Operational and Supply Chain Optimization:

Using SimPy in Python

Workgroup Four

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Abstract

The simulation seeks to create a general supply chain and manufacturing model, starting with the raw materials procurement process and ending with the order fulfillment of produced items. The research model uses a mixture of Monte Carlo and discrete event simulation to mimic real-life situations with events and delays. The ending simulation is flexible so that businesses may use their real numbers (such as production speed, order frequency, etc.) in the model to test how operational changes to those numbers may impact their key performance indicators. This model will help facilities decide which strategic initiatives are worthwhile. For example, we tested the model with different parameters, such as having one dock door for loading fulfillment orders versus two; the results showed that it was not beneficial to add a second dock door.

Introduction

Production, shipping, and storage all serve as key aspects of supply chain management. By accurately modeling a supply chain, an enterprise can strategically invest to maximize profits. Our research project helps identify the optimal operational parameters for raw materials purchasing frequency to maximize profits, considering transportation, storage fees, customer orders, production facility labor costs, storage warehouse capacity and number of warehouses, and the number of dock doors (areas where orders are loaded for shipment) through discrete event simulation. By mapping the process, we see how changing certain conditions may affect the overall business. For example, if a business is trying to determine whether they are fully utilizing the storage space they are paying for, they may run the simulation with their business conditions and determine if their inventory levels necessitate the current purchased storage space. Another use case would be if a business would like to increase customer satisfaction by decreasing order queue times, what conditions would bring about the desired change, and how much would such a change cost (more dock doors, more labor, etc.). These problems are important to organizations as they help them make better decisions and test different strategies.

Literature Review

Event-based models with various degrees of sophistication are used to describe the behavior of distinct supply chains, from forestry to generic safety stock (the amount stored in a warehouse to ensure orders are filler). While each model has different components, SimPy breaks components into three categories: active components (processes), passive components (resources), and model variables (measurements) (Weitz 2022). Active components for supply chain problems are relatively consistent, such as processing and driving times. Passive components, particularly levels and stores, differentiate the problems based on the supply chain modeled. For example, the passive components in our supply chain are the raw materials required to produce alcohol and containers, while a forestry management supply chain could use biomass (trees) as its passive component (Pinho, Coelho, and Boaventura-Cunha 2016). The question of how much safety stock a company should hold is more closely mapped onto our model, as both deal with supply chains. Our simulation focuses on purchasing, manufacturing, inventory management, warehousing, and transportation, while another supply chain simulation may work to optimize guaranteed service time or demand planning (Holden 2017).

Methods

Our research is conducted via discrete event simulation using SimPy, following industry-standard practices. The first step of the simulation is the procurement of raw materials. In most practices, businesses order raw materials on a set schedule and quantity. Orders may fluctuate, but we kept to a consistent ordering schedule for our model. Since businesses order raw materials in bulk, there is a storage fee associated with them which incurs an additional cost for the business. Since storage is also finite, the order must be rejected and sent back if the next delivery of raw materials arrives and there is not enough space. The simulation logs acceptance and rejection of raw materials events. These logs benefit procurement departments because rejecting raw material orders may strain vendor relationships. Knowing that a new strategy would result in frequent rejection of orders would suggest to the procurement department to change the ordering schedule. Our model assumes that the schedule does not fluctuate; however, vendors often ship in a tentative window and not a set schedule.

The second step in the model is converting raw materials to finished products. Most businesses know their overall manufacturing yield and production times, so this step in the simulation takes raw materials and converts them to finished products at the set production speed and yield percentage. Businesses can adjust the parameters at this step to determine the impact of their current yield on the business and what situations may occur if machines malfunction and yield decreases. Our model simplifies this process by making efficiency a random selection of 80%, 90%, or 100%.

The final component is customer ordering. The model sets up a process where a customer may start an order but choose not to complete the order (balk) if the order queue is too long. In real-life situations, the expected delivery date determines whether customers balk. If a customer chooses to place the order, they are in queue for fulfillment. At the warehouse, orders are fulfilled conditionally on the availability of inventory and dock doors for loading and shipment. An important business metric occurs in this process: order wait time, or how long a customer waits between placing an order and receiving a shipping confirmation of said order. Businesses commonly tie customer satisfaction with this metric and often employ various strategies to decrease it. However, decreasing wait time may inversely impact other metrics, such as cost, so it is important to simulate changes in the model before making executive decisions. Our model assumes that once a customer places an order, they do not cancel (reneged) it, which is unrealistic. A future iteration of this model should include the ability to renege.

In its entirety the model provides the framework for a manufacturing business to model different conditions and review the impact of changing any conditions. We could add more specificity to tailor the model to each unique business. We input some fake numbers and constraints for our hypothetical business and tested how changes affected the performance metrics highlighted at each stage of the process. The results from these tests are noted in the results section with tables and further visualizations in the appendix.

Results

Our initial model starts with a raw materials order schedule of 300 units every 30 days and a raw materials storage maximum of 450 units. We designated production as 10 units daily (fixed) with variable efficiency of 80%, 90%, and 100% per machine. We started with one production machine. Customers place 10 orders on average, daily. We modeled customer orders using a random normal distribution with bounds. The customer tolerance for order queue is 15 orders before balking. The number of dock doors can vary between one and three, and we started with one. Under these conditions, in one simulation, we found that 3,636 orders were started, but only 3,293 were placed, meaning 343 orders balked which businesses can use to quantify lost revenue. There were also 91 instances in which an attempt to fulfill an order was delayed because there was no inventory available. These instances are very expensive in real-life situations, as truck drivers would be at the loading docks waiting to get loaded and would incur extra charges for delayed pick-ups. It would also affect relations with transportation carriers, especially if the situation were to happen in this current era of truck driver shortages. Lastly, the average customer wait time from this simulation was 1.36 days. If we were to change the parameter from 1 dock door to 2 dock doors, we found 453 instances of delayed fulfillment with an average customer wait time of 1.33 days with no changes to other metrics. If a company were to decide whether an additional dock door, which would have an upfront cost along with a variable operational cost, would be worthwhile in this situation, the answer would be no, as customer wait time did not decrease significantly, and there would be increased logistics costs due to trucks waiting at the dock doors.

Conclusions

SimPy can be used to model a supply chain and manufacturing problem. Given the project runtime, our model was limited by the number of parameters we could feasibly include. Future work could expand the simulation to include additional factors, such as fluctuation in raw material order amounts, variable vendor shipping window, more nuanced interpretations of machines malfunction and yield decrease, and the ability for customers to renege on orders to increase the realism of the model. Additionally, the model can be expanded to include more manufacturing plants with unique conditions per plant. Overall, the model provides a framework for simulating manufacturing processes and would allow organizations to see how changes to the process may affect the outcomes and performance metrics to make informed business decisions.

References

Holden, Lauren. 2017. "Inventory Optimization Using a SimPy Simulation Model." Ph.D. dissertation, East Tennessee State University. Retrieved June 2, 2022. https://www.proquest.com/dissertations-theses/inventory-optimization-using-simpy-simulation/docview/1906256910/se-2?accountid=12861.

Pinho, Tatiana M, João Paulo Coelho, and José Boaventura-Cunha. 2016. “Forest-Based Supply Chain Modelling Using the SimPy Simulation Framework.” *Elsevier*, vol. 49, no. 2 (2016): 90-95. https://doi.org/10.1016/j.ifacol.2016.03.016.

Weitz, Darío. 2020. “Introduction to Simulation with SimPy.” *Towards Data Science*, June 16, 2020. Retrieved June 2022-06-03. https://towardsdatascience.com/manufacturing-simulation-using-simpy-5b432ba05d98.

Appendix/Appendices

Figure One:

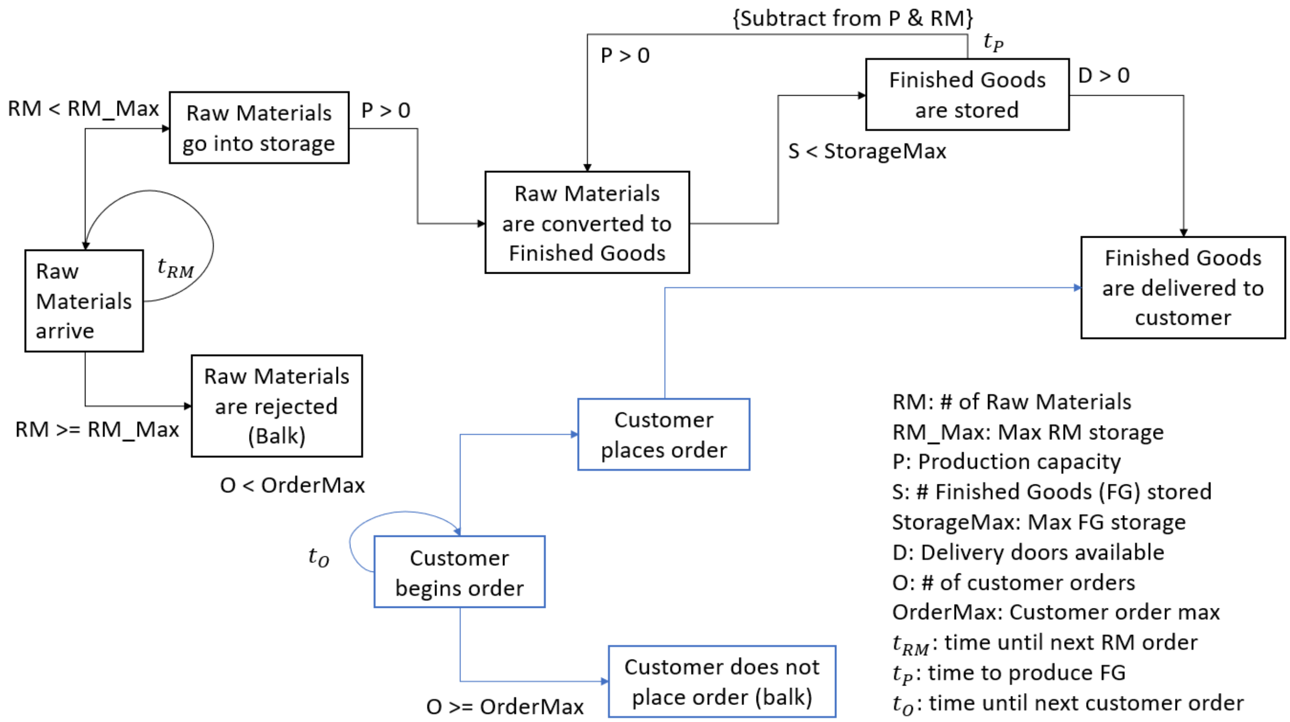


Figure Two (Simulation One):

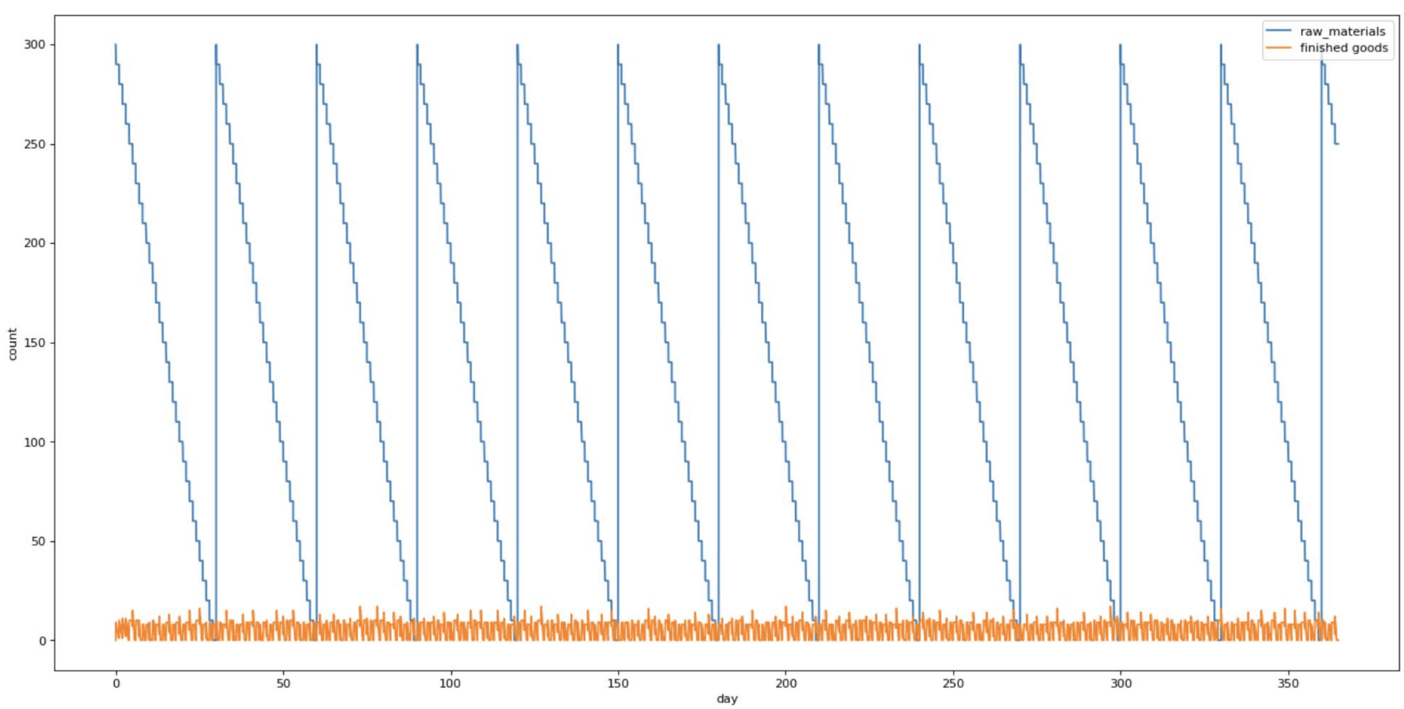
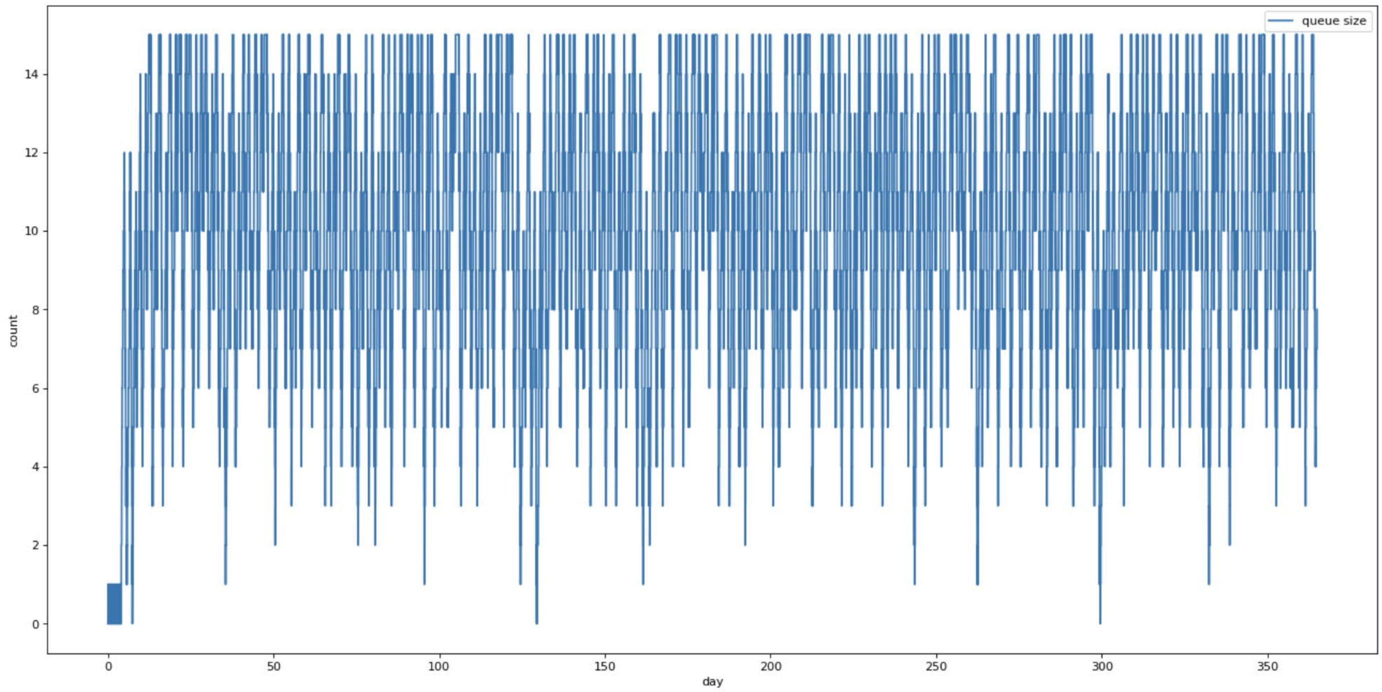


Figure Three (Simulation One):



Simulation Four (Simulation Two):

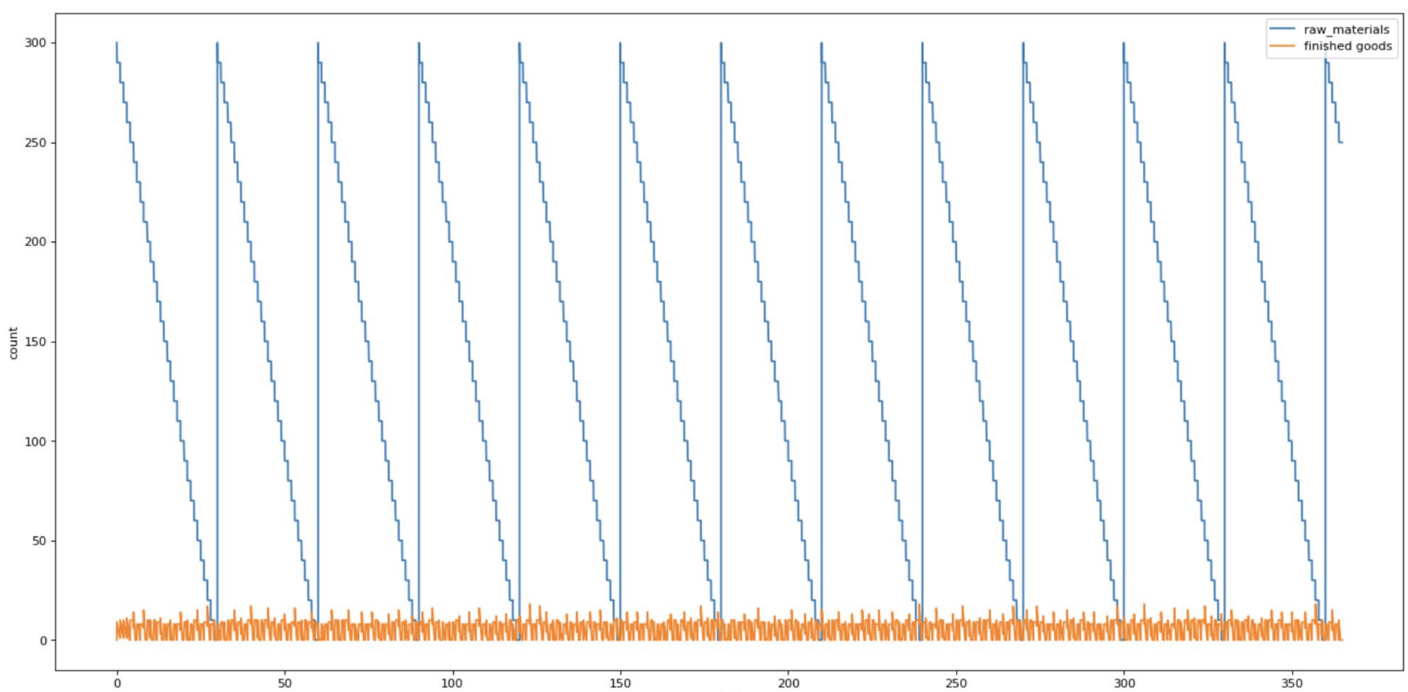


Figure Five (Simulation Two):

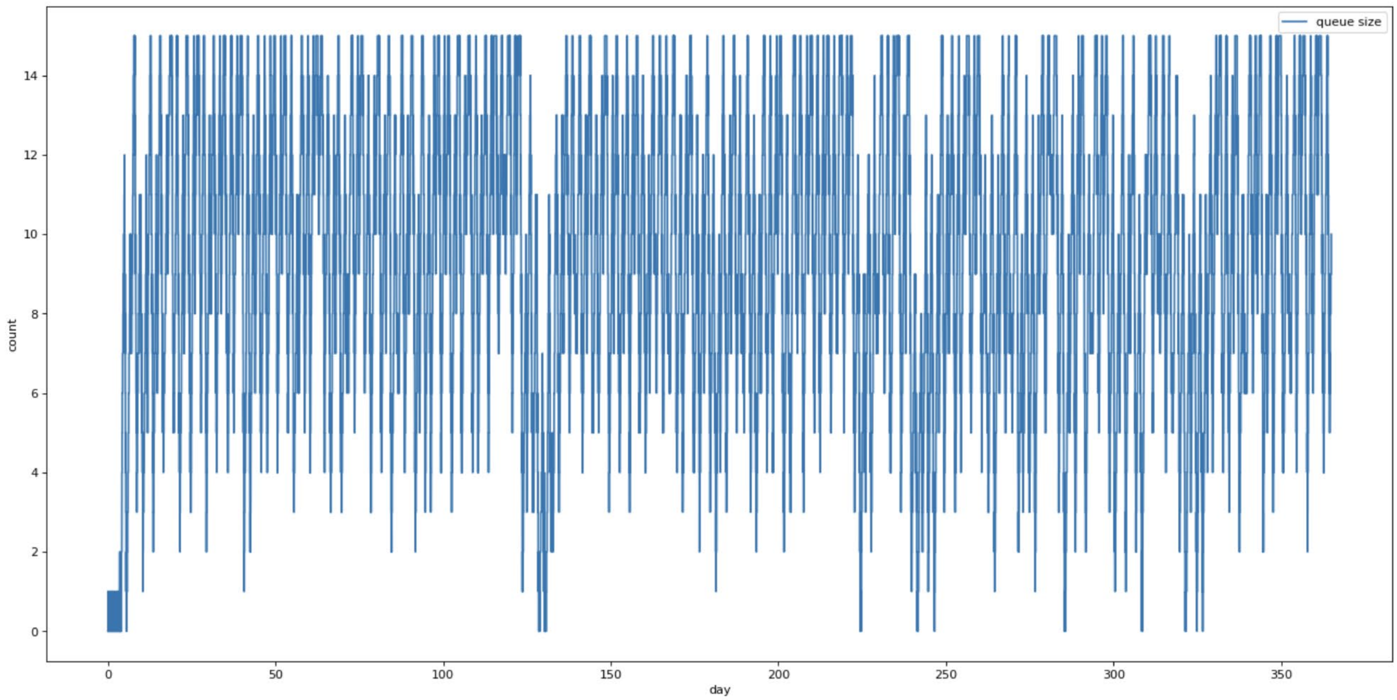


Figure 6 (Simulation One):

```
activity
Finished goods production completion             364
Raw Materials arrival                             12
Raw Materials put in storage                      12
fulfillment - begin loading                     3270
fulfillment - finish loading                    3270
fulfillment - insufficient inventory - wait      456
init                                               1
inventory report                                 365
order not placed                                 354
order placed                                    3282
order process started                           3636
start simulation                                   1
dtype: int64
```

Figure 7 (Simulation Two):

```
activity
Finished goods production completion           364
Raw Materials arrival                            12
Raw Materials put in storage                     12
fulfillment - begin loading                    3307
fulfillment - finish loading                   3307
fulfillment - insufficient inventory - wait     453
init                                              1
inventory report                                365
order not placed                                317
order placed                                   3319
order process started                          3636
start simulation                                  1
dtype: int64
```