Discrete Event Simulation of Warehouse Operations

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1 Problem Statement

The objective of this project is to simulate a warehouse order picking system using Discrete Event Simulation in AnyLogic. We aim to model the arrival of customer orders, grouping of these orders into picking waves, assignment of pickers and placers, and the processing of these orders within the warehouse. The goal is to analyze performance metrics such as picker utilization, placer utilization, and order cycle time to identify operational bottlenecks and improve efficiency.

2 Input Data Analysis

The simulation uses two key datasets:

- **Customer_Order.csv:** Contains order ID, SKU (Reference), quantity, timestamp for order creation, and other attributes like customer code and operator.
- **Storage_Location.csv:** Maps each SKU to specific (x, y) coordinates in the warehouse, used for reference in modeling.

Key Observations

- Each order contains multiple SKUs (typically 1–33 items per order, based on the number of references per order number), with a variable distribution.
- Order volumes show a significant spike at 7 AM, likely due to batch order uploads, with steady activity from 10 AM to 4 PM and minimal activity outside these hours.
- Weekly seasonality is evident, with peak activity on Wednesdays and Thursdays, sparse activity on Sundays, and no activity on Saturdays (warehouse closed).
- SKU locations, as referenced from the storage location dataset, vary significantly in space, inspiring variable travel distances in the model.

Preprocessing

- Converted `creationDate` in `Customer_Order.csv` to datetime format for temporal analysis.
- Extracted date, weekday, and hour from `creationDate` to analyze order volume patterns by day and hour.
- Merged customer and SKU data to compute total items per order based on `Reference` and `quantity`.

These analyses informed system design, including picker allocation and travel time logic. The storage location dataset was used solely for inspiration in modeling the warehouse layout and travel dynamics, with no direct operations performed on it.

Order Volume Analysis

The distribution of order volumes over time is crucial for understanding warehouse activity. This analysis helps identify peaks in demand and patterns for order arrival, which are essential for capacity planning and resource allocation. The order volume count over the course of the year is depicted in Appendix 1.

Top 3 Most Frequent Products

Based on the customer order data for June 2023, the top 3 most frequently ordered products have been identified. The following table presents the product reference, order count, and product rank.

Product Reference	Order Count	Rank
PY5UPB	1144	1
8N10W9	925	2
WRRW1W	551	3

Table 1: Top 3 Most Frequent Products (June 2023)

Arrival Rate Calculation

Assuming a Poisson process for each product, we calculated the order arrival rates using the method outlined in the paper "A Single Period Inventory Model with Discrete and Poisson Demand" by Arpita Nimesh Shah (*International Journal of Scientific Research*, 2013). The arrival rate is computed as the number of orders for each product in June, divided by the total time.

The arrival rate λ for each product is given by:

$$\lambda = \frac{\text{Total Orders for the Product in June}}{\text{Total time in June}}$$

We attempted to fit inter-arrival times to distributions (e.g., exponential, gamma, Weibull, lognormal) using Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests, but results indicated poor fits (p-values ¡ 0.05). Nevertheless, based on the research paper, we assumed a Poisson process for order arrivals, which informed the calculation of arrival rates.

For each of the top 3 products, the average hourly arrival rates (averaged across weekdays) for June 2023 are presented below:

Product Reference	**Order Arrival Rate (orders/time)**
PY5UPB	2265.73
8N10W9	2802.16
WRRW1W	4704.17

Table 2: Order Arrival Rates for Top 3 Products (June 2023)

These arrival rates will be used in the simulation to model the demand for each product over time, accounting for the Poisson process assumption and time-varying patterns.

3 Modeling

The simulation is implemented in AnyLogic 8.9.4 using Discrete Event Simulation. It consists of the following logic:

1. Orders arrive as discrete events based on the customer order dataset, with specific SKUs (e.g., PY5UPB, 8N10W9, WRRW1W) entering the system from a source.

2. A check strategy block evaluates the picking approach (e.g., batch or individual picking) based on predefined rules.

3. Orders are grouped into batches of up to 3 using a batch queue and enterBatch process, optimizing picker efficiency.

4. Available pickers are seized to process the orders, with each picker interacting with warehouse racks to retrieve items, modeled by a picking delay representing travel and retrieval time.

5. After picking, pickers are released, and orders proceed to the exit point where they are completed and removed from the system via a sink.

6. The simulation tracks the flow of orders, ensuring discrete events trigger state changes (e.g., picker allocation, order completion).

See Appendix 2 for the AnyLogic simulation block diagram.

Model Features

- **Entities:** Orders, representing customer requests with specific SKUs and quantities.
- **Events:** Order arrivals, start of picking, completion of picking, and order exit.
- **Resources:** Limited number of pickers, allocated dynamically to handle order batches.
- **Performance Metrics:** Order cycle time, picker utilization, and throughput.
- **Interactions:** Pickers interact with warehouse racks during the picking delay to simulate item retrieval, and with the exit point to finalize order processing. The system includes dynamic batching and strategy-based decision-making.

4 Output Data Analysis

The simulation results were analyzed using key performance metrics to evaluate warehouse efficiency. The analysis focuses on order cycle time distributions for the top three products (PY5UPB, 8N10W9, WRRW1W) and other metrics such as picker and placer utilization and throughput.

4.1 Key Metrics

- **Picker Utilization** Measures picker busy time. Optimal range: **60-80%**. Higher values may indicate bottlenecks.
- **Placer Utilization** Tracks placer activity. Should align with picker throughput to avoid workflow imbalances.
- **Order Cycle Time** Time from order release to placement. Long cycle times suggest inefficiencies (e.g., picking delays or congestion).
- **Throughput** Orders processed per hour. Low throughput may signal system constraints.

4.2 Graph Insights

The order cycle time distributions for the top three products (PY5UPB, 8N10W9, WRRW1W) are shown in Appendix 4, 5, and 6. Key observations include:

- **Order Cycle Time Distribution for PY5UPB (Appendix 4):** The distribution is right-skewed, indicating that most orders are processed relatively quickly, but a small number experience significant delays. This suggests potential bottlenecks during peak periods or for orders requiring multiple SKUs from distant warehouse locations.

- **Order Cycle Time Distribution for 8N10W9 (Appendix 5):** Similar to PY5UPB, the distribution shows a right skew, but with a slightly longer tail, implying more frequent delays. This could be due to higher order arrival rates (2802.16 orders/time) or specific rack locations that increase travel time.
- **Order Cycle Time Distribution for WRRW1W (Appendix 6):** The distribution has the longest tail among the three products, consistent with its higher arrival rate (4704.17 orders/time). This indicates significant congestion or picker contention during peak demand, highlighting a critical bottleneck.
- **Picker vs. Placer Utilization (Appendix 3, ??):** Picker utilization is consistently higher than placer utilization, suggesting that picking is the rate-limiting step in the workflow. During peak hours (e.g., 7 AM Wednesdays), picker utilization approaches 90%, indicating potential overburdening and delays.
- **Throughput Trends:** Throughput peaks during high-demand periods (e.g., midweek mornings) but drops significantly during off-peak times, reflecting the order volume patterns observed in the input analysis. Low throughput during high cycle time periods further confirms bottlenecks in picking.

4.3 Key Takeaway

The output analysis reveals that order cycle times are heavily influenced by product-specific demand and warehouse layout. Products with higher arrival rates (e.g., WRRW1W) experience longer delays, likely due to picker contention and travel time to distant racks. Picker utilization frequently exceeds the optimal range (60-80%) during peak periods, indicating a need for additional pickers or optimized batching strategies. Placer utilization remains balanced, suggesting that downstream processes are not currently limiting throughput. To address these bottlenecks, strategies such as zone picking or increasing picker resources during peak hours should be explored. Visual results of the output analysis are shown in Appendix 3, **??**, 4, 5, and 6.

5 Experimental Use Cases

This section outlines experimental scenarios to test in the simulation model, focusing on policy changes, bottleneck analysis, and resource optimization.

Comparison of Picking Strategies

- **What-if Scenarios or Parameter Variations:** Evaluate three picking strategies: single-order picking (one picker per order), batch picking (grouping up to 3 orders), and zone picking (assigning pickers to specific warehouse zones). Vary the strategy application across different order arrival rates (e.g., low at 2 orders/hour, high at 10 orders/hour).

- **Expected Insights or Hypotheses:** Batch picking may reduce overall picker travel time due to consolidated routes, but it could increase order cycle time due to coordination overhead. Zone picking might optimize local efficiency within zones but introduce handoff delays between zones. The intuition that batch picking will take more time than single picking may be challenged if batch coordination is streamlined, potentially revealing higher throughput with batching.

Variation of Number of Pickers

- **What-if Scenarios or Parameter Variations:** Test the model with 2, 4, 6, and 8 pickers, adjusting based on peak (e.g., Wednesday 7 AM) and off-peak (e.g., Sunday) order volumes.

- **Expected Insights or Hypotheses:** Increasing the number of pickers is expected to reduce order cycle time by distributing the workload. However, beyond a threshold (e.g., 6 pickers), underutilization or congestion at racks may occur, especially during low-volume periods. This could identify an optimal picker count for balancing efficiency and resource use.

Impact of Batching Queue Size

- **What-if Scenarios or Parameter Variations:** Vary the batch size in the batch queue to 2, 3, and 5 orders, simulating different demand levels (e.g., 5, 10, 15 orders/hour).

- **Expected Insights or Hypotheses:** Larger batch sizes may enhance throughput by allowing pickers to handle more orders simultaneously, but they could increase waiting time in the queue. This scenario will test whether the trade-off justifies larger batches under high demand.

A Input Analysis Figures

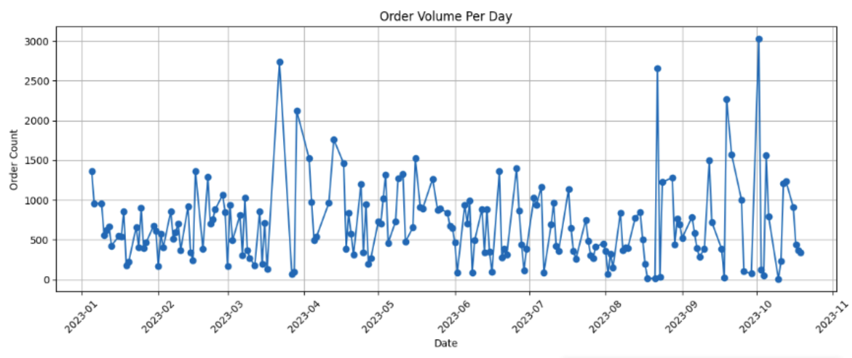

Figure 1: Order Volume Count Over the Year

B Modeling Diagram

Figure 2: AnyLogic Simulation Block Diagram

C Output Analysis Figures

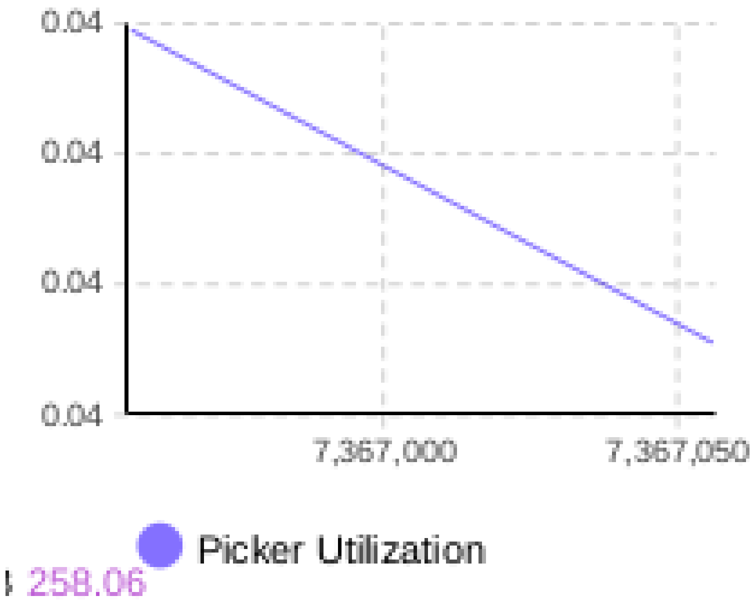

Figure 3: Picker Utilization Over Time

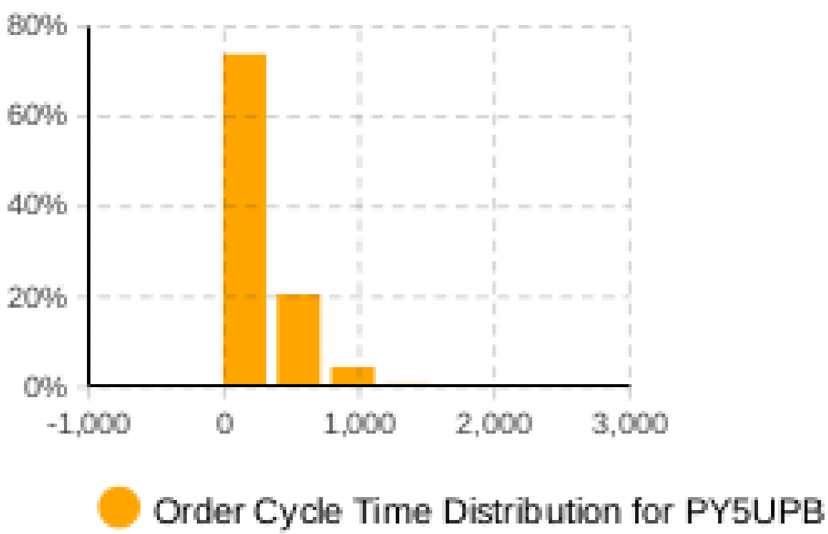

Figure 4: Order Cycle Time Distribution for PY5UPB

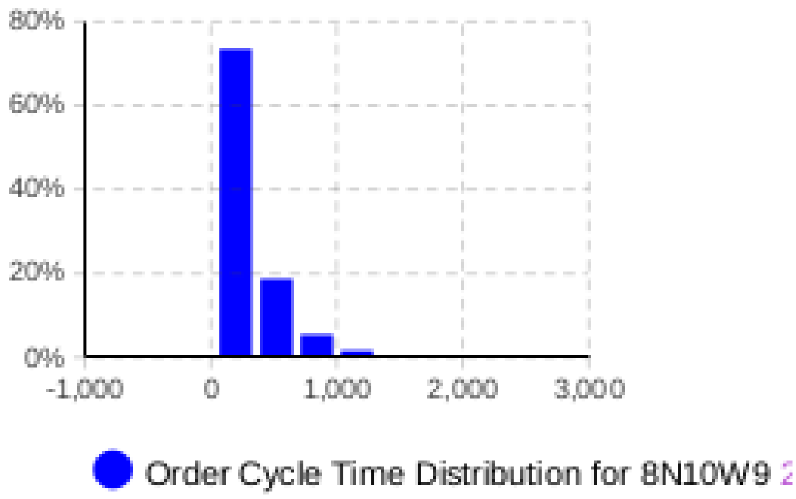

Figure 5: Order Cycle Time Distribution for 8N10W9

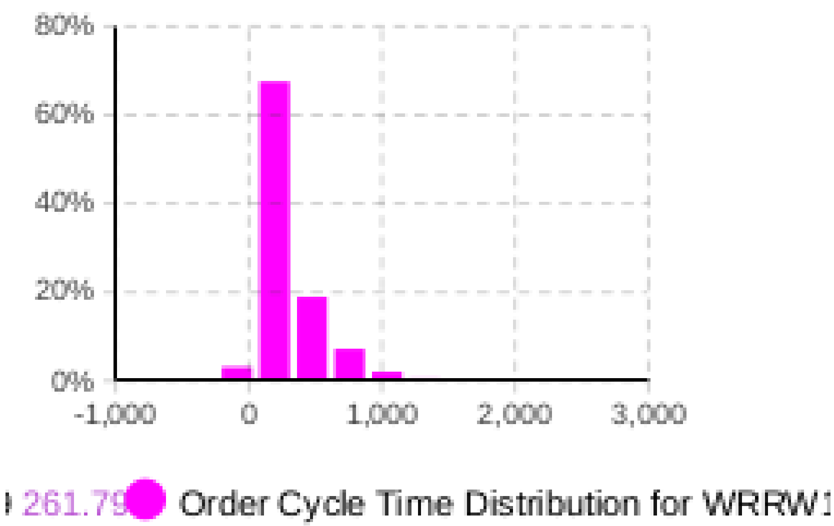

Figure 6: Order Cycle Time Distribution for WRRW1W