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# Simulation Report

**Game Strategy:**

During our initial simulation, we had a clear objective of staying as lean as possible and as JIT as possible. We forecasted our demand and attempted to adjust our Reorder point (ROP) and EOQ based on the demand forecast so that we take as little loan as possible and be debt free as much as possible. Our strategy stayed the same for the main run as well to maintain an inventory that is as lean as possible and not hold too many kits in the inventory and lose the opportunity to earn the compounded interest amount. We also focused on reducing lead times to ensure timely delivery of orders and maximize customer satisfaction. To achieve this, we closely monitored station utilization and made real-time adjustments to optimize the throughput. Additionally, we decided to invest in more machines if required to scale up production and maintain a competitive edge.

**Reorder Point (ROP) and Economic Order Quantity (EOQ) Calculation:**

To align with our lean and Just-In-Time (JIT) strategy, we calculated the Reorder Point (ROP) to ensure timely orders without overstocking. The ROP triggers reordering when inventory reaches a critical level, helping us avoid stockouts while minimizing excess inventory. The ROP formula used was:

ROP = (Average 120 days Demand * Lead Time) + Safety Stock

Given our forecast of gradually increasing demand, we initially included additional safety stock to prevent stockouts. However, to avoid holding excess inventory, we adjusted the ROP over time, reducing it from 960 to 720, and later to 480. Despite these adjustments, our lower ROP and uncertainty in demand led to stockouts on Day 156 and Day 245.

In our strategy to maximize profit by having zero inventory on the last day (Day 268), we also used forecasted demand to calculate the Economic Order Quantity (EOQ). Prior to Day 156, we set an EOQ of 12,600 units. However, this EOQ, combined with the lower ROP, was not sufficient to meet the demand, resulting in stockouts. By Day 245, we quickly recalculated the EOQ based on the updated demand data, ensuring it covered the needs from Day 245 to Day 268 without holding excess inventory, thus meeting our goal of fulfilling demand while minimizing leftover stock.

In our inventory forecasting simulation, decision-making played a central role in managing and optimizing our inventory processes. By employing a continuous, data-driven forecasting approach, we aimed to make informed decisions based on real-time data. Our method involved analyzing historical demand patterns, transforming the data into a linear form using logarithms, and applying regression models to predict future demand. These steps formed the foundation for our decisions throughout the simulation.

One of the key decisions we made early on was dividing the forecasting horizon into stages, enabling us to anticipate shifts in demand and adjust inventory levels accordingly. To further improve decision accuracy, we adopted a rolling forecast approach, continuously updating predictions as more demand data became available. This allowed us to stay agile and responsive, ensuring our decision-making was always aligned with current demand trends.

However, the simulation presented challenges that tested our decision-making framework. Specifically, we observed a discrepancy between the expected exponential growth and the actual, steadier demand trend. This difference became critical when we hit our reorder point (ROP) on the 156th day earlier than anticipated. Due to high demand at that time, our system was idle for two days while waiting for inventory replenishment. This situation underscored the importance of constantly evaluating forecast assumptions and integrating flexibility into decision-making processes.

Throughout the simulation, our decision-making considered several critical factors:

- **Demand Variability:** As demand patterns shifted, we continuously monitored data to adjust inventory thresholds and avoid stockouts or overstocking.
- **Timing of Replenishment:** Hitting the ROP earlier than expected required quick, reactive decision-making to prevent prolonged system downtime.
- **Risk of Overconfidence in Forecast Models:** The challenge we faced—where observed growth rates did not follow our forecasted exponential model—highlighted the need for caution when relying solely on predictive models. This led us to consider more real-time data adjustments in future decision-making efforts.
- **Balancing Forecast Accuracy with Flexibility:** We focused on maintaining a balance between predictive accuracy and operational flexibility. The rolling forecast approach allowed us to make periodic adjustments to align better with market realities.

To revert the forecast from its logarithmic form, we applied an exponential function to ensure that predictions reflected the growth pattern. This approach facilitated decision-making by providing a clear view of expected trends, but the simulation ultimately reminded us that continuous validation of those trends against real-time data is vital to prevent disruptions.

The graph below illustrates the number of jobs accepted over time, which provided a key metric for our decision-making process and helped us visualize demand trends over the simulation period:

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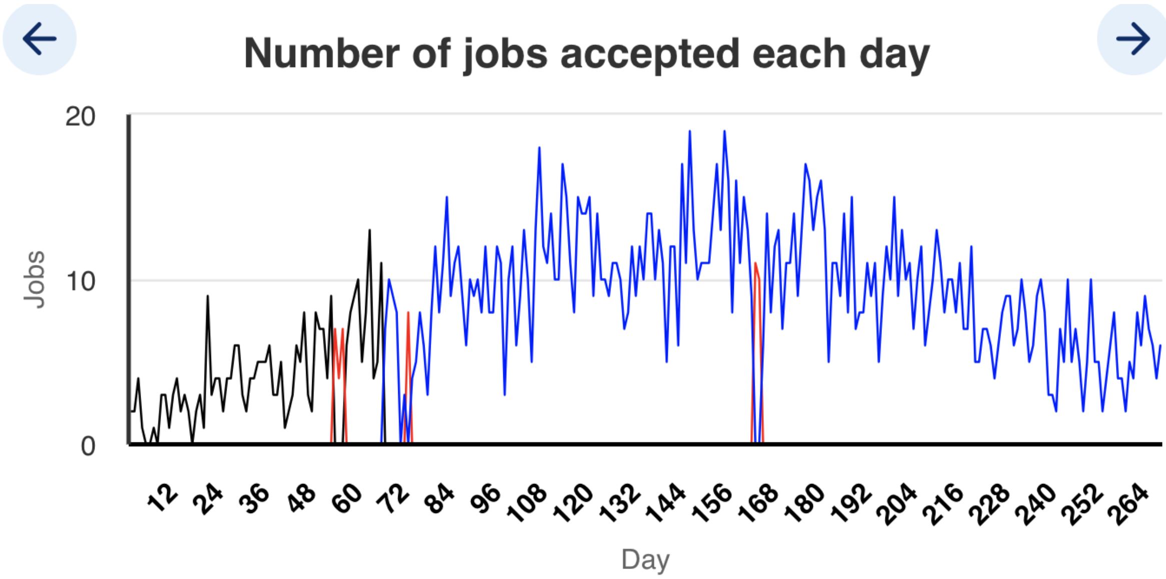


**Machine Purchase:**

**Initial Setup and Utilization Monitoring**

The simulation began with the following machine setup:

- **Station 1**: 2 machines
- **Station 2**: 1 machine
- **Station 3**: 2 machines

Our strategy was to monitor utilization rates, aiming to maintain efficiency by purchasing additional machines whenever the utilization rate exceeded 80% on average.

**First Purchase (Day 80)**

The first significant change occurred on **day 80** when we observed that the utilization rate of machines at **Station 1** was consistently near 80%, with occasional spikes to 100% due to sudden increases in demand. To prevent delays and maintain throughput, we invested in a **3rd machine for Station 1**. This proactive measure ensured smoother operations during peak periods.

**Second Purchase (Day 96)**

By **day 96**, the utilization rate for **Station 3** reached 100%, indicating a critical need for additional capacity. To handle this demand efficiently, we secured a loan and invested in a **3rd machine for Station 3**. This decision was crucial in preventing bottlenecks and maintaining overall production efficiency.

**Inventory Miss and the Impact on Station 1 (Day 145)**

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We experienced a missed inventory reorder that led to a standstill during peak demand days. As a result, a queue formed at **Station 1**, necessitating the purchase of a **4th machine on day 145** to clear the backlog. This investment was vital to restoring flow and minimizing delays in the production process.

**Responding to Increased Demand at Station 2 (Day 147)**

The increased capacity at Station 1 subsequently pushed demand onto **Station 2**, which requires two iterations per order compared to the other stations. To handle this surge, we added a **2nd machine for Station 2 by day 147**, ensuring balanced processing and preventing any new bottlenecks.

**Final Adjustment and Optimization**

As demand levels normalized, we adjusted our capacity by selling one machine from each station. This decision left us with:

- **Station 1**: 3 machines
- **Station 2**: 1 machine
- **Station 3**: 3 machines

This readjustment allowed us to optimize costs while retaining enough capacity to handle fluctuating demand efficiently.

**Our Learning:**

Through this simulation, our team gained valuable insights into inventory forecasting, demand management, and operational efficiency. We learned the need for adaptable models when actual demand deviated from expected exponential growth and the importance of real-time adjustments to prevent downtime. Financially, we balanced taking loans for machine purchases with paying them off early, while keeping cash on hand to benefit from a 10% interest rate. This experience taught us to align financial decisions with operational needs and quickly respond to changes, strengthening our teamwork and problem-solving skills for future challenges.