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Managing Supply Chain Risk by Predicting Service Disruptions
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Managing Supply Chain Risk by Predicting Service Disruptions

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Summary: This thesis analyzes the relationship among various factors that cause service disruptions in a leading medical devices company and assesses the feasibility of developing a model that could predict those disruptions. A service disruption occurs when a customer places an order, and the firm is unable to fulfill it completely and is measured by a metric called Customer Service Level (CSL) or Line Item Fill Rate (LIFR). To identify the leading indicators that affect the CSL, a holistic analysis of the entire supply chain including inventory policies, demand-forecasting methods, production scheduling, supplier performance, and so on, was performed. We came up with a prediction model that combines forecasting techniques using historical data and a regression model to predict CSL.

Introduction
Risks or uncertainties are the two words that are very much relevant in today’s global business environment. In the supply chain world, there always lies a risk of an interruption to the flow of goods, information, or finances. These disturbances may appear in the form of transportation delays, poor communication, or even natural disasters. In the context of this thesis, whenever a customer order is not completely fulfilled, the firm calls it a service disruption. The firm currently measures these service disruptions by a metric called Line Item Fill Rate (LIFR), which is simply a measurement of their Customer Service Level (CSL). This thesis deals with a situation where a leading medical devices company is trying to reduce its service disruptions caused by inadequate availability of one of its extremely critical surgical products. In the life sciences industry, a service disruption or poor service level may directly affect human lives.

The purpose of this project is to understand the relationship among various factors that affect service level and assess the feasibility of developing a model that could predict a service disruption. A CSL or LIFR is defined as the number of lines shipped over the number of lines ordered by a customer.

\[
\text{CSL or LIFR} = \frac{\text{Number of lines shipped}}{\text{Number of lines ordered}} \times 100
\]

KEY INSIGHTS
1. Deviation between planned and actual supply chain parameters such as lead-time impacts Customer Service Level.
2. Integration of disparate data sources, aligning service metrics with forecasting and considering end-to-end supply chain as a part of a network rather than as silos, will provide better visibility and predictability to improve service level.
3. Several production parameters such as batch sizes, capacity utilization, scheduling prioritization affects service level.
The company defines a LIFR higher than 95.8% to be acceptable. As the issue is highly data-intensive, we approached the problem following a six-sigma DMAIC method albeit with some modifications.

- **Define** – Firstly, we identified and defined the problem. We clearly outlined what is in scope and what is out of scope.
- **Measure** – Secondly, we understood the problem by studying the AS-IS state and measuring the Key Performance Indicators (KPI): CSL or LIFR
- **Analyze** – Thirdly, we mapped the end-to-end flow of the supply chain, from the procuring raw material to final delivery to the customer.
- **Prediction Model** – Lastly, we developed a model that explains the behavior of the KPI in order to predict service disruptions.

Qualitative Analyses

- **Root Cause-Fishbone**
  We interviewed and performed a Fishbone analysis with the key stakeholders. We identified and segmented various potential causes into categories such as Information, Inventory, Planning, Production, Materials and Forecasting to better understand cause and effect relationship.

- **Supply Side Analysis**
  We found that nearly 53% of the suppliers had lower than acceptable LIFR. Lack of data related to suppliers limited our ability to find out whether the unavailability of a specific raw material from the supplier led to a low LIFR.

- **Raw Material Availability**
  The company’s Advanced Planning System (APS) does not have information about raw material availability. Therefore, in some situations, the production unit cannot schedule an SKU in spite of an APS signal to produce, because of unavailability of raw material. If the SKU is not produced, there will be a delay in fulfilling the order at the demand locations, thereby affecting service level.

- **Production Capacity Utilization and LIFR**
  Preliminary analysis showed that only when the capacity of a line is greater than 100% utilized, we see an impact on LIFR.

- **Production Batch Size and LIFR**
  Certain SKUs are only produced a few times a year. Due to higher than required quantities produced and stocked, these SKUs have higher LIFR, as compared to SKUs that are produced several times in a year.

Quantitative Analyses

- **Data Analysis**
  The first task was to validate the current service levels by measuring the CSL. As the figure above shows, the LIFR is clearly below the desired level.

Then we looked into several clusters such as product type, manufacturing location, manufacturing lines, and so on, and their corresponding LIFR behavior. One classification was the product category and the question was whether one category performed differently from another with respect to their LIFR. The above figure shows that only the B-category was able to reach a satisfying level. Furthermore, we performed a Mann-Whitney test that let us draw statistical conclusions.

We also looked into the possible regression analysis to investigate the behavior of the entities and their impact on LIFR performance. However, none of them gave any significantly higher R² value. Therefore, we could not use the regression equation using average values of independent variables to develop a prediction model.

Deep Dive Analysis
We further dive deep to understand the reasons behind the preliminary results.
• Deviation in Total Planned Lead-Time vs. Actual Lead-Time
We took the average lead-time deviation between planned and actual lead-time and averaged it for all the applicable SKUs. The correlation between the LIFR and average deviation between planned and actual lead-time was negative although not strong, as the figure below shows. The reason for a weak correlation was that the company actually considers the effect of lead-time variability in its safety stock calculation, which cushions the variability’s impact on LIFR.

![Scatterplot of LIFR vs (Planned - Actual) Cycle Time](image)

• Coefficient of Variation of Demand and LIFR
We got very low correlation between LIFR and coefficient of demand variation because the company’s safety stock calculation takes into consideration the demand variability factor for each SKU. Hence, demand variability’s effect on LIFR is shielded.

• Safety Stock Calculation and Normality Assumption of Demand
The company assumed demand to be normally distributed, which was not a correct assumption as the figure below depicts. All the safety stocks were calculated based on demand normality assumption, and hence safety stock calculations were not accurate, potentially impacting LIFR.

• Demand Forecast Error and LIFR
MAPE (Mean Absolute Percentage Error) and LIFR were very poorly correlated because forecasting is done based on demand quantities, whereas LIFR is measured in terms of lines ordered.

Regression analysis
We then ran a multiple-regression model among several variables such as deviation in actual and planned lead-time, manufacturing frequency and Unable to Schedule (UTS) percentage data. The results of the regression analysis show that the above factors do not sufficiently explain the dependent variable.

Possible Models
Firstly, we developed a multiple-regression model: however, the model did not sufficiently explain the variation in the CSL. Secondly, we used a logistic regression model, which can be used for binary data. In our case, we converted the LIFR into a binary response variable by segmenting values of 95.8% and above as 1 and any value below as 0. This yielded us a much stronger regression equation with R^2 of 52% and all the goodness of fit tests had a high p-value. The output of a logistic regression model is a probability of an event (0 implies a disruption and 1 implies no disruption) but this output is not very useful for the company.

Finally, we come up with a hybrid model that predicts LIFR combining a regression model and forecasting techniques. A user can adjust weights between the regression and the forecasting model based on the R^2 value of the regression model. If the R^2 is low, higher percentage weight can be given to the forecasting model and if R^2 value is high, higher percentage weight can be given to the regression model. The final predicted value is a weighted average of regression and forecasting model as the figure on above illustrates.
• CSL Simulation Using Arena
We also created a simulation model to see the impact of certain variables on the number of customers lost. By modifying these variables such as target stock levels, batch size, reorder point, and so on, the impact on the service level was analyzed.

Findings

• Lead-time variability’s impact on LIFR
Seemingly, obvious factors such as long lead-time or long manufacturing cycle-time does not necessarily lead to poor service level.

• Deviation in actual versus planned lead-time adversely affects LIFR
The correlation analysis between “actual lead-time - standard lead-time” and LIFR supported our hypothesis that the variability of planned and actual parameters of an SKU affects LIFR.

• Demand forecast and LIFR
Demand forecast for the SKUs is done in quantities whereas LIFR is measured in lines shipped over lines order. Therefore, even if the demand forecast is very accurate, it does not necessarily lead to a high CSL.

• Demand variability and LIFR
The firm has an inventory model that takes into account the demand variability of an SKU while allocating the appropriate safety stock to it. Therefore, we did not see a strong correlation, as the effect of variability was already accounted for in the inventory model.

• Production batch size and LIFR
SKUs that have batch sizes higher than or comparable to their annual demand have better LIFR performance. This implies that these higher performing SKUs shield other low-performing SKUs and secondly, the batch size of the higher performing SKUs are too large, thereby incurring relatively high inventory holding cost.

• Safety stock calculation and normality assumption
The safety stock calculation of the company for SKUs assumes normal demand distribution, which is not the case. Hence, an inaccurate safety stock calculation may lead to a poor CSL.

Conclusion
We started with a problem statement to develop a model that can predict a customer service disruption; a problem that the firm wanted to resolve to have a better LIFR. In order to do so, we analyzed the end-to-end supply chain right from supplier performance and availability of raw materials, to production schedules and inventory policies. We dived deep into data to understand the relationship among various supply chain parameters, variables, and LIFR.

One key insight is that a longer lead-time does not necessarily result in a poor LIFR, instead a deviation between planned and actual lead-time affects LIFR adversely. We also found that inaccurate assumptions in calculating safety stock leads to poor CSL. Another finding is that LIFR is measured in lines shipped over lines ordered whereas SKU demand forecast is done in quantities, which means improving demand forecast may not improve LIFR. In addition, a delay in supply of raw materials or capacity constraint on a production line can lead to a delay in production of an SKU, thereby affecting LIFR. We also understood that the batch size of an SKU could also potentially affect LIFR; if batch size is comparable to a SKU’s annual demand quantity, we see near 100% LIFR performance. We also found that the inventory model of the firm considers the demand volatility to allocate safety stock, thereby shielding the effect of demand volatility on LIFR. Finally, certain human decisions that are not captured in any system affect LIFR. For example, the difference in prioritization methods for order fulfillment at different warehouse locations implies inconsistency in measuring LIFR. Eventually, we incorporated all these findings to create a framework for a model, which uses a combination of a regression model and forecasting techniques to predict LIFR performance.

The framework used in this model can be used as a building block to a more sophisticated, robust, and inclusive prediction model. The company can integrate disparate data sources, align LIFR metrics with forecasting and consider end-to-end supply chain rather than silos for better visibility and predictability. Furthermore, capturing human decisions in a system and plugging those into the model may improve the accuracy of the model. Once all the above mentioned findings are incorporated, we believe that this inclusive prediction model can help the firm take more informed data-based decisions and act proactively to mitigate the risk of a service disruption.