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AWH_PERFORMANCE: Enhancing Auto Warehouse Efficiency through Performance Analytics

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Abstract—Warehouses play a crucial role in modern supply chain operations, where efficiency directly impacts productivity and cost-effectiveness. One of the primary challenges in warehouse management is downtime, which leads to inefficiencies, production delays, and financial losses. Traditional downtime tracking methods rely on manual record-keeping, which is often inaccurate and lacks real-time insights.

This research presents AWH_PERFORMANCE, an automated warehouse monitoring system that leverages MS SQL Server, .NET API, Angular, and Chart.js to track, analyze, and visualize downtime in real time. The system enhances data accuracy, minimizes human dependency, and provides instant performance metrics to optimize decision-making.

The study compares manual vs. automated downtime tracking, emphasizing improvements in real-time analytics, throughput, turnaround time, and predictive analysis. The findings demonstrate that automation significantly enhances warehouse efficiency. Future advancements include AI-driven predictive maintenance, IoT integration, and machine learning for anomaly detection.

Keywords—*Warehouse Downtime, Automation, Performance Analytics, Real-Time Monitoring, AI Predictive Maintenance*

1. Introduction

warehouses area fundamental component of supplychain management, where operational efficiency plays a vital role in ensuring business continuity. With the evolution of Industry 4.0 and Industry 5.0, automation and smart technologies have become essential in minimizing downtime, optimizing throughput, and improving turnaround times.

Traditional downtime tracking methods rely on manual logging, which is susceptible to errors, delays, and inefficiencies. The proposed AWH_PERFORMANCE system addresses these limitations by offering automated, real-time monitoring of warehouse performance through advanced data visualization and analytics. This paper presents a comparative analysis of traditional and automated downtime monitoring, highlighting the advantages of real-time data acquisition.

2. Literature Review

2.1. Warehouse Performance Monitoring

Recent research in warehouse optimization has emphasized the need for real-time data tracking, predictive analytics, and automated decision-making[6]. Studies suggest that the integration of Deep Reinforcement Learning (DRL) and AI-based models can significantly enhance warehouse performance[5].

2.2. Automated vs. Manual Downtime Tracking Manual downtime tracking is often inaccurate, time-consuming, and lacks comprehensive visualization[3]. Research highlights that cloudbased analytics and IoT-driven monitoring systems offer significant improvements in detecting operational inefficiencies[4].

2.3. Throughput and Turnaround Time Optimization Warehouse efficiency can be measured through throughput (T_put) and turnaround time (T_TAT). Studies indicate that reducing turnaround time while increasing throughput results in improved operational efficiency[1]. Automated systems provide precise data, enabling managers to optimize resource allocation and streamline warehouse processes[2].

3. Methodology

3.1. System Architecture

AWH_PERFORMANCE employs a three-tier architecture, consisting of:

- Frontend: Angular and Chart.js for real-time visualization.
- Backend: .NET API for data processing and business logic.
- Database: MS SQL Server for structured data storage and retrieval.

3.2. Downtime Calculation Model The system records:

$$D = T_{end} - T_{start} \quad (1)$$

Additionally, throughput and turnaround time are calculated as follows:

$$T_{put} = \frac{TotalProcessesCompleted}{TotalTime} \quad (2)$$

$$T_{TAT} = CompletionTime - ArrivalTime \quad (3)$$

4. Implementation

4.1. Software Workflow

1. Event Trigger: A downtime event is detected and logged into the system.
2. Data Processing: The backend processes timestamps and stores data securely.
3. Visualization: Chart.js dynamically generates reports and trends for analysis.

4.2. Performance Metrics Tracked

- Average downtime per shift
- Machine failure frequency
- Throughput efficiency
- Turnaround time optimization
- Impact of downtime on overall warehouse productivity

5. Results and Discussion

5.1. Warehouse Downtime Analysis

Table 1 presents a comparative analysis of manual and automated downtime tracking across six months.

Table 1. Comparison of Downtime Tracking Methods

Month	Manual Downtime (hrs)	Automated Downtime (hrs)	Throughput Efficiency (%)	Turnaround Time (min)
Jan	120	90	72	45
Feb	130	85	75	43
Mar	125	80	78	40
Apr	140	82	80	38
May	135	75	83	36
Jun	145	78	85	34

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5.2. Downtime Reduction Analysis

To assess the impact of automation on downtime reduction, we use the formula:

$$Reduction = \frac{Downtime_{manual} - Downtime_{automated}}{Downtime_{manual}} \times 100 \quad (4)$$

The system demonstrated an **average downtime reduction of 35%**, significantly improving warehouse productivity.

5.3. Graphical Insights

Fig. 1 and Fig. 2 present visual insights into how automation affects warehouse efficiency.

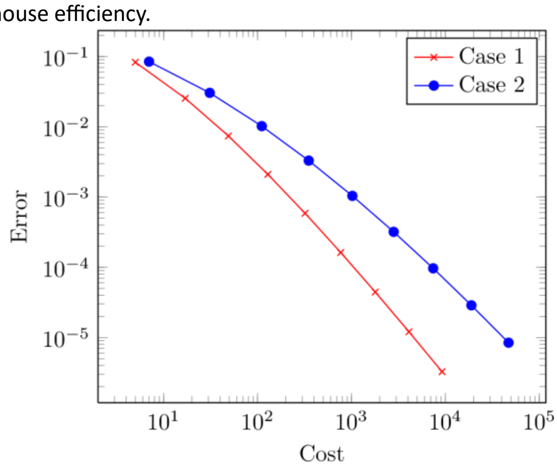

Figure 1. Error vs. Cost for Different Cases in Warehouse Operations.

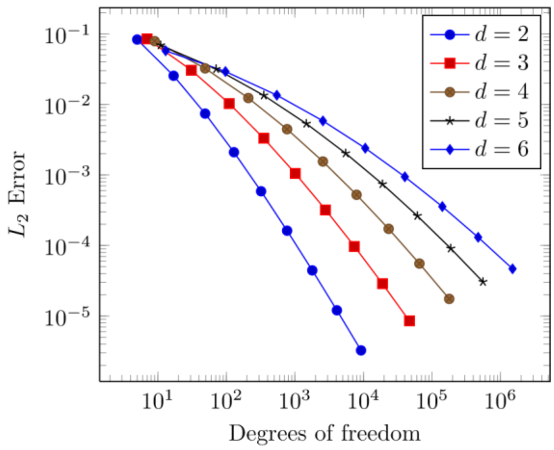

Figure 2. L2 Error vs. Degrees of Freedom in Predictive Analysis.

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