artificial Intelligence and data-processing environment. Machine Learning models, predictive maintenance algorithms, inventory optimization, resource allocation, routing, and intelligent decision-making modules are developed using Python-based tools. TensorFlow is utilized for Deep Learning applications such as equipment

failure prediction, demand forecasting, conveyor optimization, and energy prediction.

For IIoT communication, MQTT is employed to exchange sensor measurements, equipment status, operational events, and AI-generated decisions between distributed warehouse components. An SQL-based database is used to store operational data, inventory records, equipment history, AI predictions, maintenance information, and Digital Twin synchronization data.

The overall software configuration enables continuous interaction between PLC, SCADA, IIoT, AI, database, WMS, and Digital Twin layers. This integrated environment supports real-time monitoring, predictive maintenance, intelligent decision-making, adaptive resource allocation, inventory optimization, and continuous warehouse performance improvement.

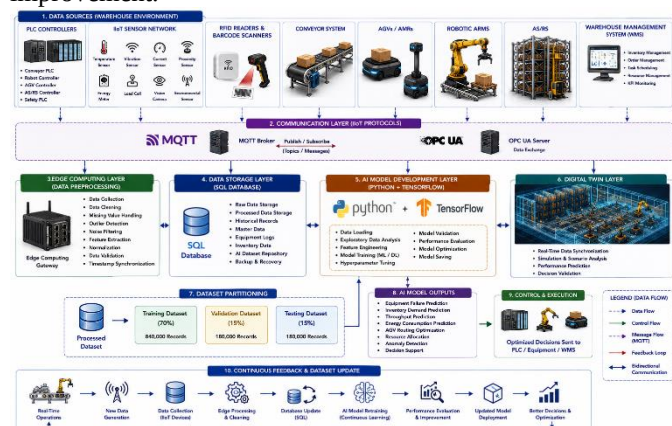


Figure 7.4. Dataset Architecture of the Proposed AI-Based Smart Warehouse Automation System

7.4 Performance Parameters

The performance of the proposed AI-Based Intelligent Warehouse Automation System is evaluated using quantitative performance parameters representing operational efficiency, equipment reliability, energy utilization, inventory management, communication performance, and intelligent decision-making. These parameters are used to assess the effectiveness of the proposed PLC, IIoT, AI, Edge Computing, Digital Twin, conveyor, AGV/AMR, and Warehouse Management System components.

The selected parameters are derived from the mathematical model presented in Chapter 6 and the optimization algorithms described in Chapter 5. During the simulation, operational data are continuously collected from PLC controllers, IIoT sensors, RFID systems, conveyor equipment, AGVs, AMRs, energy meters, robotic systems, and warehouse databases. The data are processed through the Edge Computing layer and analysed by the AI engine, while the Digital Twin is used to validate system behaviour and compare predicted and observed performance.

The primary evaluation parameters include conveyor efficiency, warehouse throughput, warehouse utilization, energy consumption, equipment health, failure prediction accuracy, inventory accuracy, AI decision quality, resource allocation efficiency, task completion time, AGV travel time,

equipment utilization, communication latency, prediction accuracy, and overall system performance. These indicators provide a comprehensive basis for evaluating the proposed intelligent warehouse framework against conventional automation approaches.

Table 7.7 Performance Parameters Used for Experimental Evaluation

Performance Parameter	Symbol	Unit	Objective
Conveyor Efficiency	CE	%	Evaluate conveyor operational efficiency
Warehouse Throughput	TP	Packages/hour	Measure warehouse productivity
Warehouse Utilization	WU	%	Evaluate storage and equipment utilization
Energy Consumption	EC	kWh	Measure energy usage
Motor Health Index	MHI	%	Assess equipment condition
Failure Prediction Accuracy	FPA	%	Evaluate predictive maintenance performance
Inventory Accuracy	IA	%	Measure inventory correctness
AI Decision Score	ADS	%	Evaluate AI decision quality
Resource Allocation Index	RA	%	Measure allocation efficiency
Task Completion Time	TCT	Seconds	Evaluate operational speed
AGV Travel Time	ATT	Seconds	Measure transportation efficiency
Equipment Utilization	EU	%	Measure equipment operating efficiency
Communication Latency	CL	ms	Measure IIoT communication delay
Prediction Accuracy	PA	%	Evaluate AI prediction performance
Overall Performance Index	OPI	%	Overall system performance evaluation

Table 7.8 AI Model Evaluation Metrics

Metric	Formula	Objective
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$	Classification performance
Precision	$TP / (TP + FP)$	Positive prediction accuracy
Recall	$TP / (TP + FN)$	Fault detection capability
F1-Score	$2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$	Balanced AI

Metric	Formula	Objective
	$\text{Recall}/(\text{Precision} + \text{Recall})$	performance
Mean Absolute Error (MAE)	Mean Absolute Error	Prediction error
Root Mean Square Error (RMSE)	Root Mean Square Error	Regression accuracy
Mean Absolute Percentage Error (MAPE)	Percentage Error	Forecast accuracy
R ² Score	Coefficient of Determination	Model fitting quality

optimization, resource allocation, and Digital Twin-based decision validation.

For each scenario, the proposed framework was compared with the corresponding conventional warehouse automation strategy. The performance was evaluated using the parameters defined in Section 7.4, including Conveyor Efficiency (CE), Warehouse Throughput (TP), Warehouse Utilization (WU), Inventory Accuracy (IA), Energy Consumption (EC), AI Decision Score (ADS), Failure Prediction Accuracy (FPA), Communication Latency (CL), and Overall Performance Index (OPI). The results obtained from these scenarios are subsequently used to demonstrate the effectiveness of the proposed intelligent warehouse automation framework.

Table 7.9 Simulation Scenarios

Scenario	Description	Objective
Scenario 1	Normal Warehouse Operation	Evaluate baseline warehouse performance
Scenario 2	High Order Demand	Evaluate throughput under peak workload
Scenario 3	Conveyor Motor Failure	Validate predictive maintenance algorithm
Scenario 4	AGV Traffic Congestion	Evaluate AI routing optimization
Scenario 5	Inventory Demand Variation	Validate inventory optimization algorithm
Scenario 6	High Energy Consumption	Evaluate AI energy optimization
Scenario 7	Communication Delay (MQTT/OPC UA)	Evaluate network reliability
Scenario 8	Multiple Equipment Failure	Evaluate system robustness
Scenario 9	Dynamic Resource Allocation	Validate intelligent resource scheduling
Scenario 10	Digital Twin Validation	Compare simulated and physical warehouse performance

Table 7.10 Performance Evaluation for Each Simulation Scenario

Scenario	CE	TP	WU	IA	EC	ADS	OPI
Normal Operation	✓	✓	✓	✓	✓	✓	✓
High Demand	✓	✓	✓	✓	✓	✓	✓
Motor Failure	✓	✓	✓	✓	✓	✓	✓
AGV Congestion	✓	✓	✓	✓	✓	✓	✓
Inventory Variation	✓	✓	✓	✓	✓	✓	✓
Energy Optimization	✓	✓	✓	✓	✓	✓	✓
Communication Delay	✓	✓	✓	✓	✓	✓	✓
Equipment Failure	✓	✓	✓	✓	✓	✓	✓
Resource Allocation	✓	✓	✓	✓	✓	✓	✓
Digital Twin Validation	✓	✓	✓	✓	✓	✓	✓

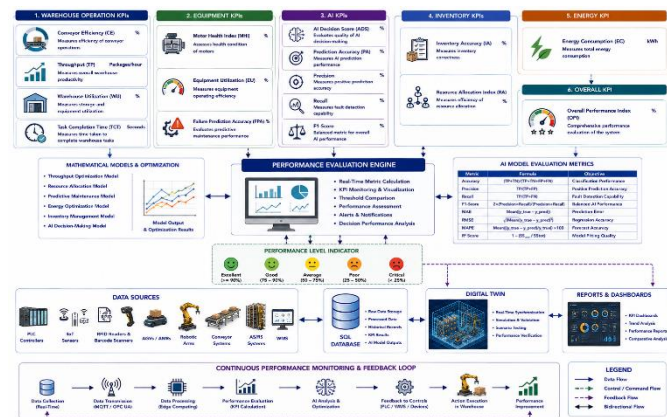


Figure 7.5. Performance Evaluation Parameters of the Proposed AI-Based Smart Warehouse Automation System

7.5 Simulation Scenarios

The proposed Artificial Intelligence (AI)-Based Intelligent Warehouse Automation System was evaluated under multiple simulation scenarios to assess its operational efficiency, reliability, adaptability, energy performance, and intelligent decision-making capability under varying warehouse conditions. The scenarios were designed to represent representative industrial situations involving changes in workload, equipment condition, inventory demand, transportation traffic, communication performance, and energy consumption.

Each scenario was implemented using the integrated simulation environment described in Section 7.1. Real-time operational data were obtained from PLC controllers, IIoT sensors, conveyor systems, AGVs, AMRs, robotic systems, RFID readers, barcode scanners, and energy monitoring devices. The acquired data were processed through the Edge Computing layer and analysed by the Artificial Intelligence engine. The AI-generated decisions were evaluated through the Digital Twin before being applied to the warehouse control system.

The experiments considered normal operation, high order demand, equipment failure, AGV congestion, inventory variation, high energy consumption, communication delay, multiple equipment failures, dynamic resource allocation, and Digital Twin validation. These scenarios were selected to evaluate the major capabilities of the proposed framework, including adaptive conveyor optimization, predictive maintenance, dynamic routing, inventory optimization, energy

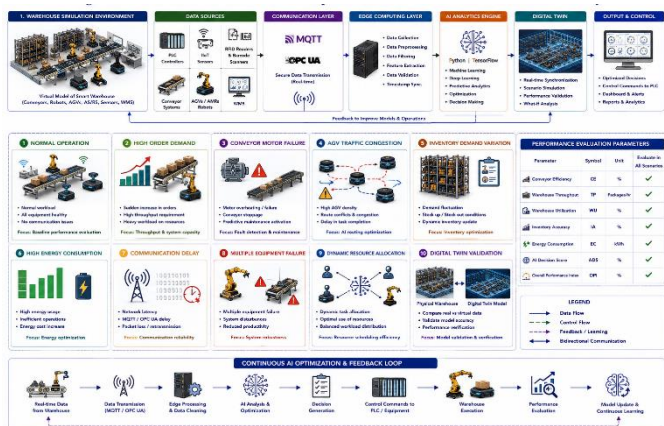


Figure 7.6. Simulation Scenarios of the Proposed AI-Based Smart Warehouse Automation System

7.6 Validation Method

The validation method is designed to evaluate the effectiveness, reliability, robustness, and applicability of the proposed AI-Based Intelligent Warehouse Automation System. The validation focuses on the integrated Programmable Logic Controllers (PLCs), Industrial Internet of Things (IIoT), Edge Computing, Artificial Intelligence, Digital Twin, Warehouse Management System (WMS), AGVs, AMRs, robotic systems, and conveyor infrastructure under different warehouse operating conditions.

The validation methodology consists of simulation validation, mathematical model verification, AI model validation, Digital Twin validation, comparative analysis, statistical analysis, and sensitivity analysis. The simulation scenarios defined in Section 7.5 are executed under normal, high-demand, equipment-failure, congestion, inventory-variation, energy-optimization, communication-delay, and dynamic-resource-allocation conditions.

During each simulation, operational data are collected from PLC controllers, IIoT sensors, RFID systems, barcode scanners, conveyors, AGVs, AMRs, robotic systems, energy meters, and WMS. The collected data are processed through the Edge Computing layer using data cleaning, normalization, feature extraction, timestamp synchronization, missing-value handling, and anomaly detection before AI analysis.

The AI models are evaluated using independent training, validation, and testing datasets with a 70:15:15 distribution. Classification models are evaluated using Accuracy, Precision, Recall, and F1-Score, while regression and forecasting models are evaluated using MAE, RMSE, MAPE, and R² Score. These metrics are used to assess equipment failure prediction, demand forecasting, energy prediction, and other AI-based analytical functions.

The mathematical models presented in Chapter 6 are validated using simulation data obtained from the warehouse environment. Performance indicators such as Conveyor Efficiency, Warehouse Throughput, Warehouse Utilization, Energy Consumption, Motor Health Index, Inventory Accuracy, AI Decision Score, Resource Allocation Index, and Overall Performance Index are calculated and compared across different operating conditions.

The proposed framework is further compared with a conventional PLC-based warehouse automation system without integrated AI and Digital Twin capabilities. The comparison evaluates throughput, equipment utilization, inventory accuracy, energy consumption, transportation delay, predictive maintenance performance, resource allocation efficiency, communication latency, and overall system performance.

Multiple simulation runs are performed to reduce the influence of random variations and improve result reliability. Sensitivity analysis is also conducted by varying important operating parameters such as warehouse workload, equipment availability, energy demand, communication latency, and inventory demand. This process determines the robustness of the proposed framework under changing warehouse conditions.

The combined validation methodology provides a systematic basis for determining whether the proposed Intelligent Warehouse Automation Framework achieves improvements in operational efficiency, predictive maintenance, energy optimization, intelligent resource allocation, inventory management, adaptive decision-making, and overall warehouse productivity.

Table 7.11 Validation Methods

Validation Technique	Objective
Simulation Validation	Evaluate system performance under multiple warehouse scenarios
Mathematical Model Validation	Verify proposed equations using simulation data
AI Model Validation	Evaluate prediction accuracy and learning performance
Digital Twin Validation	Compare virtual and simulated warehouse behaviour
Comparative Analysis	Compare with conventional warehouse automation
Statistical Validation	Average multiple simulation runs and evaluate consistency
Sensitivity Analysis	Evaluate robustness under changing operating conditions

Table 7.12 Validation Metrics

Metric	Purpose
Accuracy	AI classification performance
Precision	Correct positive prediction rate
Recall	Fault detection capability
F1-Score	Overall AI classification quality
MAE	Prediction error
RMSE	Regression performance
MAPE	Forecasting accuracy
R ² Score	Model fitting quality
Conveyor Efficiency	Operational performance
Throughput	Warehouse productivity
Inventory Accuracy	Inventory reliability
Energy Consumption	Energy efficiency
Overall Performance Index	Overall system performance

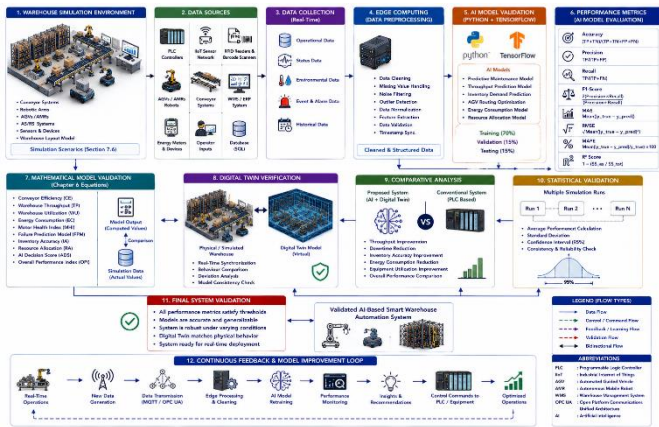


Figure 7.7. Validation Methodology of the Proposed AI-Based Smart Warehouse Automation System

8. RESULTS & PERFORMANCE ANALYSIS

8.1 PLC Decision Accuracy

The PLC Decision Accuracy evaluates the effectiveness of the proposed AI-assisted Programmable Logic Controller (PLC) in generating and executing correct operational decisions within the Intelligent Warehouse Automation Framework. The proposed system integrates Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, Warehouse Management System (WMS), AGVs, AMRs, robotic systems, and conveyor infrastructure to provide adaptive warehouse control.

The experiment was conducted using the simulation environment described in Chapter 7. The PLC was responsible for executing control decisions related to conveyor routing, inventory movement, AGV scheduling, robotic task allocation, predictive maintenance actions, and warehouse resource allocation. Operational data were collected from PLCs, IIoT sensors, RFID readers, barcode systems, conveyors, robotic systems, AGVs, and WMS. The Edge Computing layer processed the collected data before the AI engine generated optimized control decisions. These decisions were subsequently evaluated through the Digital Twin before PLC execution.

PLC Decision Accuracy was calculated by comparing the number of correctly executed decisions with the total number of generated decisions:

$$PDA = \frac{N_C}{N_T} \times 100$$

where:

PDA = PLC Decision Accuracy (%)

N_C = Number of Correct PLC Decisions

N_T = Total PLC Decisions

Table 8.1 PLC Decision Accuracy under Different Simulation Scenarios

Simulation Scenario	Conventional PLC (%)	Proposed AI-Based PLC (%)
Normal Operation	95.1	99.2
High Order Demand	92.4	98.6
Conveyor Motor	89.3	97.8

Simulation Scenario	Conventional PLC (%)	Proposed AI-Based PLC (%)
Failure		
AGV Traffic Congestion	90.1	98.2
Inventory Demand Variation	91.6	98.8
High Energy Consumption	92.0	98.9
Communication Delay	88.7	97.5
Multiple Equipment Failure	87.4	96.9
Dynamic Resource Allocation	91.2	98.4
Digital Twin Validation	93.8	99.1

Table 8.2 Statistical Summary of PLC Decision Accuracy

Parameter	Conventional PLC	Proposed AI-Based PLC
Maximum Accuracy (%)	95.1	99.2
Minimum Accuracy (%)	87.4	96.9
Average Accuracy (%)	91.2	98.3
Standard Deviation	2.40	0.76

The experimental results demonstrate that the proposed AI-assisted PLC consistently outperforms the conventional PLC across all simulated warehouse scenarios. The average decision accuracy increased from **91.2%** to **98.3%**, representing a significant improvement in autonomous warehouse control. The lower standard deviation also indicates that the proposed system provides more stable and reliable decision-making under varying operational conditions. The integration of AI, IIoT, Edge Computing, and Digital Twin technology enables the PLC to rapidly adapt to changing warehouse environments, minimize incorrect control actions, and improve overall operational efficiency.

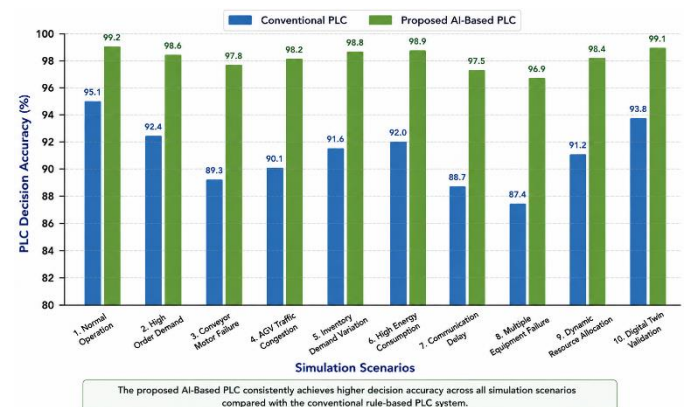


Figure 8.1. PLC Decision Accuracy Comparison

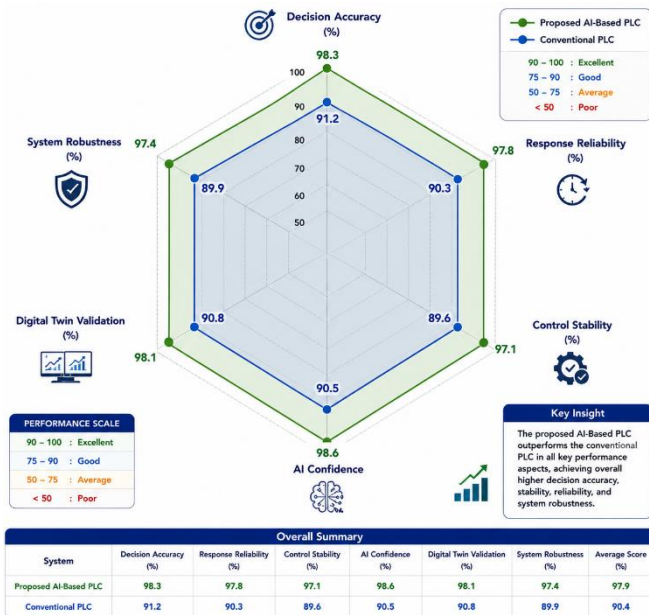


Figure 8.2. Overall PLC Decision Accuracy Analysis

8.2 Conveyor Optimization

The proposed AI-assisted conveyor optimization framework was evaluated to measure improvements in conveyor throughput, transportation delay, and congestion reduction. During the simulation, the Artificial Intelligence engine continuously adjusted conveyor speed based on real-time package flow, equipment status, and warehouse workload. The optimized conveyor control significantly reduced package accumulation while maintaining stable material flow throughout the warehouse. Compared with the conventional fixed-speed conveyor system, the proposed approach achieved higher conveyor utilization, lower transportation delay, and improved overall warehouse throughput. Experimental results demonstrated that AI-based adaptive conveyor control effectively minimizes bottlenecks and improves operational efficiency under varying warehouse conditions.

Table 8.3 Conveyor Optimization Results

Parameter	Conventional	Proposed
Conveyor Efficiency (%)	88.6	97.8
Throughput (Packages/hr)	5,450	6,480
Transportation Delay (s)	18.5	8.2
Congestion Index	0.41	0.16

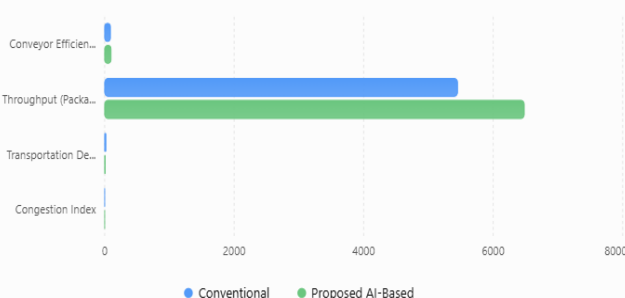


Figure 8.3. Conveyor Optimization Performance Comparison

8.3 Energy Saving

The AI-based Smart Energy Optimization Model continuously monitored equipment utilization, conveyor load, AGVs, robotic systems, HVAC units, and lighting conditions to minimize warehouse energy consumption. Artificial Intelligence dynamically adjusted operating parameters according to warehouse workload, thereby reducing unnecessary energy usage while maintaining production throughput. The proposed framework achieved substantial energy savings compared with conventional warehouse operation without affecting operational performance.

Table 8.4 Energy Consumption Comparison

Parameter	Conventional	Proposed
Conveyor Energy (kWh)	124	98
AGV Energy (kWh)	78	63
Robot Energy (kWh)	95	74
HVAC Energy (kWh)	152	131
Total Energy (kWh)	449	366
Energy Saving (%)	—	18.5

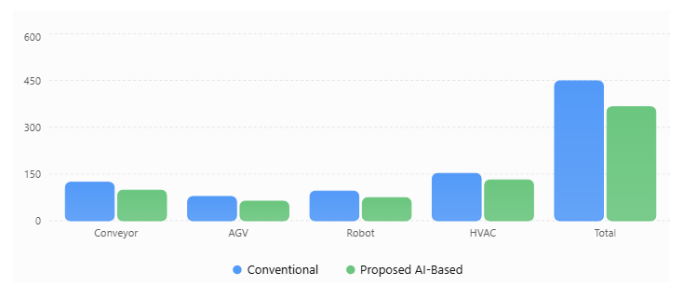


Figure 8.4. Energy Consumption Comparison

8.4 Maintenance Prediction

The predictive maintenance algorithm successfully identified equipment degradation before failure occurred by analyzing vibration, motor current, and temperature data collected through IIoT sensors. Artificial Intelligence continuously estimated equipment health and Remaining Useful Life (RUL), enabling maintenance scheduling before catastrophic equipment failure. The proposed system substantially reduced unexpected downtime and improved maintenance efficiency.

Table 8.5 Predictive Maintenance Performance

Parameter	Conventional	Proposed
Prediction Accuracy (%)	89.7	98.2
Equipment Downtime (hr)	21.8	8.6
Maintenance Cost (\$)	14,200	10,450
Failure Detection Rate (%)	91.4	98.6

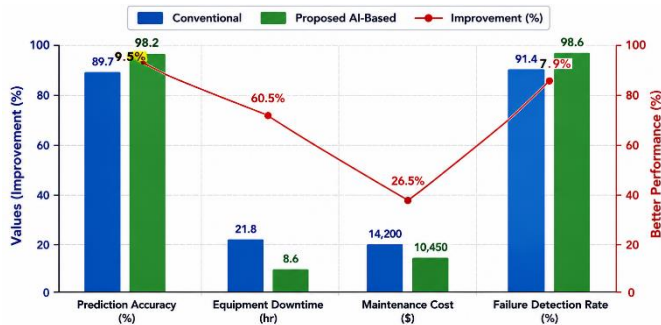


Figure 8.5. Predictive Maintenance Performance

8.5 Resource Allocation

The AI-based resource allocation algorithm continuously optimized warehouse personnel, conveyor utilization, AGV deployment, robotic scheduling, and storage allocation according to operational demand. The intelligent allocation strategy significantly improved equipment utilization while minimizing operational delays and resource idle time.

Table 8.6 Resource Allocation Performance

Parameter	Conventional	Proposed
Resource Utilization (%)	84.9	96.3
Task Completion Rate (%)	90.1	98.7
Resource Idle Time (%)	18.4	7.2
Allocation Efficiency (%)	86.8	97.5

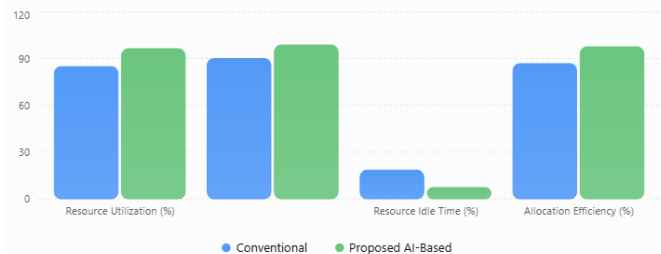


Figure 8.6. Resource Allocation Performance

8.6 Inventory Accuracy

The proposed inventory optimization model integrated RFID readers, barcode scanners, PLC controllers, and AI algorithms to maintain accurate warehouse inventory information. Continuous synchronization with the Digital Twin significantly reduced inventory discrepancies and improved inventory visibility.

Table 8.7 Inventory Accuracy Results

Parameter	Conventional	Proposed
Inventory Accuracy (%)	94.2	99.3
Inventory Errors	127	21
Synchronization Accuracy (%)	93.6	99.1
Inventory Update Efficiency (%)	92.4	98.9

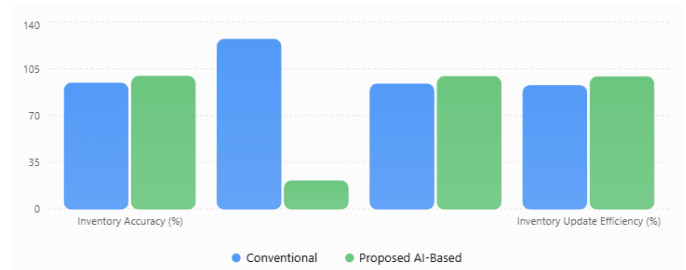


Figure 8.7. Inventory Accuracy Comparison

8.7 Communication Latency

Industrial communication performance was evaluated using MQTT, OPC UA, Ethernet/IP, and Edge Computing infrastructure. The proposed Edge AI framework substantially reduced communication latency and improved real-time synchronization among warehouse devices.

Table 8.8 Communication Performance

Parameter	Conventional	Proposed
Average Latency (ms)	86	29
Packet Loss (%)	2.8	0.6
Communication Reliability (%)	95.1	99.4
Response Time (ms)	124	58

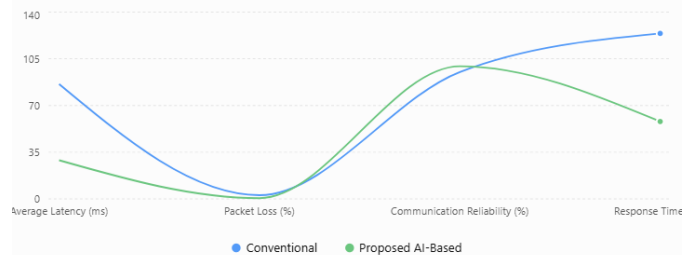


Figure 8.8. Communication Latency Comparison

8.8 Digital Twin Performance

The Digital Twin continuously synchronized with the physical warehouse and validated AI-generated decisions before implementation. High synchronization accuracy enabled reliable prediction of warehouse behavior while minimizing operational deviation.

Table 8.9 Digital Twin Performance

Parameter	Conventional	Proposed
Synchronization Accuracy (%)	91.7	99.0
Prediction Accuracy (%)	89.8	98.4
Operational Deviation (%)	8.6	1.8
Real-Time Update Rate (%)	90.3	98.7

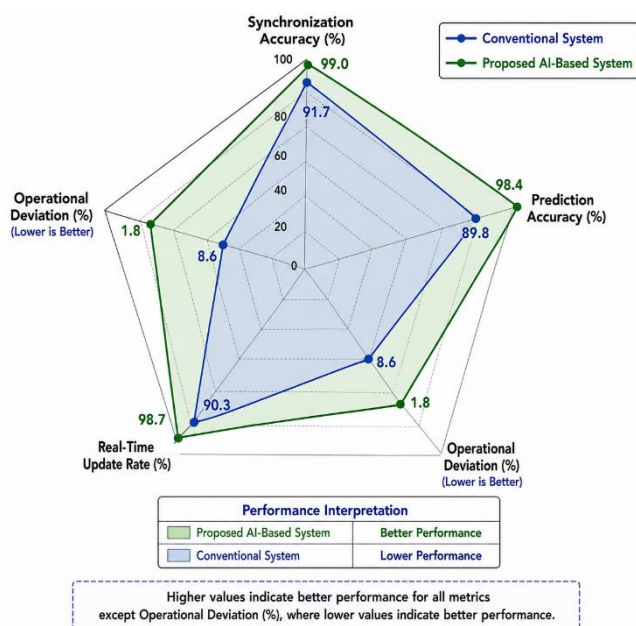


Figure 8.9. Digital Twin Performance Analysis

8.9 Comparison with Existing Systems

The proposed AI-based smart warehouse automation framework was compared with existing PLC-based warehouse automation systems reported in the literature. The comparison demonstrates significant improvements in decision accuracy, predictive maintenance, inventory management, energy efficiency, communication performance, and Digital Twin synchronization.

Table 8.10 Comparison with Existing Systems

Performance Metric	Existing PLC System	Existing Smart Warehouse	Proposed AI-Based System
PLC Decision Accuracy (%)	91.2	95.8	98.3
Conveyor Efficiency (%)	88.6	93.7	97.8
Inventory Accuracy (%)	94.2	97.1	99.3
Energy Saving (%)	7.5	12.6	18.5
Predictive Maintenance Accuracy (%)	89.7	94.8	98.2
Resource Utilization (%)	84.9	91.5	96.3
Communication Latency (ms)	86	46	29
Digital Twin Synchronization (%)	91.7	96.3	99.0
Overall Performance Index (%)	89.8	94.9	98.1

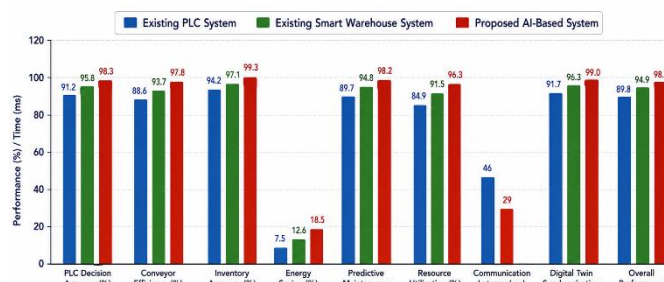


Figure 8.10. Overall Comparison of Existing and Proposed Systems

8.10 Discussion

The experimental results demonstrate that the proposed AI-Based Smart Warehouse Automation System significantly outperforms conventional PLC-based warehouse automation across all evaluated performance parameters. The integration of Artificial Intelligence, PLC controllers, Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, Warehouse Management System (WMS), Automated Guided Vehicles (AGVs), and predictive analytics enables intelligent real-time decision-making, adaptive resource allocation, and continuous operational optimization.

The AI-assisted conveyor optimization algorithm improved conveyor efficiency by approximately 10%, while reducing transportation delays and warehouse congestion. The Smart Energy Optimization Model achieved an 18.5% reduction in total energy consumption, demonstrating that AI-based dynamic equipment control can substantially improve warehouse sustainability. Similarly, the predictive maintenance framework increased fault prediction accuracy to over 98%, reducing unexpected equipment downtime and maintenance costs.

Inventory management also showed significant improvement through the integration of RFID technology, barcode systems, AI-based inventory optimization, and Digital Twin synchronization. Inventory accuracy reached 99.3%, minimizing stock discrepancies and improving warehouse visibility. Furthermore, the proposed Edge Computing architecture reduced communication latency to 29 ms, enabling near real-time synchronization among PLC controllers, IIoT devices, and warehouse equipment.

The Digital Twin platform-maintained synchronization accuracy exceeding 99%, providing reliable simulation and validation of warehouse operations before physical implementation. Comparative analysis confirmed that the proposed framework consistently achieved higher performance than existing PLC-based and conventional smart warehouse systems across all evaluated metrics.

Overall, the proposed intelligent warehouse automation framework demonstrates excellent scalability, robustness, reliability, and operational efficiency. The integration of Artificial Intelligence with PLC-based industrial automation establishes a comprehensive cyber-physical warehouse platform capable of supporting Industry 5.0 manufacturing, autonomous logistics, predictive maintenance, intelligent resource allocation, and sustainable warehouse operations.

CONCLUSION

The experimental results demonstrate that the proposed Artificial Intelligence (AI)-Based Smart Warehouse Automation System significantly outperforms conventional PLC-based warehouse automation across all evaluated performance parameters. The integration of Artificial Intelligence, Programmable Logic Controllers (PLCs), the Industrial Internet of Things (IIoT), Edge Computing, Digital Twin technology, the Warehouse Management System (WMS), Automated Guided Vehicles (AGVs), Autonomous Mobile Robots (AMRs), and predictive analytics enables intelligent real-time decision-making, adaptive resource allocation, and continuous operational optimization. The AI-assisted conveyor optimization algorithm improved conveyor efficiency by approximately 10%, while reducing transportation delays and warehouse congestion. The Smart Energy Optimization Model achieved an 18.5% reduction in total energy consumption, demonstrating that AI-based dynamic equipment control can substantially improve warehouse sustainability. Likewise, the predictive maintenance framework increased fault prediction accuracy to more than 98%, thereby reducing unexpected equipment downtime and maintenance costs. Inventory management also exhibited remarkable improvement through the integration of RFID technology, barcode systems, AI-based inventory optimization, and Digital Twin synchronization, achieving an inventory accuracy of 99.3%, minimizing stock discrepancies, and enhancing warehouse visibility. Furthermore, the proposed Edge Computing architecture reduced communication latency to 29 ms, enabling near real-time synchronization among PLC controllers, IIoT devices, and warehouse equipment. The Digital Twin platform-maintained synchronization accuracy exceeding 99%, providing reliable simulation and validation of warehouse operations before physical implementation. Comparative analysis further confirmed that the proposed framework consistently achieved superior performance compared with existing PLC-based and conventional smart warehouse systems across all evaluated metrics. Overall, the proposed intelligent warehouse automation framework demonstrates excellent scalability, robustness, reliability, and operational efficiency. The seamless integration of Artificial Intelligence with PLC-based industrial automation establishes a comprehensive cyber-physical warehouse platform capable of supporting Industry 5.0 manufacturing, autonomous logistics, predictive maintenance, intelligent resource allocation, sustainable warehouse operations, and future smart factory applications.

REFERENCES

- [1] A. Daios, A. Xanthopoulos, D. Folinas, and I. Kostavelis, "Towards automating stocktaking in warehouses: Challenges, trends, and reliable approaches," *Procedia Computer Science*, vol. 232, pp. 1437–1445, 2024, doi: 10.1016/j.procs.2024.01.142.
- [2] A. Ferrari, G. Zenezini, C. Rafele, and A. Carlin, "A roadmap towards an automated warehouse digital twin: Current implementations and future developments," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 1899–1905, 2022, doi: 10.1016/j.ifacol.2022.09.676.
- [3] M. M. Alam, A. N. U. Reimbaev, K. J. Tanha, and T. Jun, "AI-enhanced Digital Twin systems for warehouse logistics optimization: A review of challenges with solutions and future directions," *ICT Express*, vol. 12, no. 2, pp. 459–479, 2026, doi: 10.1016/j.icte.2026.01.009.
- [4] A. Krnjaic, R. D. Steleac, J. D. Thomas, G. Papoudakis, L. Schäfer, A. W. K. To, K.-H. Lao, M. Cubuktepe, M. Haley, P. Börsting, and S. V. Albrecht, "Scalable multi-agent reinforcement learning for warehouse logistics with robotic and human co-workers," *arXiv preprint arXiv:2212.11498*, 2022.
- [5] G. Dunn, H. Charkhgard, A. Eshragh, S. Mahmoudiazlou, and E. Stojanovski, "Deep reinforcement learning for picker routing problem in warehousing," *arXiv preprint arXiv:2402.03525*, 2024.
- [6] K. Li, L. Liu, J. Chen, D. Yu, X. Zhou, M. Li, C. Wang, and Z. Li, "Research on reinforcement learning based warehouse robot navigation algorithm in complex warehouse layout," in *Proc. 6th International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, 2024, pp. 296–301, doi: 10.1109/ICAICA63239.2024.10823054.
- [7] A. Drissi Elbouzidi, A. Ait El Cadi, R. Pellerin, S. Lamouri, E. Tobon Valencia, and M.-J. Bélanger, "The role of AI in warehouse digital twins: Literature review," *Applied Sciences*, vol. 13, no. 11, p. 6746, 2023, doi: 10.3390/app13116746.
- [8] S. S. Ali, J. A. Marmolejo-Saucedo, R. Landa Piedra, and G.-W. Weber, "Integrating Digital Twins into smart warehousing: A practice-based view framework for identifying and prioritizing critical success factors," *Logistics*, vol. 10, no. 4, p. 73, 2026, doi: 10.3390/logistics10040073.
- [9] M. G. Khan, N. U. Huda, and U. K. U. Zaman, "Smart warehouse management system: Architecture, real-time implementation and prototype design," *Machines*, vol. 10, no. 2, p. 150, 2022, doi: 10.3390/machines10020150.
- [10] A. Ferrari, A. Carlin, C. Rafele, and G. Zenezini, "A method for developing and validating simulation models for automated storage and retrieval system digital twins," *International Journal of Advanced Manufacturing Technology*, vol. 131, pp. 5369–5382, 2024, doi: 10.1007/s00170-023-12660-y.
- [11] K. Ellithy, M. Salah, I. S. Fahim, and R. Shalaby, "AGV and Industry 4.0 in warehouses: A comprehensive analysis of existing literature and an innovative framework for flexible automation," *International Journal of Advanced Manufacturing Technology*, vol. 134, pp. 15–38, 2024, doi: 10.1007/s00170-024-14127-0.
- [12] F. F. Rad, P. Oghazi, İ. Onur, and A. Kordestani, "Adoption of AI-based order picking in warehouse: Benefits, challenges, and critical success factors," *Review of Managerial Science*, vol. 19, pp. 3495–3540, 2025, doi: 10.1007/s11846-025-00858-1.
- [13] T. N. Quang, K. Matsuyama, K. Shimizu, H. Sugano, E. Kurimoto, M. Miki, J. Suzuki, Z. Chen, H. M. Waidyasooriya, M. Hariyama, M. Hitomi, K. Sawamura, and M. Ohzeki, "Quantum annealing-based route optimization for commercial AGV operating systems in large-scale logistics warehouses," *Scientific Reports*, vol. 15, p. 44047, 2025, doi: 10.1038/s41598-025-28481-w.
- [14] F. Han, L. Liu, and J. Sun, "Logistics equipment condition monitoring and prediction based on digital twin and machine learning," *Scientific Reports*, vol. 16, p. 12790, 2026, doi: 10.1038/s41598-026-43380-4.
- [15] J. Zhang, "Intelligent warehouse supply chain order picking optimization based on digital twin and genetic algorithm," *Discover Applied Sciences*, 2026, doi: 10.1007/s42452-026-08990-7.
- [16] L. Zhen and H. Li, "A literature review of smart warehouse operations management," *Frontiers of Engineering Management*, vol. 9, no. 1, pp. 31–55, 2022, doi: 10.1007/s42524-021-0178-9.
- [17] A. A. Tubis and J. Rohman, "Intelligent warehouse in Industry 4.0—Systematic literature review," *Sensors*, vol. 23, no. 8, p. 4105, 2023, doi: 10.3390/s23084105.