# Executive summary

**Reducing Variability in Order Quantity**

## Research Question

In this thesis I tried to target two kinds of variations Cummins deals with:

1) Variation between the quantity of SKU to be ordered at different point of time (planned Vs. Planned)
2) Variation between different Purchase orders (PO)

At the end of the thesis, I have tried to give a recommendation on what should be the ideal/maximum value of CV (coefficient of variation) should be for the POs placed. This will help Cummins to cut down the variation before the demand reaches the suppliers.

## Current process

### Distribution centers

Current distribution network of spare parts where MDCs order the parts for 2nd layer PDCs is as follows:

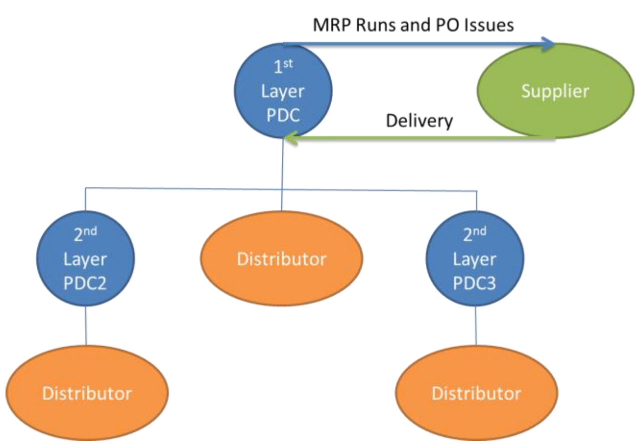


**Figure 1 Supply Demand Network**

# Methodology

## Planned vs Firmed

Here I have compared the variation between the planned order quantities of a part vs. the quantities which were eventually ordered.

## Firmed vs Firmed

In firmed vs. firmed, I compared the variation between the orders placed of the same part at different point in time. I used a common but effective method of Coefficient of Variation

Coefficient of Variation (CV) is defined as the ratio of standard deviation over the mean

$$Cv = \frac{\sigma}{\mu}$$

The primary advantage of CV is that it behaves as the normalized measure of the distribution which is useful to compare when the Mean varies significantly.

### Results

### Firmed vs. Firmed

The resulted value of CV was 3.2

When the analysis was done by eliminating the parts which were ordered only once, the value of CV came out to be 2.57.

| | Average coefficient of variation | CV (without one time orders) | % Change |
|---|---|---|---|
| A | 1.93 | 1.76 | 8.81% |
| B | 2.24 | 1.97 | 12.05% |
| C | 2.55 | 2.21 | 13.33% |
| D | 2.8 | 2.45 | 12.50% |
| E | 3.56 | 2.88 | 19.10% |
| N | 4.41 | 3.48 | 21.09% |
| 4 | 2.03 | 1.87 | 7.88% |
| 3 | 2.72 | 2.38 | 12.50% |
| 2 | 3.37 | 2.8 | 16.91% |
| 1 | 3.7 | 2.98 | 19.46% |
| 0 | 4.18 | 3.33 | 20.33% |

**Table 1 CVs (without parts which were ordered only once)**

### Regression model

The value of the CVs were found to be much higher than expected, therefore it was necessary to build a model which can predict the value of CV depending upon the different drivers. The drivers which were available for the analysis of CV were: Safety stock, Unit cost, Lot size (minimum batch size), Lead time, Mean and Standard deviation.

In the first linear regression model, I came up with a model with R-square of 0.44. To refine the data, I took the help of the residual values. This time I was able to reach the R-square value of 0.83

The final model obtained was:

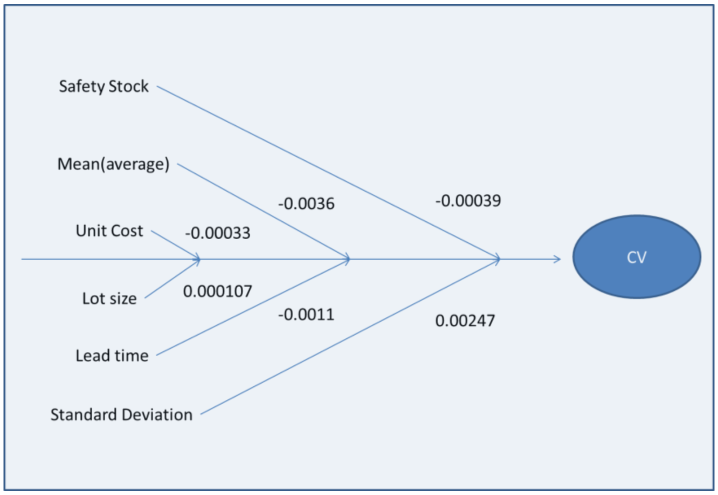


Figure 2 Final Regression Model

$$y = -0.0036 * mean - 0.0011 * lead\ time - 0.00033 * unit\ cost + 0.000107 * lot\ size + 0.00247 * SD - 0.00039 * Safety\ Stock$$

# Conclusions and Recommendations

## Effects of improvement in Coefficient of Variation value

If any firm can control the value of CV then the effects would be as follows:

1) The firm would be able to manage the inventory better in the whole supply chain due to low variability
2) Suppliers will be able to plan their capacity
3) Lead time would be near accurate
4) Transshipments will decrease
5) Quality of the products might improve
6) Supplier relationship will improve

## Recommendations

An important area which any firm needs to look is the variability in the customer demand. It is very important to measure the intensity of the bull-whip effect which is travelling through the supply chain.

It is also important that different parts should be treated differently. From the analysis, it was observed that there was no significant difference between the variation of Parts with code ‘A’ and other parts.

The other important process which needs to be looked into is the planning of the MRP cycle. It is definitely difficult to forecast the demand of a part 18 months prior to placing the order but the data revealed that the planned quantity was not even changed just one week before the PO release date.

## Assumptions

Due to constraints of time and data availability, there were a few assumptions which were taken in the process.

- The quantity of the safety stocks for different parts was constant over the duration of the analysis
- The six parameters used in the model are relevant and can be linearly associated with the final value of CV. The model was tested for higher degree but was rejected due to inconsistency
- The data obtained was highly variable in nature except for certain percentage of parts. It was assumed that these parts represented meaningful data and therefore only this data set was chosen for the designing of the model

## Scope for improvement

To improve this process, the two most important things to keep in mind are:

1) Organized collection of data –. At the moment not all data is being captured. During the data analysis, I found a peculiar pattern in the data. The planned quantity was almost always less than the actual order. The reason for this pattern to emerge was simple; at the moment Cummins only keeps the data of the parts whose POs actually gets placed.
2) Avoid errors in data set – avoiding errors in the data sets is sometimes more important than a good collection of data. Wrong data or errors in data can lead to awfully inaccurate results which we may not even realize at the time of research. In some cases multiple lead times were found for the same part bought from the same supplier.