ISYE6644 Final Report - Large Scale Warehouse Simulation

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Abstract

In the context of setting up a new warehouse, it is imperative for a company to ascertain the most advantageous allocation of resources in order to augment the efficacy of order fulfillment. This undertaking necessitates a thorough examination of the customary operational protocols that a warehouse of considerable magnitude commonly confronts on a day-to-day basis. A meticulously constructed flowchart is formulated to delineate these protocols, and the Arena simulation software is employed to generate valuable insights that can furnish suggestions for the optimization of warehouse operations. Two improvements were evaluated. The first was to the asset-tagging process, and the second was to the receive process. The asset-tagging process yielded minimal improvements, while the receive process was found to be viable. Evaluating both improvements together did not yield significant improvements over simply improving the receive proccess.

1 Background

1.1 Overview

Efficient warehouse operations are essential for businesses to reduce costs, improve customer satisfaction, and gain a competitive advantage. In this paper, we present a case study that uses Arena simulation software to optimize the operations of a large-scale warehouse based on real-life parameters and randomized data. The research was conducted in collaboration with a team member who works for a multinational goods services provider. We utilized his experiences to generate a simulation model that accurately reflects the dynamics of a warehouse.

The simulation model incorporates a variety of factors that can affect warehouse performance, such as inbound shipment quantity, product receiving delays, order processing times, product wait times, workstation utilization, and warehouse staff utilization. We used the model to evaluate the effectiveness of two changes in the operational strategy. The first is to focus on the reduction of receiving time by the adaption of new digital tools and the second is to offload asset tagging of non-serialized parts up the supply chain to third-party logistics. We also evaluated the effectiveness of combining both changes together.

Our evaluation concludes that optimizing the receiving time by investing in a digital tool is an effective way to reduce the average product receive time. However, paying third-party logistics to add an asset tag does not significantly improve the average product receive time. The investment made in passing the costs up the supply chain has a long-term return on investment.

We also used randomized data over multiple runs in our simulation to test the robustness of our results and to account for variability in warehouse operations. Our findings suggest that our results hold even under different conditions, demonstrating the reliability and applicability of our simulation model.

Our research provides practical insights for businesses looking to optimize their warehouse operations and improve supply chain management.

1.2 Literature Review

The use of simulation to model and optimize warehouse operations has become increasingly popular in recent years. Simulation software provides a way to create virtual models of a warehouse and test various scenarios in order to identify the most efficient and effective ways to manage inventory, labor, and equipment. One such software that has gained popularity in the field is Arena, with 3615 companies tracked using this software by HG Insights (https://discovery.hgdata.com/product/arena-simulation).

Arena is a powerful simulation software tool that allows users to model complex systems and processes. It has been used in a variety of applications, including manufacturing, logistics, and service industries. In the context of warehouse simulation, Arena has been used to study a range of issues such as storage capacity, material handling, and order picking.

A study [1] focused on optimizing the allocation of storage locations for various product types. The Arena simulation was utilized and it allowed the researchers to compare different storage policies and evaluate their impact on the warehouse's overall performance. The results showed that a "random storage" policy performed better than a "dedicated storage" policy, which allocated specific storage locations to each product type. While another study [6] concentrated on simulating a warehouse for a retail company, with the aim of optimizing the picking process. The simulation model identified bottlenecks in the system and tested different scenarios, such as changing the layout of the warehouse or adjusting the number of pickers. The researchers found that the most effective solution was to increase the number of pickers during peak hours.

A similar study [5] modeled a warehouse for a company that distributes consumer goods. The simulation evaluated the impact of different order-picking strategies on the warehouse's productivity and efficiency. It showed that a "batch picking" strategy, where multiple orders are picked at the same time, was more efficient than a "piece picking" strategy, where orders are picked one by one.

The use of Arena to simulate large-scale warehouses has been shown to be a powerful tool for optimizing warehouse operations. The software allows researchers to test various scenarios in a virtual environment, without the need for expensive real-world experiments. The studies reviewed here demonstrate the effectiveness of Arena in identifying areas for improvement and testing different solutions to improve warehouse performance.

2 Method

2.1 Overall Warehouse Management Process

The present study focuses on the simulation of a large-scale warehouse from the point at which inventory shipments are received from vendors to the point at which orders are fulfilled from the warehouse. The overall process is illustrated in Figure 1 (see figure 1) and is divided into two sub-models: Receiving to Storage and Retrieval to Shipment. Each sub-model is further broken down into a detailed step-by-step process. It is assumed that the same set of "faceless" associates is involved in both the Receiving to Storage and Retrieval to Shipment processes. Those associates work 8 hours a day, 7 days a week, for 30 days total. The whole simulation length is for one month of working hours - 30 days in total. We assumed it was a normal month without the need to take into consideration seasonal, time-series factors, or micro-economic trends.

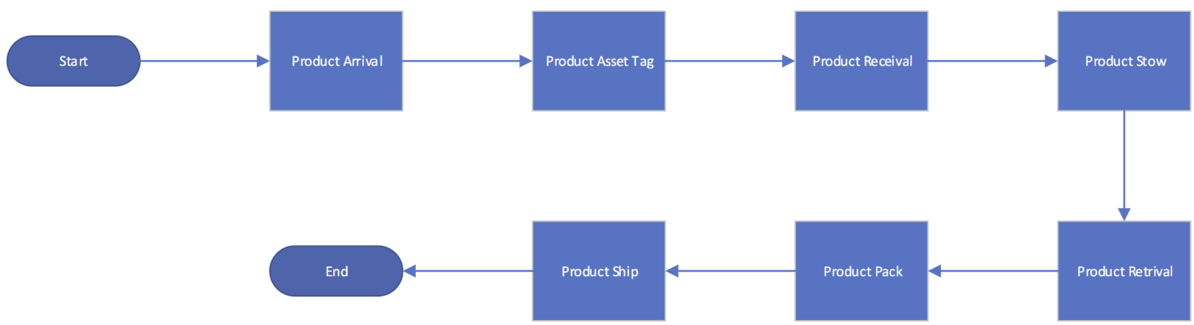

Figure 1: Warehouse Management Process

The set of input assumptions presented below was derived from the real-life experiences of a team member who works in close association with a fully manual warehouse. These assumptions were incorporated into the simulation model to ensure that the simulated outcomes closely mimic the real-world scenarios encountered in a warehouse environment. Due to the trial version limitation of having no more than 150 units in the system at any given time, some of the inputs needed to be scaled to support software limitations and are marked as such.

2.2 Receiving to Storage Process

- Number of receiving docks: 5
- Product Arrival: 1 truck every 4 hours with 70 products (Inbound product limited due to software limitations)
- Inspection Delay: 25 seconds per product - assumed to be exponential with a mean of 25 seconds. Inspection failure rate: 2%.

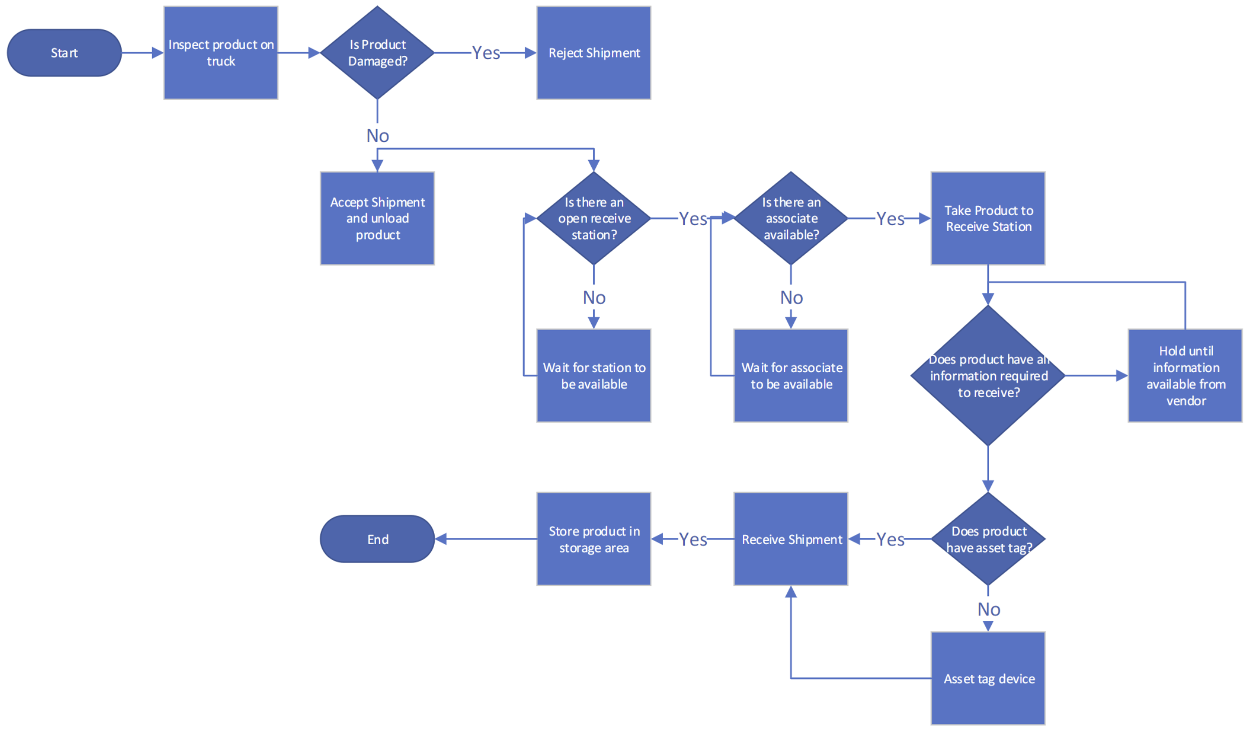

Figure 2: Receiving to Storage

- Products with missing paperwork: 0.5%.
- Product receipt wait time due to vendor delay in communication: 4 hours - assumed to be exponential with a mean of 4 hours.
- Inbound Products with Asset Tag: 83%.
- Receive Product: Triangular distribution with minimum 0.25 minutes, most likely value 0.8 minutes, and maximum 1.1 minutes.
- Product Storage Delay: 7 minutes.

2.3 Product Retrieval to Ship Process

- Orders are released at 2-hour intervals, following an exponential distribution with a mean of 2 hours.
- The number of orders per release is modeled using a triangular distribution with parameters 5, 15, and 20. (Delivery orders are limited due to software limitations)
- Search for products takes on average 7 seconds, modeled using an exponential distribution with a mean of 7 seconds.

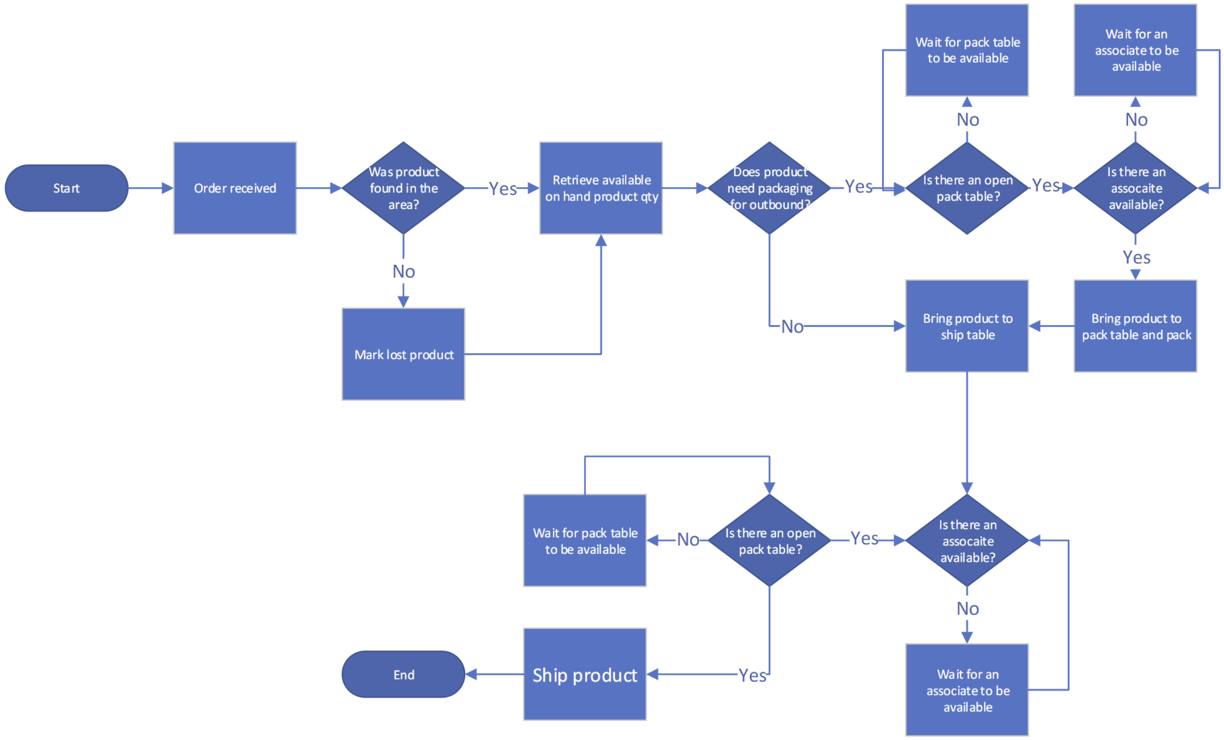

Figure 3: Product Retrieval to Ship

- Product packaging for outbound takes on average 3 minutes, modeled using an exponential distribution with a mean of 3 minutes.
- Shipping of parcels takes on average 2 minutes, modeled using an exponential distribution with a mean of 2 minutes.

2.4 Operational Process Outline

The retrieval and storage processes were based on the requirements for a major international retail company based in the United States, where one team member is involved as an engineer supporting process operations. However, limitations had to be implemented due to the Student Edition of Arena being limited to 150 entities in the system at one time.

Product arrivals were created at a constant rate of 4 per hour, each containing 75 entities. The arrivals can be thought of as shipments, and the entities as packages that require processing by an associate before storage.

The operational process starts on truck arrival at the docking station. Once the truck is docked, an associate inspects the product on the truck. The bill of lading is a shipment document used to verify inbound shipment at the receiving dock. An associate verifies the paperwork and unloads the pallets. Once the pallets are unloaded the load is inspected for damages and damaged inventory is recorded and shipment receives are rejected or scrapped from inventory. The product is then moved to a receiving station from a pool of 5. From an associate pool of 7, one is seized to process the package. If either a station or an associate is not available, the product waits in a queue until one of them becomes available. The product paperwork is then inspected and the ones with missing information are pulled away from the line. This product is then held in a queue until sufficient information is received from the vendor. Once all information is available and verified, the product is received in the inventory by use of an asset tag. If the product is missing an asset tag, a new asset tag is added and then the product is received. The receive station is then released. The product is moved into storage and the associate is released.

An associate from a pool of 7 is seized to process each package. There is an initial delay to inspect the product, modeled as exponential distribution with a mean of 25 seconds. If the package does not pass inspection, it is not accepted, and the associate is then released back into the pool of resources. If the product does pass inspection, a receiving station resource is seized to process the product, and there is a check to see if the product has the information required to receive it. If it does not, the associate is released into the pool while waiting for this information to be updated. The package is then delayed for an average of 4 hours, modeled by an exponential distribution. The same associate is then seized to continue processing the package. If the product does have the correct receiving information (or this has been acquired), the product is checked for an asset tag. If there is no asset tag, there is another exponential delay with a mean of 10 seconds before the product can be received, as it requires tagging. The product is then received, which is modeled as a triangular (0.25, 0.9, 1.1) distribution, and the receiving station is released. The package is then finally stored, which is modeled as an exponential distribution with a mean of 7 minutes. The associate is then released.

The retrieval process was modelled, but needed to be removed in order to avoid exceeding Arena's limit of 150 entities in the Student Edition, and we will focus on storage.

2.5 Distributions Utilized

We modeled most of the process delays above as exponential. Although exponential delays are 'generally inappropriate for modeling process delay times', Erlang distributions are 'often used to represent the time required to complete a task' (Kelton et al., 2015, p.603-4). We are essentially using an Erlang distribution with a shape parameter of 1 (k=1) since we are interested in the time the first event of interest occurs (for example, the product passes the initial inspection, or the information about the product is updated). Our experience in supply chain logistics also backs up these assumptions.

A triangular delay was used to model the actual receiving of the product, as we can be fairly certain of the range (minimum, mean, and maximum), but have little further information related to this. Furthermore, our experience in this area indicates that this delay would be difficult to model as it depends on the size of the package. According to research (Kelton et al., 2015, p.610, Hess, 2000, p.12), a triangular distribution is useful when the exact form of the distribution is not known, but the expected range and mean can be estimated. This is in line with our situation.

2.6 Improvements to Evaluate

We identified two key aspects of the process which could be considered to improve efficiency:

- Receiving the product: In a warehouse setting, all products upon arrival need to be received as inventory. The receiving process is a set of verifications that validate the inbound manufacturing part number and serial number prior to receiving in the system. In our base operations model, these checks and validations are a manual process. The associates first verify the products by validating the serial numbers of the product in a vendor portal. The associate scans the serial number in the vendor portal and validates the manufacturing part is valid. This process relies on vendor portal processing times.

  As a part of the analysis, we evaluated the impact of setting up a digital information flow between the vendor portal and our warehouse database. As a result, the verification can be done internally based on information sent from the vendor. This reduces the verification time as quick checks can be setup using automated tools internal to the company.

- Asset tagging the product: All inbound inventory is not asset tagged. There are certain manufactured products that do not contain a unique id for product identification. When the vendor ships them, they are accounted for in quantities or purchase orders. The warehouse operations evaluated rely on a serial number level check for inventory management. As a result, each product needs to be asset tagged if it arrives without one. This task however is time-consuming and increases product wait time prior to receiving.

  As a part of the analysis, we evaluated the impact of offloading this task to the vendors by paying an added cost in the contracts for the additional service provided. A direct measure was projected by calculating the time savings in the product receiving task.

3 Analysis

3.1 Initialization Bias

Under our initial conditions, we ran a finite-horizon simulation of 45 replications for one month. This duration length should minimize any initialization bias. This can be confirmed analytically, as we ran 45 replications of a single day, and the mean total time of each entity (package) in the system across replications was 0.757 ± 0.020 hours. On the other hand, running 45 replications of 30 days resulted in a mean total time of each entity in the system of 0.763 ± 0.004 hours. Any initialization bias should be more evident when running the simulation for a shorter time, yet a difference between 1 day and 30 days only results in a mean difference of 0.006 hours for total entity time in the system. This amounts to about 21.6 seconds per replication, which is not significant in this model. The 30-day mean confidence interval is also well within the 1-day mean confidence interval, and we also see a significant reduction in the confidence interval width when running the model longer. We are therefore confident that any initialization bias is not a factor when running the model for 30 days. We would prefer to run the model for longer than 30 days but risk the model causing errors due to the restriction of 150 entities in the Student Edition of Arena.

3.2 Analysis of the Current System (Original System)

Under 45 replications for one month, we found that the mean total time across replications of each package in the system was 0.762 ± 0.0045 hours, and the model was able to accept 4409.84 ± 2.75 shipments over the 30 days. Associate utilization time was 36% and receive station utilization time was 12.4%. Packages had a mean time (across replications) of 0.61 hours waiting in the queue.

3.3 Analysis of the System with Asset Tag Procedure Removed (Asset Tag Improvement)

As described above, one cost-saving measure would be to pay the vendor to apply the asset tag, in which case we can expect all received products to have an asset tag. We ran the model again after removing this part of the process. We can verify that the model run correctly as the counts of the product without an asset tag were recorded at 0. Again, under 45 replications for one month, the model was able to accept the same number of packages (4410.67 ± 2.55); and associate utilization time was approximately the same at 36%. The mean time across replications for each package in the system was 0.756 ± 0.0038 hours. It appears that paying the vendor to apply the asset tag results in very little improvement in the efficiency of the system. The improvement measured in terms of the time it takes to process each package is approximate 0.006 hours, or 21.6 seconds, which is actually only barely outside the confidence intervals. We estimate that the cost of paying a vendor to apply the asset tag would cost approximately \$1.50 per product. The number of products without an asset tag (averaged across 45 replications over a month) was 752.67 ± 8.53; therefore the cost of paying the vendor to tag the products would be approximate \$1129.00 each month. Comparative to the incurred costs, the total operational savings from offloading this task is \$81.21 for 752.67 products.

3.4 Analysis of Improvement to Receive Process (Receive Improvements)

The second cost-saving measure considered was an improvement to the receiving process. The current system receives products with a minimum of 0.25 minutes, a mean of 0.8 minutes, and a maximum of 1.1 minutes. We estimate that this can be reduced to a minimum of 0.15, a mean of 0.3, and a maximum of 0.5, and ran the model with this improvement. This time, the mean time across replications that each package spent in the system was 0.718 ± 0.004 hours, which is an improvement of approximately 0.044 hours, or 2.64 minutes. Associate utilization dropped by 2% to 34%, and receive station utilization time dropped by 3.1% to 9.3%.

3.5 Analysis of Both Improvements Together (Both Improvements)

We then ran the model with both cost-saving measures applied together. The mean time across replications of each package in the system was 0.714 ± 0.0029 hours. Associate utilization remained at approximately 34% and receive station utilization dropped very marginally by 0.1% to 9.2%. There appears to be no little further benefit to paying vendors to asset tag the products, even when combined with improvements to receiving.

3.6 Summary of Results

The following table summarized the results with averages across 45 replications, with times in hours and utilization as a percentage.

Comparison of Systems				
	Original System	Asset Tag Improvement	Receive Process Improvements	Both Improvements Together
Time in system (hours)	0.762	0.756	0.718	0.714
Associate Utilization	36%	36%	34%	34%
Receive Station Utilization	12.4%	11.6%	9.3%	9.2%
Queue for Associate (hours)	0.61	0.60	0.57	0.57

4 Conclusions

The most effective improvement to the current system is to improve the receive time process. This results in a decrease of 2.64 minutes for each package in the system. Receive station utilization also decreases by 3.1%, which could become a factor when scaling up this operation, although receive station utilization is not an issue in this smaller system.

The investment costs could vary depending on the different systems the company chooses to invest in; however, there is a potential that an improvement to the receiving process could result in cost savings.

With the improvement to the receiving process, we have a time saved of 2.64 minutes per package, and we can estimate the associate cost as $18 per hour, with 7 associates and 4410 products. Savings, therefore, amount to $3492.72 per month.

5 Limitations and Further Study

We were limited to the Student Edition of Arena since it is restricted to 150 entities. In the large multinational company where our team member works, we would likely have to dramatically increase the number of entities in the system; however, we needed to scale everything down to avoid the model giving an error due to exceeding 150 entities, including removing the retrieval system, which was initially programmed as the second part of our model. For further study, we suggest scaling up the model, and including the retrieval system. Having access to more than 150 entities would also likely allow us to use the technique of Common Random Numbers to compare our systems more accurately. However, we were unable to do this as splitting the model into two in order to evaluate two systems resulted in more than 150 elements in the system.

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