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IE3100R Systems Design Project

Impact of Cycle Time Variability on Demand Fulfilment Rate

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Project Overview

COMPANY BACKGROUND

Global leader in semiconductors and systems for automotive, industrial and multimarket sectors

Regional Headquarters in Asia
Focused on final test manufacturing and test innovation

Commitment to product quality and continual production process improvement

PROBLEM STATEMENT

Problem?
Less than optimal demand fulfilment rate

Why?
High Cycle Time Variability due to inefficiencies in resource utilisation

* Want to know…
Will reducing cycle time variability improve demand fulfilment?
Is there any better way to improve demand fulfilment?

PROJECT OBJECTIVES

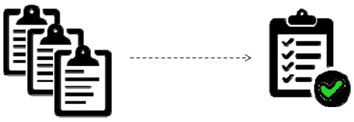
Statistical Analysis of Product Cycle Times
Propose distribution fittings for product cycle time

Development of Simulation Model
Validation by reproducing historical data

Determine impact of reducing cycle time variability on delivery performance
Study demand fulfilment rate based on experimental designs using simulation model

Data Analysis

DATA PROCESSING

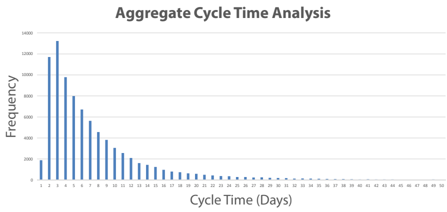


Synchronisation of raw data across all stages
- Lot preparation; Lot completion; Demand clip

Account for missing lots and invalid data

Calculation of cycle time and demand fulfilment based on raw data

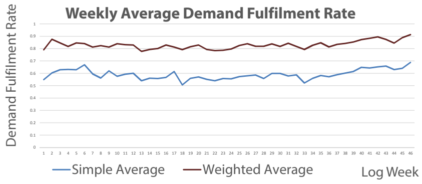
CYCLE TIME ANALYSIS



Cycle Time is highly variable & right-skewed
- Mean = 7.52 days with Std Deviation = 9.24 days
- Median = 4.82 days

Company's expectation = 5 – 12 days
- Only 33% of lots fall within this range

DEMAND ANALYSIS



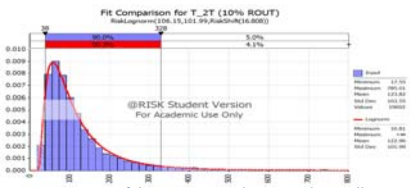
Average Weekly Demand Fulfilment calculated ranged between 50% - 70% over the period of study

Weighted Average indicates that delivery performance is better if we look at total volume of demand fulfilled.

In general, orders with larger sizes are more likely to be fulfilled on time

Simulation

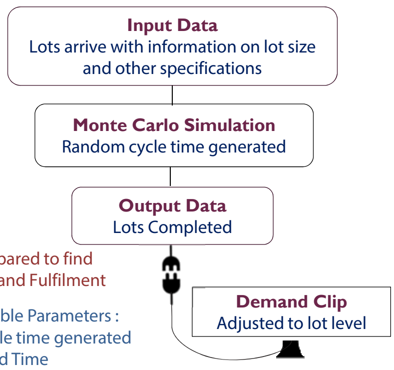
DISTRIBUTION FITTING



Categorisation of lots was implemented to allow a more representative fitting than using aggregate level
- 3 possible categorisation methods :
  - ✗ Product Basic Type
  - ✗ Product Package Type
  - ✓ **Route Type** (provided the best representation)

@Risk software used to perform distribution fitting, using the AIC / BIC criterion
- Generally lognormal with varying parameter estimated

SIMULATION OVERVIEW

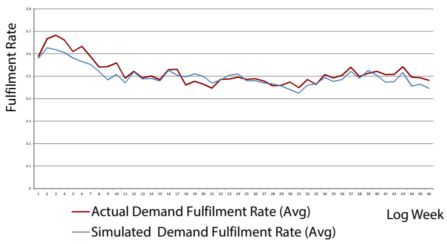


Compared to find Demand Fulfilment

Variable Parameters :
- Cycle time generated
- Lead Time

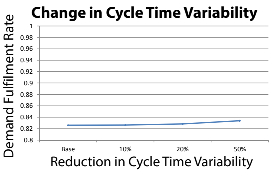
BASE CASE

Assumptions:
- All lots of the same Route Type have similar cycle time distributions
- Completed lots are used to fulfil backlogs first, if there are any

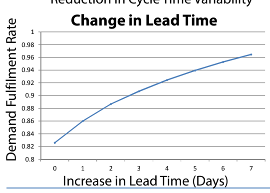


Results

CHANGING VARIABILITY V.S. LEAD TIME



Reduction in cycle time variability:
Insignificant impact on demand fulfilment rate



Increase in lead time:
Significant improvement in demand fulfilment rate

RESULT DISCUSSION

Top 3 route types by volume

Route Type	Estimated Lead Time (Days)	Average Cycle time (Days)	Expected Delay (Days)
A	5.00	3.08	-1.92
B	3.00	11.97	8.97
C	4.00	7.86	3.86

→ For most route types, the average cycle time exceeded the respective lead times used (as estimated using simulation models)

→ In such cases, reducing variability would have little effect on improving demand fulfilment rates

→ Extending lead times would have much greater impact

RECOMMENDATIONS

Short term

Focus on extending lead times
- Double-check data on average cycle time with line planners
- Coordinate with upstream processes to obtain lots on schedule

Long term

- Focus on improving average cycle time rather than cycle time variability
- Close gap between lead times and cycle times

Academic Year 2014 / 2015

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