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EVALUATION OF SUPPLY CHAIN STRATEGY FOR A HEAVY EQUIPMENT MANUFACTURER

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ABSTRACT

A global heavy equipment manufacturer is concerned that their make-to-order strategy is creating long lead times and low availability of product mix, which in turn is negatively impacting sales. To address this concern, the company has proposed a segmented supply chain strategy, with high-demand products made to stock and custom products made to order. Genpact was tasked with evaluating the proposed strategy change, and a discrete event simulation model was developed and deployed that identified a set of optimal supply chain policies. The recommended supply chain policies improved the key lead-time metric performance from 30% to 85% with no increase in inventory costs. Furthermore, the model demonstrated that demand forecast accuracy and production improvements could increase lead time metric to 93% and decrease inventory costs by 50%.

1 INTRODUCTION

To improve customer satisfaction and to capture lost sales due to long shipment turn-around times, the company has developed a "make-to-stock" segmentation strategy with three tiers of product. Tier 1 products are stocked, standard, high-demand items with no customizations. Tier 2 items are tier 1 products with minor customization, and tier 3 items are made to order. The goal of the new strategy is to ship 95% of tier 1 orders with seven days of order receipt. The simulation model was developed to test which inventory policies should be adopted and how much inventory will result from those policies.

2 ASSUMPTIONS AND APPROACH

The model was based on using historical order data and historical forecast data. This allowed for the testing of realistic order request dates, as well as forecast data used as inputs to inventory policy calculations. Simulated performance could then be compared to historical performance. Production lead times, transportation lead times, production capacity constraints, and manufacturing calendars were provided and incorporated into the model.

The operational logic was based on the definitions of product tiers. Tier 1 products are stocked at a physical inventory (distribution centers). Customer orders are filled directly from inventory. Inventory replenishment orders are placed daily based on current inventory position (on hand plus on order) compared to a calculated target level. Tier 2 products are pulled from tier 1 inventory and have additional lead time before complete. Tier 3 SKUs are direct order from plant and are not stocked. Additionally, production rates are set in the model logic and are calculated based on forecasted demand less any on hand inventory.

The inventory policies to be tested are parameterized by two variables: DaysOnHandTarget and PlanningHorizon. DaysOnHandTarget determines how many days' worth of demand should be set for each inventory each month. The PlanningHorizon determines how many months' demand should be considered in the DaysOnHandTarget calculation. The demand profile for these products are seasonal, and this demand variation was important for the company to consider.

3 INITIAL RESULTS AND ADDITIONAL PARAMETERS

Initial results indicated that a segmented product strategy could increase the lead-time metric from 30% to 63% with an decreased inventory cost of roughly 10% under current inventory policies. The most aggressive set of inventory policies would result in 90% lead-time metric value, but at roughly double the current inventory cost. However, detailed analysis indicated that two factors were limiting the performance of the system by driving over-production: forecast accuracy and production policies.

Analysis of the historical forecast and order data indicated that the forecast accuracy was significantly greater than the actual demand. Forecast demand is the primary input to production level and average daily demand calculations used to set target inventory levels. Additionally, baseline production policies used by the company required a daily rate to be maintained regardless of daily demand, and rates must be held for a minimum of three months before changing. These required daily production rates and rate lock policies drive additional over-production.

With these findings in mind, two additional model variable were defined: ForecastType and ProductionConstraints. ForecastType allows the use of historical forecast (the initial approach), or “perfect” forecast (by using order data as forecast data). ProductionConstraints enables a minimum daily production rate to be defined (which could be zero) and parameterizes the rate-lock period.

4 RESULTS AND CONCLUSIONS

Experiments with these parameters determined that significant improvement in inventory cost could be achieved, resulting in a 93% lead-time metric performance with a decrease in inventory costs. Figure 1 highlights the decrease in inventory costs due to flexible production and forecast accuracy. Figure 2 is a Pareto chart of inventory cost versus lead-time metric for all simulated scenarios.

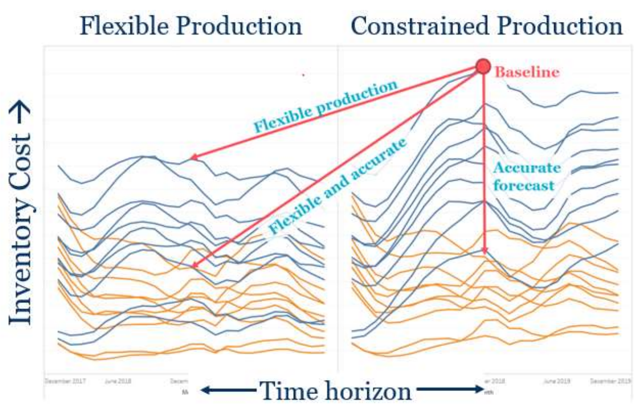

Figure 1: Inventory cost performance of extended scenario parameters (flexible production and forecast accuracy).

Figure 2: Inventory cost versus lead-time metric for all simulated scenarios.