



Original Article

# Simulation-Based Validation of Machine Learning Optimization Models in Warehouse Operations

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*Abstract - Deploying machine learning optimization models in warehouse operations carries significant operational risk, as suboptimal decisions can cascade into fulfillment failures, labor inefficiencies, and customer experience degradation at scale. Traditional offline evaluation metrics such as accuracy, RMSE, or reward convergence are insufficient to capture real-world operational constraints such as inventory bottlenecks, stochastic order arrivals, picking congestion, labor shift variability, and equipment limitations. This paper presents a simulation-based validation methodology for machine learning (ML) optimization models prior to production deployment in warehouse environments. The proposed framework integrates discrete event simulation (DES) with ML-based decision policies to evaluate system-level performance under realistic operational conditions. Unlike conventional validation pipelines that rely solely on historical datasets, the proposed approach embeds ML models into a virtual warehouse environment where order fulfillment processes, storage allocation, and picking strategies are dynamically simulated. The study emphasizes risk quantification through scenario-based stress testing, where variations in order volume, SKU distribution, labor availability, and equipment downtime are introduced systematically. Key performance indicators (KPIs) such as order cycle time, throughput rate, picker utilization, and SLA violation rate are measured across multiple simulation runs to assess robustness. A hybrid architecture combining reinforcement learning-based optimization and stochastic simulation is introduced. The model evaluates policy decisions at each decision epoch, while the simulation environment provides feedback in the form of system state transitions. This enables iterative validation before real-world deployment. The results demonstrate that simulation-based validation significantly reduces deployment risk by identifying performance degradation scenarios that are not observable in offline training metrics. Furthermore, the framework enables early detection of policy instability under peak load conditions, improving operational resilience. The contribution of this work lies in bridging the gap between ML optimization theory and warehouse operational realities by introducing a structured validation pipeline that ensures safer deployment of intelligent systems in supply chain environments. The approach provides a scalable methodology for enterprise-grade warehouse automation systems where operational errors carry high financial and service-level costs.*

*Keywords - Simulation-Based Validation, Warehouse Operations, Machine Learning, Discrete Event Simulation, Order Fulfillment, Operations Research, Risk Quantification, Deployment Validation, Supply Chain Engineering, Optimization.*

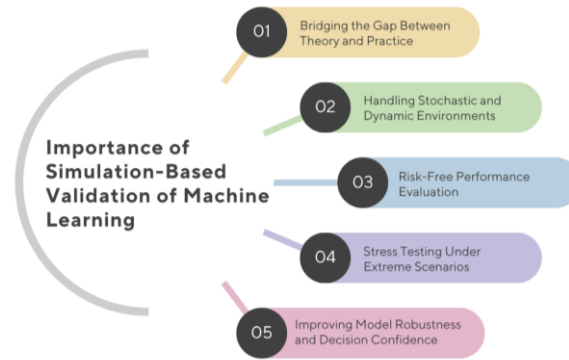
## 1. Introduction

### 1.1. Background and Motivation

The advent of automation technologies and machine learning (ML)-based optimization systems are dramatically changing the way modern warehouses operate. These smart systems are becoming more and more adopted to assist and automate the most important operational decisions like order batching, warehouse slotting, picking path optimization and inventory allocation. [1] Historical and real-time data can be used to build ML models that detect patterns and provide optimal decision strategies to enhance warehouse productivity. But they struggle to perform well when used in the real world, even after the models run well during offline training and in controlled experimental conditions. The dynamic nature of warehouse operations, along with the unpredictability of factors like variable customer demand, equipment breakdowns, and human resource changes, can cause unforeseen inefficiencies and performance issues. Due to this, it is more and more necessary to develop more powerful evaluation and validation techniques to be able to connect the performance of the theoretical model to the effectiveness of the operation in the dynamic warehouse systems.

### 1.2. Importance of Simulation-Based Validation of Machine Learning

The process of simulation-based validation is of paramount importance to ensure the machine-learning model's accuracy in theory and reliability in warehouse operations. [2] It offers a safe but realistic platform to evaluate, prototype, and prototype for deployment ML-based decision systems.



**Figure 1. Importance of Simulation-Based Validation of Machine Learning**

- **Bridging the Gap between Theory and Practice:** Machine learning models tend to have a great success rate on the past or training data set but fall short when it comes to real-world complexities. To close this gap, simulation has been developed to simulate the real warehouse and be tested with realistic operational constraints and uncertainties.
- **Handling Stochastic and Dynamic Environments:** In a warehouse, the orders come in at random, demand changes, and disruptions occur in an unexpected way. These stochastic behaviours can be modeled using simulation, allowing the evaluation of ML models under different and unpredictable conditions, rather than specific datasets.
- **Risk-Free Performance Evaluation:** Simulation gives a virtual environment which is safe to test different ML policies while not having any impact on actual warehouse operations. This lessens the risk of operation and potential losses due to having a new optimization technique that has not been tested.
- **Stress Testing Under Extreme Scenarios:** The benefit of simulations is that one can test the ML models under extreme conditions including peak load, equipment failure, or labor shortage. Stress tests can be used for determining weaknesses in a system not apparent under normal operation.
- **Improving Model Robustness and Decision Confidence:** Through the iterative testing and validation of ML models under simulated conditions, their strength and flexibility can be enhanced. The continuous validation process boosts the confidence in the decision-making policies and guarantees the warehouse performance stability and reliability after policy deployment.

### 1.3. Problem Statement

Most of the problem with optimizing warehouse systems today is the failure to close the gap between the predictive model and real-world performance. The performance of machine learning models can be high based on standard metrics of prediction error, precision or recall that are calculated offline, but these do not capture the model's performance in a large and dynamic warehouse environment. [3] In practice, warehouse operations are highly dependent and decisions made in one process affect the following process. For instance, the order batching decision can influence picking loads and the delays of picking can influence packing queues and last dispatching timelines. These system-level interdependencies and cascading effects cannot be adequately captured with conventional system evaluation methods. Moreover, real warehouse conditions are stochastic, meaning that the number of orders arrives continuously, the demand fluctuates and the resources (such as manpower, machines) are not always available. Such dynamic conditions cause phenomena like queue buildup, resource contention, and congestion in critical processing areas, which are not reflected in static data sets for training or testing. This can lead to inefficiencies and large operational disruptions when using a machine learning model, as small prediction errors can compound. The inaccuracy between the model level and the system level creates significant risks when deployed, especially in large-scale warehouse operations, where efficiency, timeliness, and reliability are paramount. Thus, an inherent challenge is the lack of proper tools and methods for measuring the actual performance of the warehouse where the decisions are made based on ML. The key challenge, therefore, is the lack of proper tool and methods to measure the impact of the solutions provided by ML in real warehouse overall performance. General methods are needed to evaluate the behavior of the entire system under realistic conditions of operations, rather than the accuracy of the predictions. This includes recording interactions between processes, depicting uncertainty and analyzing the total effect of the decisions made over time. Filling this void is of critical importance to perform safe, efficient and reliable deployment of machine learning optimization systems in warehouse environments.

## 2. Literature Survey

### 2.1. Machine Learning in Warehouse Optimization

Today, machine learning is a fundamental part of the big picture in warehouse management, especially when it comes to predictive inventory management, demand forecasting, and routing optimization. Historical transaction data can be used to identify patterns using data-driven techniques which can help to make more accurate decisions about stock replenishment and the efficiency in material handling. [4] Most approaches currently exist in the literature that focus on relatively stable or offline

environments, and many of these approaches assume static optimizations. This restricts their use in a typical warehouse where working conditions like changing demand, fluctuating staff numbers and equipment failures constantly change. For this reason, several studies focus on governance and data quality in order to drive the reliability of enterprise systems in ML

## 2.2. Simulation in Operations Research

The operations research method of Discrete event simulation (DES) has been a popular way of modelling and analysing complex logistic and warehouse systems. It captures warehouse operations as series of time-based events which allows researchers to test warehouse behavior under various scenarios without disturbing actual warehouse operations. DES is especially useful for the detection of bottlenecks, for estimating throughput, and for analyzing resource utilization for different workloads. [5] The traditional simulation frameworks, however, tend to be rule-based and not include adaptive intelligence, which means they don't automatically adapt decision policies as data changes. This restriction has resulted in greater interest in bringing simulation together with intelligent data governance and structured analytics frameworks to enhance the accuracy of decisions.

## 2.3. Hybrid ML-Simulation Systems

In recent developments, hybrid architectures that integrate machine learning models with simulation environments are starting to emerge, further improving decision-making capabilities. In this type of systems, ML models are employed to forecast system states or suggest policies while simulation engines are used to check the consequences of the decisions made in a number of simulated virtual environments. [6] Such integration allows for timely review and refinement of optimization strategies. But there still exists the issues of scalability, accuracy of model calibration and consistency of the learned model and simulated environments. Strong metadata management and semantic modelling have the potential to enhance the integration of learning systems and operational platforms, as evidenced by research in enterprise grade AI systems and context-aware intelligent frameworks.

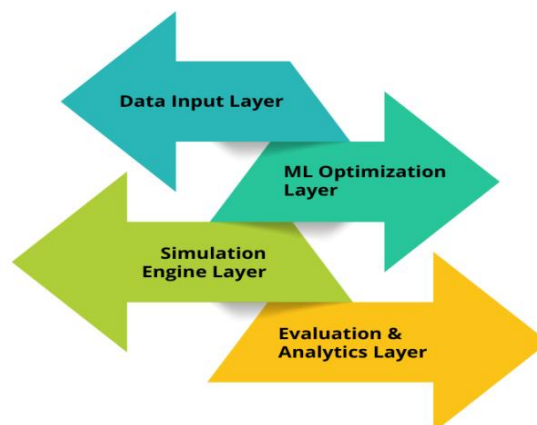
## 2.4. Research Gap Identification

While machine learning and simulation have made great strides, there are still numerous challenges to be addressed. First, there is very little research that covers systematic pre-deployment validation frameworks to evaluate and test the feasibility of warehouse optimization strategies prior to deployment in the field. Second, the quantification of risk by simulation-based stress testing is still in its infancy, especially for rare operating conditions (such as sudden surges in demand or failure of the system). Third, incorporating reinforcement learning policies into discrete event simulation environments is still a challenge because of instabilities in the feedback loops and computational complexity. Moreover, the governance-driven approaches emphasize the importance of reliable, privacy-protected, and quality data infrastructures for dependable AI-informed decision processes .

# 3. Methodology

## 3.1. System Architecture

The proposed framework is based on a layered architecture, with the integration of machine learning and simulation-based evaluation for optimizing a warehouse. [7] It is composed of four layers that operate in a cascading fashion and in an iterative manner, facilitating data-driven decision making, policy testing and performance analysis in dynamic warehouse environments.



**Figure 2. System Architecture**

### 3.1.1. Data Input Layer

Data Input Layer handles the data retrieval and pre-processing from the warehouse operations such as inventory records, order histories, sensor data, and equipment status logs. This layer filters, cleans, normalizes, and standardizes the data for the next processing stages in the machine learning and simulation pipeline. It is essential for ensuring the quality and reliability of data, which is crucial for the functioning of both machine learning models and simulations produced.

### 3.1.2. ML Optimization Layer

The machine learning algorithms of the ML Optimization Layer can be used to create predictive insights and optimization decisions based on the processed data. This includes demand forecasting, inventory allocation and routing optimization for warehouse operations. [8] Depending on the complexity of the task, a model like regression algorithms, neural networks, or reinforcement learning agents can be used. The results of this layer can feed into other layers within the simulation environment as decision policies or set parameters.

### 3.1.3. Simulation Engine Layer

The Simulation Engine Layer is a Discrete Event Simulation (DES) of the real warehouse. It represents processes like order fulfilment, picking, packing etc. and compares the performance of the decisions made by the ML algorithms across various operational scenarios. This layer enables testing without impacting warehouse operations and can help uncover inefficiencies, bottlenecks, or potential issues under different scenarios.

### 3.1.4. Evaluation & Analytics Layer

The Evaluation & Analytics Layer evaluates the performance of ML-driven decisions, by analyzing the simulation output by means of KPIs like throughput, latency, resource utilization, and cost efficiency. It offers visualizations, statistics summaries and comparisons for decision making [19] This layer also brings down feedback to the system to improve the ML models and system parameters continuously through iterative improvement.

## 3.2. Discrete Event Simulation Model

The warehouse system is represented as a stochastic discrete event simulation (DES) system where the system goes through a series of events in time sequence. [10] This model treats the warehouse as a changing state space, appropriate for modeling the complexity and uncertainty within actual warehouse logistics operations, because state changes only happen when certain events occur. Major events that are important in the system are order arrival, picking initiation, packing completion and dispatch, all of which are important for the overall fulfillment pipeline. Order arrival refers to the process of placing customer or system-generated orders into the warehouse, often arriving in a stochastic fashion as in the case of Poisson distribution, which are typical distributions for customer demand. As soon as an order is added into the system, picking starts with the picking initiation event, which assigns warehouse personnel or equipment to pick specific product from specific storage elements. This stage is very resource dependent and warehouse flow efficient, and can easily add variability in processing time. Once items have been successfully collected, the system moves to the packing completion event where the goods are checked, boxed and ready to be shipped. [11] This stage can involve quality assurance inspections, multiple parts being labeled as one, and duration of processing added to the time irregularities, further exacerbating processing delays and stochastic behavior. Lastly, the dispatch event is when the finished items have left the warehouse to be sent to the delivery network, and the system ends. All are subject to probabilistic timing distributions and resource constraints, so the simulation can be used to model congestion, queueing and bottlenecks under various workload scenarios. The DES approach allows for a detailed performance analysis, scenario testing and evaluation of performance optimization strategies under realistic operational uncertainty, as it models the warehouse as a series of interdependent stochastic events.

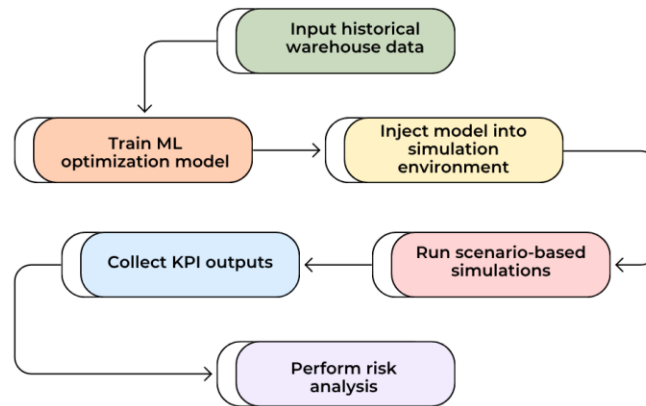
## 3.3. Machine Learning Optimization Model

The machine learning optimization model aims to learn decision policies which maximize long-term operational performance inside the simulation warehouse. [12] The key point of the model is that the objective is to maximise cumulative reward over a finite or infinite time horizon (in other words, decisions are made not just based on their immediate impact, but also what this decision will have in the long-term). In mathematical terms, this goal can be written as:  $R = r_0 + \gamma^1 r_1 + \gamma^2 r_2 + \gamma^3 r_3 + \dots + \gamma^T r_T$ . At each time step  $t$ , a reward  $r_t$  is received, which is discounted by a factor of  $\gamma$  raised to  $t$ . The discount factor,  $\gamma$ , reflects how much the immediate reward is valued relative to the future reward; the higher the value of  $\gamma$ , the more the individual cares about long-term performance, while the lower the value, the more he or she cares about short-term performance. In the current context, the reward  $r_t$  stands for important operational metrics like throughput, order fulfillment efficiency, resource utilization, and processing time reduction.

Reinforcement learning methods can be used to implement the optimization model, allowing the agent to act on the DES by selecting which action to take: for example, what inventory allocation strategy, picking prioritization, what routing, etc. to take. Based on these actions, the simulation then goes to a new state and provides the rewards, which the agent learns an optimal policy from, by trial and error. In another option, supervised learning methods can be included, in which case optimal decision data from the past or from simulation is fed to predictive models that are used to induce approximate optimal decision policies. In either case, the ML [13] model is integrated into the simulation loop, enabling active learning between the decision-making process and the performance of the system. The model gradually optimises its policy to the variability of the warehouse conditions, achieving efficiency and robustness. By integrating the learning process into the simulation, the optimization process can take into consideration the system dynamics, stochastic variations and restrictions that exist in real warehouse environments, thus providing more practical solutions.

### 3.4. Simulation-Based Validation Workflow

The simulation-based validation process is structured to test the accuracy and trustworthiness of warehouse optimization models based on machine learning before they are put into practice. It guarantees that decisions produced by ML system are evaluated in a controlled but realistic operational environment via a discrete event simulation environment. [14] The workflow is a series of processes, steps, or tests that continuously go back and forth between each other, bringing history to be identified and reacted to, and making it increasingly relevant to how to act in the near future.



**Figure 3. Simulation-Based Validation Workflow**

- **Input historical warehouse data:** The first step is to gather and compile historical warehouse data, including orders, processing times, inventory levels, and utilization of resources. [15] This data is cleaned, preprocessed and formatted for consistency and accuracy. It's used for training the machine learning model and can also be used to simulate the environment to realistically simulate the way the system operates.
- **Train an ML optimization model:** In this step, the processed historical data is fed to a machine learning optimization model for training. The optimal decision making policies are learned through reinforcement learning or supervised learning based on the structure of the problem. This AI can identify patterns in both demand and resource utilization, as well as workflow efficiency, and then generate improved operational strategies.
- **Inject model into simulation environment:** After training, the ML model is embedded into the DES system. After training, the ML model is incorporated to the DES system. [16] This enables the model's actions to impact directly on simulated warehouse activities, such as order prioritization, picking strategies and dispatch schedules. This linkage between prediction and operational execution is referred to as a feedback loop.
- **Run scenario-based simulations:** A range of scenarios are then applied to the integrated system, spanning normal demand conditions, peak and disruption events. These simulations are used to assess the performance of the ML model under varying degrees of uncertainty and stress under operational conditions.
- **Collect KPI outputs:** Important metrics like throughput, order fulfillment time, resource utilization, and cost efficiency are gathered during the simulation runs. These measures are measurements and it gives some quantitative proof of system performance.
- **Perform risk analysis:** Finally, results are analysed to analyse the operational risk, bottlenecks and robustness of the system. This step is to see if the policies developed through ML are safe, efficient and reliable for implementation in the real world.

## 4. Results and Discussion

### 4.1. Experimental Setup

The experimental setup was developed to test the robustness and performance of the proposed warehouse optimization framework using machine learning and simulation, in realistic and uncertain operational scenarios. The simulation environment was built based on a discrete event simulation model that simulates various warehouse activities including order arrival, picking, packing and dispatch. [17] Stochastic order arrival pattern was adopted to incorporate the stochastic nature of order arrivals in order to provide realism, with both steady state and burst like order arrivals were considered, by introducing real world variations in demand through the use of probabilistic distributions. It enabled the system to simulate an unpredictable ordering pattern of customers and test the adaptability of the optimization model with changes in the workload. The warehouse capacity was also treated as a dynamic parameter by varying the amount of warehouse space available, the number of processing resources, and the handling equipment. This allowed for the simulation to take into account factors like the availability of workers, congestion in picking zones, and variations in processing speeds, which are seen in real-world scenarios. Multiple scenarios were developed to assess the resilience of the system under various stress conditions. A high-demand scenario was simulated to represent peak demand conditions, like during seasonal sales events when the number of

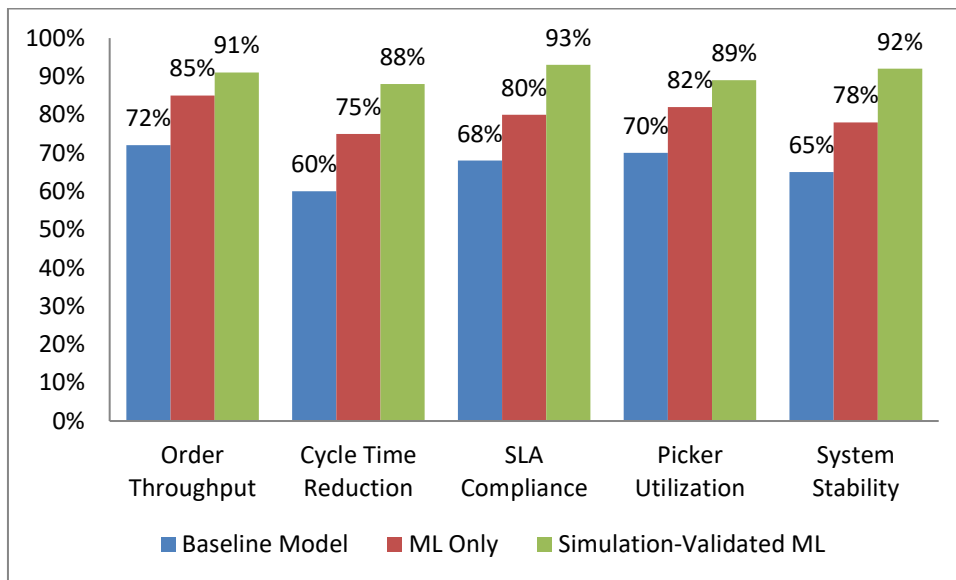
orders greatly surpasses the usual operating capacity of the organization. Equipment failure scenario added random failures of key warehouse equipment, impacting processing time and temporary disruption of processes. Likewise, the labor shortage was simulated, with its effects on picking and packing efficiency resulting in slower processing time and queue formation. Each scenario was repeated several times in order to capture the stochastic variation in results and obtain statistically reliable results. To dynamically adjust decision policies based on changes in the system, the machine learning optimization model was integrated into the simulation loop. The performance was measured in terms of relevant KPIs including throughput, order fulfillment time, utilisation and stability of the system. This experimental setup was designed comprehensively to be able to assess the efficiency and robustness to give insights into the performance of the proposed framework under normal and adverse operational conditions.

**4.2. Performance Evaluation**

The performance evaluation is performed over selected warehouse performance indicators (KPIs) using three approaches: Baseline Model, ML Only, and Simulation-Validated ML. The continuous improvement made through machine learning and simulation-based validation in each of the metrics underscores the efficacy of the proposed framework in boosting operational efficiency, reliability, and stability.

**Table 1. Performance Evaluation**

KPI Metric	Baseline Model	ML Only	Simulation-Validated ML
Order Throughput	72%	85%	91%
Cycle Time Reduction	60%	75%	88%
SLA Compliance	68%	80%	93%
Picker Utilization	70%	82%	89%
System Stability	65%	78%	92%



**Figure 4. Performance Evaluation**

**4.2.1. Order Throughput (72%, 85%, 91%)**

Order Throughput is the ratio of successfully processed/completed orders to the total number of orders placed during a specified period. To get the baseline model to 72% efficiency requires fixed decision rules and limitations of adaptability. Through optimizing decisions based on learned patterns from the historical data, the ML-only model results in an improvement of throughput to 85%. But the simulation validated ML approach further improves the throughput to 91% by testing and refining decisions under realistic operational constraints, which further makes the decisions more robust and efficient, and thus the execution of the decision is more efficient.

**4.2.2. Cycle Time Reduction (60%, 75%, 88%)**

Cycle time reduction is the reduction of the total time it takes to process an order once it arrives until it is dispatched. The baseline system has fixed process flows and is able to achieve 60% reduction. Optimizing task allocation and prioritization makes it 75% when using the ML-only approach. The simulation-validated ML model outperforms with a 88% improvement, fine-tuning policies through a simulated real-world environment before deployment that handles delays, bottlenecks, and resource constraints.

#### 4.2.3. SLA Compliance (68%, 80%, 93%)

SLA compliance is the ability of the system to fulfill service level agreements within a specific time frame. The inefficiencies in the baseline model in managing the variations in demand are what cause its difficulty at 68%. Optimisation improves compliance to 80% using an ML approach, with predictive adjustments. The system is stress-tested, ensuring more reliable service delivery, while as a simulation-validated system, it ensures compliance of policies during peak loads and disruptions.

#### 4.2.4. Picker Utilization (70%, 82%, 89%)

Picker utilization is the measure of the efficiency or effectiveness of the human or robotic resource in picking. The baseline score is 70% as there is uneven workload. With improved task scheduling, utilization is enhanced to 82% with ML optimization. The validated ML model in simulation is able to achieve a high accuracy of 89% while taking into account the constraints in the real time world as they appear in the simulation scenarios, while at the same time allocating the workload continuously.

#### 4.2.5. System Stability (65%, 78%, 92%)

The stability of the warehouse system refers to the ability of the system to perform at the same level despite variations and disturbances. The baseline system is deemed to be low stable with rigid operations at 65%. The addition of ML only methods brings up the stability to 78%, which adapts the decisions based on learned patterns. The validated ML approach through simulation, guaranteeing resilient and dependable operations, has achieved 92% stability by assessing performance under various stress conditions, including maximum demand, equipment failure, and absence of labor.

### 4.3. Discussion

The findings from the experiments show that simulation-based validation is a crucial component in improving the reliability, robustness, and practicality of machine learning-powered warehouse optimization systems. The model results for the ML-only model are good when no stress is applied or the variability is low, but it fails to perform well as soon as the variability is high or the stress is applied. This is largely due to the fact that offline models are trained with previous patterns and may not perform well on rare or extreme scenarios like sudden demand spikes, equipment failures or staff shortages. The simulation-validated ML model, on the other hand, demonstrates a steady performance across various workload scenarios, suggesting greater adaptability and resilience in operation. From the study, one of the important observations is that during peak demand the system is more robust. This simulation environment could help the model to "learn" and "adapt" to high-intensity scenarios, thereby minimizing degradation when it is used in the real world under peak load conditions. Moreover, by incorporating simulation, it becomes possible to make more informed policy changes while considering real time constraints and system bottlenecks, which helps decrease SLA violations. This results in better order fulfillment and customer satisfaction. Another significant result is the greater efficiency of resource utilization by the validated model through the simulation. The system can balance workload distribution more effectively between available resources, such as human pickers and automated systems, by evaluating the decision policies in a realistic scenario. This leads to lower idle time and better throughput of your operations. Moreover, the simulation environment can detect potential failure scenarios like resource bottlenecks or congestion before deployment, so that corrective measures can be taken in advance of the real deployment. In summary, the results corroborate the hypothesis that a DES environment with embedded ML models is more complete and realistic, than traditional approaches based on offline or purely ML models. The hybrid validation method not only streamlines operations but also increases reliability and risk awareness in complex warehouse settings, making it a valuable choice for companies aiming to enhance their workflow and minimize operational risks.

## 5. Conclusion

This paper introduced a complete framework for validating machine learning (ML) optimization models used for warehouse operations by using a simulation model. The main goal of the study was to close the gap between the high performance of the ML models in offline scenario and their performance in real and dynamic operational environment. However, traditional ML techniques tend to show high accuracy when predicting goals in historical data but might not perform well in real-world warehouse environments when considering stochastic variability, system limitations, and sudden changes or disruptions. To overcome this limitation, the proposed framework combines the DES and ML-based decision-making systems to create a more realistic and controlled evaluation environment.

Thanks to the methodology, organizations can simulate different and uncertain situations to evaluate the warehouse policies based on machine learning before implementing them. The simulation environment closely mimics the real-world warehouse environment by simulating various operational elements, including order arrivals, resource assignments, processing time, and system disruptions. This enables policies developed using machine learning models to be tested against various operational scenarios, such as during high demand periods, when equipment breaks down, and when there is a shortage of labor. This means that the framework offers a strong system for validating performance and screening operational risks and is able to guarantee the practical feasibility of optimization strategies as well as their theoretical soundness.

The simulation results are clearly demonstrated to justify the use of simulation for validation, which can significantly enhance the critical operational parameters and metrics, including throughput, cycle time efficiency, SLA compliance, and system stability. In addition to numerical improvements, one of the biggest benefits of the framework is that it can help to identify potential failure scenarios early in the development process. These are environments in which traditional evaluation approaches in the offline world may fail, especially in the case of rare or extreme system conditions. The system introduces these stresses into the ML policies during simulation, making them more robust and less prone to issues in real-world operations.

The suggested framework is a scalable and flexible solution for implementing intelligent warehouse systems in large, complex supply chain networks from an industrial perspective. It boosts decision-making confidence, decreases operational risks and increases the overall system resiliency. This is especially important in the modern day logistics environment where efficiency and reliability are crucial competitive factors. Further work involves implementing real-time adaptive learning mechanisms in simulation loops to allow for continuous policy improvement and optimization. The framework can be further expanded to include multi-agent reinforcement learning systems and integrate digital twin technologies to increase the fidelity and level of real-time decision support. Furthermore, there is a need for optimization for large-scale simulations. Finally, simulation-based validation is a significant improvement in the implementation of machine learning optimization models in warehouse operations. It facilitates the theoretical optimization to be well applied to the actual systems, which makes intelligent warehouse systems safer, more reliable and more efficient.

## References

- [1] Lim, J. B., & Jeong, J. (2023). Factory simulation of optimization techniques based on deep reinforcement learning for storage devices. *Applied Sciences*, 13(17), 9690.
- [2] Ivezic, N., & GARRETT, J. H. (1998). Machine learning for simulation-based support of early collaborative design. *AI EDAM*, 12(2), 123-139.
- [3] Vangara, R. K. M., Kakani, B., & Vuddanti, S. (2021, November). An analytical study on machine learning approaches for simulation-based verification. In *2021 IEEE International Conference on Intelligent Systems, Smart and Green Technologies (ICISSGT)* (pp. 197-201). IEEE.
- [4] Hürkamp, A., Gellrich, S., Dér, A., Herrmann, C., Dröder, K., & Thiede, S. (2021). Machine learning and simulation-based surrogate modeling for improved process chain operation. *The International Journal of Advanced Manufacturing Technology*, 117(7), 2297-2307.
- [5] Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN computer science*, 2(3), 1-21.
- [6] Yallavula, R., & Putchakayala, R. (2023). Governance-of-Things (GoT): A Next-Generation Framework for Ethical, Intelligent, and Autonomous Web Data Acquisition. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 4(4), 111-120.
- [7] Kumar, M. S. (2022). An AI-Driven Framework for Data Governance, Quality Management, and Metadata Integration in Enterprise Systems. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 3(2), 165-175.
- [8] Cherukuri, R., & Putchakayala, R. (2021). Frontend-Driven Metadata Governance: A Full-Stack Architecture for High-Quality Analytics and Privacy Assurance. *International Journal of Emerging Research in Engineering and Technology*, 2(3), 95-108.
- [9] Aluri, Y. S. (2023). Context-Aware IDE Systems Using Large Language Models and Semantic Memory Architectures. *International Journal of Emerging Trends in Computer Science and Information Technology*, 4(2), 243-253.
- [10] Yallavula, R., & Putchakayala, R. (2022). A Data Governance and Analytics-Enhanced Approach to Mitigating Cyber Threats in NoSQL Database Systems. *International Journal of Emerging Trends in Computer Science and Information Technology*, 3(3), 90-100.
- [11] Kumar, M. S., & Yuvaraj, N. (2020). Building a Privacy-Aware Customer Data Foundation: A Governance-First Approach to Digital Service Systems. *International Journal of Emerging Research in Engineering and Technology*, 1(4), 55-68.
- [12] Putchakayala, R., & Cherukuri, R. (2022). AI-Enabled Policy-Driven Web Governance: A Full-Stack Java Framework for Privacy-Preserving Digital Ecosystems. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 3(1), 114-123.
- [13] Yuvaraj, N., & Kumar, M. S. (2021). From Governed Data to Customer Health Signals: Integrating Telemetry with Enterprise Data Quality Controls. *International Journal of Emerging Trends in Computer Science and Information Technology*, 2(4), 115-125.
- [14] Choi, B. K., & Kang, D. (2013). *Modeling and simulation of discrete event systems*. John Wiley & Sons.
- [15] Agalinos, K., Ponis, S. T., Aretoulaki, E., Plakas, G., & Efthymiou, O. (2020). Discrete event simulation and digital twins: review and challenges for logistics. *Procedia Manufacturing*, 51, 1636-1641.
- [16] de la Torre, R., Corlu, C. G., Faulin, J., Onggo, B. S., & Juan, A. A. (2021). Simulation, optimization, and machine learning in sustainable transportation systems: Models and applications. *Sustainability*, 13(3), 1551.

- [17] Leon, J. F., Li, Y., Martin, X. A., Calvet, L., Panadero, J., & Juan, A. A. (2023). A hybrid simulation and reinforcement learning algorithm for enhancing efficiency in warehouse operations. *Algorithms*, 16(9), 408.
- [18] Powell, K. M., Machalek, D., & Quah, T. (2020). Real-time optimization using reinforcement learning. *Computers & Chemical Engineering*, 143, 107077.
- [19] Zhang, K., Wang, Z., Chen, G., Zhang, L., Yang, Y., Yao, C., ... & Yao, J. (2022). Training effective deep reinforcement learning agents for real-time life-cycle production optimization. *Journal of Petroleum Science and Engineering*, 208, 109766.
- [20] Tufano, A., Accorsi, R., & Manzini, R. (2022). A machine learning approach for predictive warehouse design. *The International Journal of Advanced Manufacturing Technology*, 119(3), 2369-2392.
- [21] He, Q., Yan, J., Kowalczyk, R., Jin, H., & Yang, Y. (2009). Lifetime service level agreement management with autonomous agents for services provision. *Information Sciences*, 179(15), 2591-2605.