Analytics for Supply Chain Optimisation

Harshvardhan Uttarwar (✉ hsu2101@columbia.edu)

Columbia University Fu Foundation School of Engineering and Applied Science   https://orcid.org/0000-0002-0295-2959

Research Article

Analytics for Supply Chain Optimisation

Harshvardhan Uttarwar, MS in Industrial Engineering, Columbia University (hsu2101@columbia.edu)

Abstract – Supply Chain analytics has gained greater significance this decade aiding in efficiency and responsiveness of a supply chain leading to a competitive advantage in almost every industry. Small scale industries and organisations are either unaware or reluctant to apply analytics and digitise their supply chain for multiple reasons. This paper is an effort to demonstrate the effect of supply chain analytics on a company and its current constraints. A detailed description of diverse analytics to aid in the surge of productivity at XYZ plant is presented. An underlying objective of this research was to impact all three aspects – *strategy*, *design* and *execution* of the supply chain to boost profits and optimise the system in consideration.

Keywords – LP, Simulation, R, TOC, SC analytics

I. Introduction

Supply chain (SC) optimisation is a key factor required for the efficient and responsive functioning of any industrial organization. It requires improvement in three broad and distinct categories: 1. Strategy, 2. Design and 3. Execution. *Strategic* improvement of any supply chain requires statistical distributions, customer analysis, competitor analysis, PESTLE analysis and SWOT analysis to better understand the as-is SC situation and thus shape the strategy to be followed.

Optimising the SC *Design* aspect includes but is not limited to:

1. Basic statistics, deviation and compliance analysis applied to safety measurement and evaluation
2. Mathematical programming and economic analysis applied to economic performance sustainability
3. Queuing theory and simulation modelling applied to SC physical design

Several analytic approaches to help with the performance of *order fulfilment*, i.e. theory of constraints, pull inventory, constraint-based inventory management, statistical process control and logistics models are part of improving the *Execution* aspect of any supply chain.

In this paper, the focus is to elevate all three categories by applying an analytical approach to optimise and solve major issues experienced by the company. In greater detail; supplier segmentation is performed for a better understanding of the strategic aspect while mathematical programming in R is accomplished to analyse data distributions in turn leading to improved SC strategy.

The research also aims to understand SC's capability in meeting reduced order cycle-times (time from order placement to full order delivery) along with addressing the issue of independent arrivals of trucks at the SC's logistics terminals via R programming.

A supplier analysis is carried out to determine the number of suppliers in each category and an alternate proposal is presented to improve supplier segmentation leading to increased profits.

Simulation and linear programming is executed to maximise profit aiding in addressing SC design obstacles. Simulation is the process of building models (of varying levels of complexity) that attempt to simulate a real-world situation in a way that does not interfere with the real-world system, does not cost anywhere near as much as developing a system and provides the ability to safely run numerous versions of a developed model in a compressed timeframe.

These features make simulation an excellent tool to conduct 'what-if' analyses. In this paper, a simulation is performed, to understand the financial effect of adding a truck unloading dock to the existing system. Linear programming (LP) is applied to help with SC facilities design; constraints are identified, reported and a new manufacturing system is proposed to meet customer demand. Four factors are identified to determine constraints for multiple products and address insufficient manufacturing.

Lastly, the 'Theory of Constraints' (TOC) approach is adopted to improve the supply chain execution aspect and propose a product-mix which maximises profit. TOC utilises a method of managing a constraint resource in order to maximise the throughput of the entire system. Data collected for identifying a constraint includes process times for every workstation, profits per product, operational expenses and units of raw

material required. The recommended product-mix directly impacts and maximizes gross profits of the organisation.

II.   Literature review

Supply chains typically generate massive amounts of data. Supply chain analytics helps to make sense of all this data — uncovering patterns and generating insights.

Different types of supply chain analytics include:

Descriptive analytics - Provides visibility and a single source of truth across the supply chain, for both internal and external systems and data.

Predictive analytics - Helps an organization understand the most likely outcome or future scenario and its business implications. For example, using predictive analytics can project and mitigate disruptions and risks.

Prescriptive analytics - Helps organizations solve problems and collaborate for maximum business value. Helps businesses collaborate with logistic partners to reduce time and effort in mitigating disruptions.

Cognitive analytics - Aids an organization to answer complex questions in natural language — in the way a person or team of people might respond to a question such as "How might we improve or optimize X?"

Supply chain analytics is also the foundation for applying cognitive technologies, such as artificial intelligence (AI), to the supply chain process. Cognitive technologies understand, reason, learn and interact like a human, but at enormous capacity and speed. This advanced form of supply chain analytics is ushering in a new era of supply chain optimization. [1]

Suning Zhu, Jiahe Song, Benjamin T. Hazen, Kang Lee and Casey Cegielski examined how supply chain analytics (SCA) capabilities support operational supply chain transparency. [2]

Bongsug (Kevin) Chae, David Olson and Chwen Sheuto tried to better understand the role of supply chain analytics (SCA) on supply chain planning satisfaction and operational performance. Based on the data collected from 537 manufacturing plants, they test hypotheses exploring the relationships among three resources - data management resources (DMR), IT-enabled planning resources and performance management resources (PMR) with supply chain planning satisfaction, and operational performance. The analysis supports that DMR should be considered a key building block of manufacturers' business analytics initiatives for supply chains. [3]

Providing too much service capacity to operate a system involves excessive cost. But not providing enough service capacity results in excessive waiting time and cost. In this study, the queuing characteristics at the Riverside Specialist Clinic of the Federal Medical Centre , Makurdi were analysed by Kembe, M. M, Onah, E. S and Iorkegh, S using a multi-server queuing model and the waiting and service costs determined with a view to determining the optimal service level. This model can also be used by decision and other policy makers to solve other multi-server queuing problems. [4]

Utilizing data collected from direct observation, personal interviews and questionnaires in service centers within the south east and south-south geopolitical zones of Nigeria, estimates of some queuing situations parameters were obtained, including a forecast of the effect of an increase in the number of service providers on the efficiency of service delivery.

A study conducted by Uzochukwu Amakom discovered that considerable time is wasted by customers in banks, hospitals and post offices due to incompetence of service providers, non-compliance with the required queue discipline, lack of automation of necessary facilities and this time has some huge costs. [5]

A very necessary preliminary step in the whole strategy process is a 'state-of-play' analysis of key vision elements. Examples of such an analysis and how statistical distributions can be used to help appraise the vision elements include Normal Distribution and Poisson distribution. These processes can be automated and applied to multiple datasets via R programming. [6] [7]

To study a complex system, an objective method combining various approaches (statistics, R, GIS, descriptive analysis and graphical plotting) was performed by Polina Lemenkova. Methodology of the research includes following clusters: R programming language for writing codes, statistical analysis, mathematical algorithms for data processing, analysis and visualizing diagrams, GIS for digitizing bathymetric profiles and spatial analysis. The statistical analysis of the data taken from the bathymetric profiles was applied to environmental factors, i.e. coordinates, depths, geological properties sediment thickness, slope angles, etc. [8] Finally, factor analysis was performed by R libraries to analyse impact factors of the Mariana Trench ecosystem. The research demonstrated that coding on R language provides a powerful and highly effective statistical tools,

mathematical algorithms of factor analysis to study ocean trench formation. [9]

Waheed Babatunde Yahya, Muhammed Kabir Garba, Samuel Oluwasuyi Ige and Adekunle Ezekiel Adeyosoye demonstrate the use of linear programming methods as applicable in the manufacturing industry. Data were collected as extracts from the records of KASMO Industry Limited, Osogbo, Nigeria, on four types of sales packages adopted for selling her medicated soap product which include 1 tablet per pack, 3 tablets per pack, 12 tablets per pack and 120 tablets per pack. [10] Based on the costs of raw materials, the maximum profit that would accrue to the company given the product mix was determined. The analysis was carried out with R statistical package using the library "lpSolve". [11]

Jafar Rezaei wrote a paper to develop a new approach of supplier segmentation that considers the various variables used in existing literature to segment suppliers. [12] As the basis for this new approach, he developed three requirements to make an overarching approach to supplier segmentation - Firstly, supplier segmentation should be based on their long-term potential, which he proposes to assess in terms of supplier capabilities and willingness to cooperate. Secondly, other functional areas beyond purchasing have to be considered while segmenting suppliers. Thirdly, supplier segmentation should be viewed as a step in a longitudinal process that includes selecting suppliers, segmenting them, managing the relationship with them and actively developing their role over time. He illustrated the proposed approach by segmenting the suppliers of a company in the food industry. [13]

III.   Objectives and Analytical Approach

Customers, suppliers, logistics providers, SC managers are facing issues in supply chain strategy, design and execution. The problems are affecting customer deliveries and inventory levels with some items on stock-out whilst other items having excess inventory. Solving these problems will improve company reputation and profitability significantly. The issues started in Jan 2021 and have intensified over the 3 months since then. These issues will be addressed by a cross-regional team coordinated by an SC leader from XYZ's parent company.

a. *Supply chain strategy objectives and methodology* –
   1. To evaluate current order cycle time (time from order placement to full order delivery)

using R programming and optimising the offer time to stimulate sales.
   2. To understand as-is situation of supplier segmentation and propose a plan to improve the situation.
   3. To assess the issue of arrival rate of trucks at the SC's logistics terminals using R programming and offer insights.

b. *Supply chain design objectives and methodology* –
   4. Run a simulation to analyse time required for recovering an investment in building and additional truck unloading dock.
   5. Perform linear programming to identify and economically elevate the constraints to satisfy demand.

c. *Supply chain execution objectives and methodology* –
   6. To use 'Theory of Constraints' approach to discover a product-mix for a specific assembly line resulting in maximised profits.

IV.   Data Analysis

a. *Assessment of Order Cycle Time with R*

Order cycle time is the time required from order placement to full order delivery. This aspect of the supply chain significantly affects customer satisfaction in turn affecting sales and profits. Shorter order cycle times resulting in highly responsive supply chains for satisfying customer orders, play a key role in the success of any organisation.

A part of this research, consists of evaluating the order cycle time offered to customers by XYZ company and analysing the corresponding data. Preliminary research showed that the current order cycle time offer to customers is 34 hours. An analysis is performed to check whether order cycle time can be reduced to 29 hours.

Initially the plan was to analyse cycle time data in to excel and discover insights for optimisation. Later discussions with the management team helped realise that, if this process is automated, it would save the team a lot of time every time it plans on analysing the real-time data. R programming was implemented to automate the entire process, saving a lot of valuable time for the team.

The first step was to find mean and the standard deviation of order cycle time. 507 data points were analysed to ensure significant accuracy of the results. Using *DescTools()* function in R, we can find the basic statistics of data under consideration.

The data followed Normal statistical distribution with current mean cycle time actually achieved was 23.68 hours with a standard deviation of 2.85 units.

$$\mu = (\sum(X*f) \div \sum f)$$
$$\sigma = SQRT(\sum(f*(X-\mu)2)/(\sum f)-1))$$

To get an idea of the data distribution, a summary table (Table 1) of all data points is constructed.

Order Cycle-Time	Frequency
15 Hours	02
16 Hours	02
17 Hours	04
18 Hours	09
19 Hours	12
20 Hours	35
21 Hours	49
22 Hours	57
23 Hours	68
24 Hours	72
25 Hours	67
26 Hours	53
27 Hours	39
28 Hours	19
29 Hours	08
30 Hours	04
31 Hours	02
32 Hours	03
33 Hours	01
34 Hours	01

Table 1 Frequency Table of Order Cycle-Times

The R program for analysing data is -

```
>library(DescTools)
>MyDataFrame<-read.csv("CT.csv", header=TRUE)
>Desc(MyDataFrame$Duration)
>pnorm(q=29,mean=mean(MyDataFrame$Duration),
sd=sd(MyDataFrame$Duration), lower.tail = T)
```

Here, with the first command, *DescTools()* function is added from the library of R, and the function can now be utilised. The *read()* command opens the data file and makes all data points available to us for statistical analysis. Here, 'CT.csv' is the name of file (in .csv format) which holds all data and the 'header=TRUE' parameter simply tells R that columns in this file have respective names in the first row. The purpose of this first command is to tell R that the data frame to be analysed is in 'CT.csv' file.

Column name of order cycle times in the actual data file is 'Duration', and it has other columns too which currently are of no interest. Running the

Desc() function quantifies and provides us with number of data points, mean, median, range, standard deviation, kurtosis, skewness and some other statistics. In this case, the data points in 'Duration' column need to be selected for analysis and the '$' sign is used for selecting any column, as shown in the above mentioned code.

In excel, this analysis would first require us to find the Z value for considered data and then find probability P(X<=29) with the formulae –

$$Z = (X - \mu)/ \sigma$$
=NORM.DIST(29,μ, σ,TRUE)*100

In R, to find probability P(X<29), the function pnorm() is implemented; parameters required include – q (in this case 29), mean, standard deviation and whether we need P(q<=29) or P(q>=29), also called as lower tail = T/F.

Fig. 1 is a screenshot of the output when this line of code was run, and the probability was 96.89%.


```
> pnorm(q=29, mean = mean(MyDataFrame$Dur
[1] 0.9689372
```

Figure 1 Output when pnorm() is Executed

In conclusion, P(x<=29) = 96.89% is a significant assurance of order fulfilment, and reduction of the offered order cycle-time to 29 hours is a good idea. Better responsiveness and reduced cycle time attracts customers and stimulates profits. Assessment of the already available and real-time data provided insights about reducing the offered cycle time by about 15% which in turn would result in significantly increased customer base an profits.

b. *Supplier Segmentation and Planning*

Analytics can be used to help develop strategies and to choose the strategies most suited to the SC's goals. Faced with a competitive global market, firms have downsized, focused on core competencies and attempted to manage their relationships with suppliers more effectively. There are multiple methods for supplier segmentation; with the method employed, the level of involvement and investment in terms of time, money and efforts determines the type of the relationship. The supplier analysis carried out according to the given template for determining the number of suppliers in each category produced a sub-optimal result.

The template in Fig. 2 indicates 4 types of suppliers – captive buyer, strategic, non-critical and captive supplier according to company's and suppliers'

level of investment. Here 'strategic' suppliers are the desired suppliers who aid in parallel growth of the suppliers and buyers. 'Captive Buyer' signifies that XYZ has too much invested in the supplier, but supplier has the freedom to switch and can assert dominance over XYZ. 'Captive Suppliers' could be tolerated because of the high level of amounts the supplier has invested, suppliers don't really have significant power over the buyer, but this is an unhealthy relationship and could affect SC performance in later stages. The target is to reduce non critical suppliers and increase the number of strategic suppliers who deal with XYZ.

Company's Level of Investment	High	Captive buyer	Strategic
	Low	Non Critical	Captive Supplier
		Low	High
		Suppliers' level of Investment	

Figure 2 Supplier Segmentation Template

On categorising multiple suppliers, the result (shown in Fig. 3) yielded only 1 desired strategic supplier whereas 10 noncritical suppliers and 4 suppliers investing in the supply chain lesser than the company XYZ. This is a very suboptimal result and can affect XYZs' supply chain drastically in the long run.

As-Is Supplier Segmentation Result			
Company's Level of Investment	High	4	1
	Low	10	3
		Low	High
		Suppliers' level of Investment	

Figure 3 As-Is Supplier Segmentation

The first and foremost recommendation would be to cultivate more strategic suppliers who would aid in uncertainties reducing losses incurred. A reduction of suppliers who invest lesser than XYZ in the supply chain is also necessary for more flexibility to deal with demand uncertainties and establish better authority.

Another aspect to consider would be to cut down non critical suppliers significantly, to save costs and generate value by instead investing in strategic relationships.

Recommended Supplier Segmentation			
Company's Level of Investment	High	2	4
	Low	4	3
		Low	High
		Suppliers' level of Investment	

Figure 4 Recommended Supplier Segmentation

Desired situation shown in Fig. 4 consists of reduction in 28% of the total suppliers. Additionally, and more importantly, XYZ should decide to lift its number of strategic suppliers from 1 to 4 and to reduce the number of suppliers it is captive to from 4 to 2. Reducing the non-critical

suppliers to 4 would also result in some significant savings which could be invested in strategic suppliers in turn resulting much greater value. Suppliers exert a strong influence on throughput time and work-in-process inventory, and play an often critical role in new product development.

A necessary eight step, five month plan to undergo this transformation is proposed (Table 2) and time required for specific steps is estimated.

Steps	What to do	Days required
1	Set and define a strategic supply item.	3
2	Set a selection criteria for strategic partners.	5
3	Identify strategic supply items from procurement base	21
4	Identify potential strategic suppliers according to criteria	10
5	Draft formal strategic partnership agreement documents	14
6	Gain approval of executive team to proceed	20
7	Engage and negotiate with identified potential strategic suppliers	80
8	Report progress and plan next steps	10

Table 2 Plan to Achieve Desired Supplier Segmentation

In this case, the criteria for identifying potential strategic suppliers can be –
- Quality and Reliability
- Order Cycle Time and Flexibility
- Service and Transparency
- Minimum order quantity
- Financial stability of the supplier

Companies that integrate their supplier base effectively with their internal engineering, manufacturing, and purchasing operations benefit from reduced costs, shorter lead times, lower development risks, and compressed development cycles.

c. Evaluating Truck Arrival Rates with R

A pressing issue in the XYZ company was at a truck unloading terminal at a specific industrial plant. This logistic terminal was turning out to be the most inefficient workstation and was the so called bottleneck in said plant. The primary focus was to evaluate the as-is condition of the terminal and provide recommendations, but a subsequent

simulation is also performed for improved SC performance and is explained later in this paper.

The focus was to assess arrival rate of trucks at the logistic terminal and discover some insights as well as provide recommendations. This process was required to be automated and quick whenever the management team decides to analyse arrival rates. R programming was decided to be done after several discussions with the management and analyst teams. Total of 120 data points were available for evaluating arrival rates and proving recommendations. The data file was named 'TA' and consisted of two columns- 'APH' short for Arrivals per hour and 'Count', which increased by 1 unit each row.

The data was seen to follow Poisson distribution and the arrival rate variability was to be discovered. The code to be run in R –

```
>library(DescTools)
>MyDataFrame <- read.csv("TA.csv", header=TRUE)
>Desc(MyDataFrame$APH)
>x <- max(MyDataFrame$APH)
> for (i in 1:x)
{
 print("Probability that X is less than",)
print(i)
print(sum(dpois(x=1:i,lambda=mean(MyDataFrame$
APH))),digits=4)
}
```

The first task was to add DescTools() from the R library. Then opening the 'TA' file available in comma separated values format and assigning it to *MyDataFrame()*. In this case the data file had headers and the column with truck arrival data was named 'APH', hence the parameter *header* should be assigned to value *TRUE*. On running the code - 'Desc(MyDataFrame$APH)', basic statistics like mean and standard deviation for truck arrivals can be seen (Fig. 5).

Figure 5 Desc() Output on Truck Arrivals Data

As shown in the figure, the data was slightly skewed with a mean of 5.90 trucks per hour. The

standard deviation of data was 2.12 units with a range of 11.

A *FOR* loop in R was used calculate probabilities of multiple truck arrivals. Maximum truck arrivals per hour was determined (in this case 13) and a for loop was used to determine cumulative probabilities starting from P(X=1) and ending at P(X=13), but the code is edited accordingly and will run continuously to find P(X=max value in the respective column). The *dpois()* function results in probabilities of exactly 'X' arrivals in 1 hr across the terminals, following Poisson distribution and the parameters required are – X (in this case, 1 to 13) and lambda (5.90). The *sum()* function is also utilised for calculating cumulative probabilities. A screenshot of the output scree in shown in Fig. 6.

Figure 6 dpois() Output on Truck Arrivals Data

From Table 3, we can infer that summed probability of arrival rates one through ten, represent about 95% of the arrival distribution

For X =	Probability	Cumulative Probability
0	0.003	0.00
1	0.016	0.02
2	0.048	0.07
3	0.094	0.16
4	0.138	0.30
5	0.163	0.46
6	0.160	0.62
7	0.135	0.75
8	0.100	0.85
9	0.065	0.92
10	0.039	0.96
11	0.021	0.98
12	0.010	0.99
13	0.005	1.00

Table 3 Summary Table of all Probabilities

In this particular case, the SC's logistics terminals would suffer from peak overloading and trough over-resourcing with such an arrival pattern resulting in redundant costs.

A two-part recommendation was provided in response to this problem, that a cross-functional improvement team be allocated with the objective of studying and then reducing the arrival rate variability experienced. Subsequently, to help the team, a simulation is provided where operational and financial effects of adding another logistic terminal can be observed and analysed.

d. Simulation of Adding a Logistic Terminal

In this excel analysis, we observe the financial and operational consequences of adding a logistic terminal for truck unloading in an attempt to de-bottleneck the workstation and improve efficiency. Simulation modelling is the process of creating and analysing a digital prototype of a physical model to predict its performance in the real world. The objective is to evaluate alternative supply chain designs with respect to quality, lead-times and costs as the key performance parameters.

The team at XYZ had a file with 120 data points as mentioned earlier; the file had 1 important column - APH – Arrivals per hour. After cleaning the data file, and evaluating the arrival rate variability in the previous analysis, 4 more columns were added - D – Delayed, , TBU – To be Unloaded, UC – Unload Capacity, AU – Actually Unloaded.

The formula for items in 'Delayed' column is – =IF(TBU-AU<0,0,TBU-AU), which in other words mean that if difference between cell value in 'To be Unloaded' column and 'Actually Unloaded' column of previous hour is at least one truck, Delay value will be a real number or else it will be mentioned as zero.

The TBU data points could be calculated by summing up delayed trucks and new arrivals for the hour in consideration. The unload capacity in as-is state is of 5 trucks every hour and the aim is to observe the system simulation when unload capacity is increased by one truck per hour. The 'Actually Unloaded' can be calculated using the formula - =IF(UC<TBU,UC,TBU).

The total delayed trucks, truck arrivals and trucks actually unloaded are calculated. The average arrival rate per hour is 5.9, which was previously calculated using DescTools() function in R.

Here a total of 708 truck arrivals is observed; we assume that every truck delayed is delayed for an hour, thus total delay being 6763 hours in the as-is state. 593 trucks were actually unloaded in 120 hours out of 708 arrivals, demonstrating a significant scope for optimisation. A sample data file format of 11 data points is shown in Table 4.

Hour	D	APH	TBU	UC	AU
1	0	3	3	5	3
2	0	3	3	5	3
3	0	4	4	5	4
4	0	3	3	5	3
5	0	5	5	5	5
6	0	6	6	5	5
7	1	6	7	5	5
8	2	7	9	5	5
9	4	7	11	5	5
10	6	8	14	5	5
11	9	8	17	5	5

Table 4 Sample Data File Format

Now, if we add another truck unloading terminal to the system, the resulting table gives us and unloading capacity of six trucks per hour. Table 5 is a comparison table of delay hours, and trucks unloaded, on considering an additional truck unloading dock.

Resulting total delay hours according to the simulation (Table 5) are only 825; a significant reduction of 88% in delay is observed in turn simultaneously improving efficiency and responsiveness of the supply chain. 105 trucks are unloaded additionally to the 593 trucks unloaded in current system, thus increasing total actual unloading of trucks by 18%.

Terminals	D	APH	TBU	UC	AU
5	6763	708			593
6	825	708			698

Table 5 Simulation Results

Analysing the financial aspect of adding a terminal, we need to consider opportunity cost incurred per hour, total delay in as is system and simulated system, and capital expenditure to build an unloading dock in India.

The estimated delay cost per hour is Rs. 1,583 which is calculated by taking into consideration selling price/unit, total hours and average potential units received per hour.

If we consider all the data points to be distributed among 5 days (120 hours), the total cost of delay for one day in a 5 terminal system would be – (total delay hours * 1583) /5 = (6763 * 1583) / 5 = Rs. 21,41,617

Similarly to find the total delay cost for one day in a 6 terminal system, the formula would be –
(825 * 1583) / 5 = Rs. 2,61,250
Resulting savings for every day by adding 1 truck unloading terminal are Rs. 18,80,367.
The estimated capital expenditure required to build this terminal is Rs. 1,74,87,41,000. Number of days required to recover cost of dock can be calculated by the formula, capex divided by daily savings – (1,74,87,41,000)/(18,80,367) = 930 days or 2.5 years. This simulation was presented to XYZs' management team to aid them in an informed decision making of investment in building one additional truck unloading dock.

e. Linear Programming to Identify and Elevate Constraints

Data provided by the XYZ's owners and operations team was used to estimate the parameters of the linear programming model. The LP model was solved using MS-Excel software to determine and elevate constraints required for manufacturing the most economical product mix by XYZ and therefore provide an optimum solution.

A data collection procedure was quantitative in nature and the data is obtained from the personal interview with the business owners and analysts along with their existing records. The relevant information on the price (in Indian Rupees, Rs) per unit is summarized in Fig. 7.

Maximise profit = 3200X1 + 3500X2 + 2700X3 + 3700X4
Subject to following constraints shown in Table 6.

		Sign	Constraints
Material Availability	X1	<=	260000
	X2	<=	99000
	X3	<=	270000
	X4	<=	145000
Current Cust. Contracts	X1	>=	1500
	X2	>=	1250
	X3	>=	2900
	X4	>=	1425
Max Weekly Demand	X1	<=	2550
	X2	<=	1998
	X3	<=	3700
	X4	<=	2200
Weekly Capacity	X1	<=	2300
	X2	<=	2200
	X3	<=	4000
	X4	<=	2500

Table 6 Constraints in the Current System

The LP spreadsheet is constructed very carefully, including the SUM- PRODUCT equations for total profit and the LHS constraint cells. On entering all

	Product	Material needed/unit	Material Availability/week	Mfg Capacity(units/week)	Demand/week	Profit/unit	Current Customer contracts(units/week)
X1	Accessary 1	100	260000	2300	2550	3200	1500
X2	Accessary 2	55	99000	2200	1998	3500	1250
X3	Accessary 3	72	270000	4000	3700	2700	2900
X4	Accessary 4	68	145000	2500	2200	3700	1425

Figure 7 As-Is System Parameters

XYZ wants to know the best capacity configuration to maximise earnings (profits). The design choice involves selecting an installed capacity for each of their four main products. The four constraints considered in this analysis are – material availability, current customer contracts, maximum weekly demand and weekly manufacturing capacity. The decision variables in this LP are the number of units made weekly for each product type:

Let X1 be Aluminium alloy units/week
Let X2 be Titanium units/week
Let X3 be Plastic units/week
Let X4 be Carbon fibre units/week
Using the data in Fig. 7, the objective function can be written as:

the key information in Excel, Solver can be used to analyse constraints in the current system. Solver is a Microsoft Excel add-in program used for what-if analysis. Solver can be used to determine the maximum or minimum value of one cell (objective cell) by changing other cells. Fig. 8 is a screenshot of the Excel Solver used to solve this problem and analyse constraints using Linear Programming method. Cell K276 is 'Total Profit' and M282 to M297 are 'Constraints. The variable cells to be changed are set as the decision variables, i.e. the weekly make cells (units manufactured per week for each product). 'Max' and 'Simplex LP' method are selected and the result of these actions is shown in Table 7.
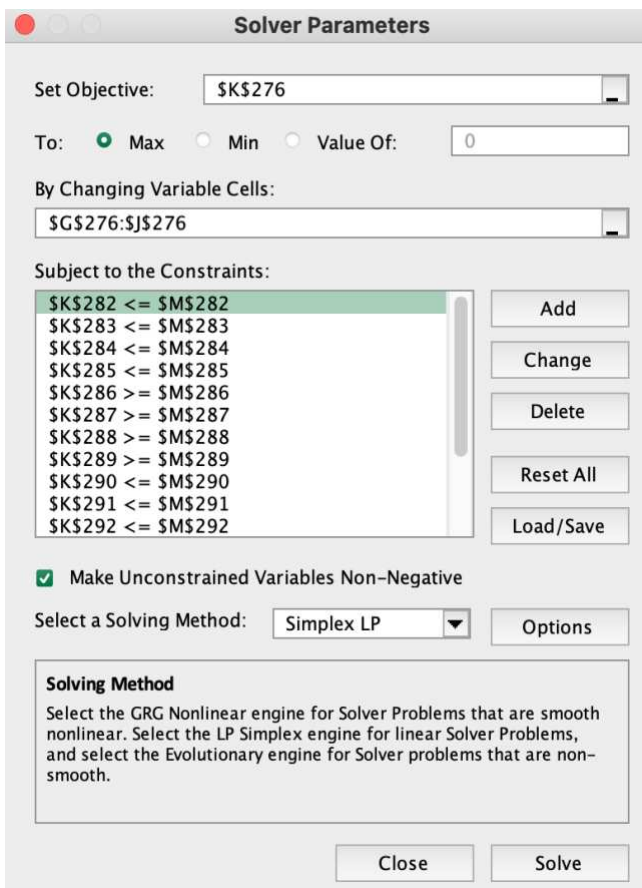
Figure 8 Excel Solver for LP

As highlighted in Table 7, three key issues can be observed:

1. Production of XYZ's highest and second highest profitability items (titanium and carbon-fibre products) is limited by raw material availability.
2. Production of the third highest profitable item is limited by production capacity.
3. Only the lowest profitable item (plastic product type) is limited by current market demand.

		LHS	Sign	RHS
Material Availability	X1	230000	<=	260000
	X2	99000	<=	99000
	X3	266400	<=	270000
	X4	145000	<=	145000
Current Cust. Contracts	X1	2300	>=	1500
	X2	1800	>=	1250
	X3	3700	>=	2900
	X4	2132	>=	1425
Max Weekly Demand	X1	2300	<=	2550
	X2	1800	<=	1998
	X3	3700	<=	3700
	X4	2132	<=	2200
Weekly Capacity	X1	2300	<=	2300
	X2	1800	<=	2200
	X3	3700	<=	4000
	X4	2132	<=	2500

Table 7 Current System Performance

Final results of the current system parameters are shown in Table 8; the total weekly profit calculated by Solver amounted to Rs. 3,15,39,706. 2300 units of Aluminium alloy are manufactured every week (maximum amongst all four product types). The management team believed this to be a sub-optimal result and so required an optimal design for the new facility.

	X1	X2	X3	X4	Total Profit
Weekly make	2300	1800	3700	2132	31539706
Profit/ unit	3200	3500	2700	3700	
Material used	230000	99000	266400	145000	

Table 8 Key Findings of Current System

In addition to process improvements and kaizen suggestions, multiple system parameters were recommended and a simulation of constraint performance is shown in Table 9. One major recommendation provided to the management team was to increase weekly manufacturing capacity of aluminium alloy products to 2600 units via subcontracting or capital investments in infrastructure. Secondly, Procurement department must be given the task of renegotiating the supply amounts of raw material required for titanium and carbon fibre products with current suppliers or opening negotiations for additional supply from new strategic suppliers. Raw material supply should be increased to 1,10,000 and 1,50,000 units for titanium and carbon fibre units respectively to satisfy current market demand while minimising excess production and costs incurred.

		LHS	Sign	RHS
Material Availability	X1	255000	<=	260000
	X2	109890	<=	110000
	X3	266400	<=	270000
	X4	149600	<=	150000
Current Cust. Contracts	X1	2550	>=	1500
	X2	1998	>=	1250
	X3	3700	>=	2900
	X4	2200	>=	1425

Max Weekly Demand	X1	2550	<=	2550
	X2	1998	<=	1998
	X3	3700	<=	3700
	X4	2200	<=	2200
Weekly Capacity	X1	2550	<=	2600
	X2	1998	<=	2200
	X3	3700	<=	4000
	X4	2200	<=	2500

Table 9 Recommended System Parameters

The results of a simulation, in which weekly manufacturing capacity and raw material availability was elevated, are shown in Table 10. Weekly make of all products except plastic units is elevated and a 6% increase in weekly profits can be observed amounting to a significant annual profit increase of Rs. 9,06,51,208.

	X1	X2	X3	X4	Total Profit
Weekly make	2550	1998	3700	2200	33283000
Profit/ unit	3200	3500	2700	3700	
Material used	255000	109890	266400	149600	

Table 10 Results of Recommended System Parameters

Another important recommendation would be to invest in marketing and sales team for plastic units with the objective to increase demand. In conclusion, multiple constraints were identified, as well as quantified recommendations were provided using Linear Programming to maximise profits while simultaneously improving service levels and goodwill of XYZ.

f. Theory of Constraints approach for optimal product-mix

The theory of constraints (TOC) is about improving an SC's throughput, levels of inventory and operating costs. This analysis models the selection of a product mix with the TOC model integrating activity-based cost with the capacity of production-related activities. The TOC product-mix heuristic is largely capable of maximizing the company's net profitability. In doing this, the following assumptions are made: all products have a common due date; the products are discrete units and consequently an integer solution is necessary; capacity available to meet demand is limited and cannot be increased at the bottleneck resource in the short term.

Consider the SC represented by the five workstations (Ws) and key operational data of the system is shown in Table 11. Four major products are being considered and, the demand and selling price/unit (Indian Rupees) is shown in rows 2 and 3. Subsequently, there are 4 sets of raw materials – RM 1, RM 2, RM 3 and RM 4. The requirement of each set of raw material, for 1 unit of each product can be observed. Additionally, process time (in minutes) required for manufacturing one unit of each product on every workstation is provided in Table 11.

Product -	A	B	C	D
Weekly Demand	300	240	210	195
Selling Price	4700	5200	4300	5900
RM 1 needed	1	0	0	0
RM 2 needed	0	1	1	0
RM 3 needed	0	0	1	0
RM 4 needed	1	0	0	1
Ws1 Cycle-time	0	0	6	6
Ws2 Cycle-time	6	6	0	6
Ws3 Cycle-time	11	0	11	0
Ws4 Cycle-time	0	8	8	8
Ws5 Cycle-time	9	9	0	0

Table 11 Key Operational Parameters of the System

The facility manufactures and is working for 6 days every week. Each day, the plant has 16 operational hours including overtime and all workstations have 85 available working hours every week. Raw material and operational cost was determined after rigorous data collection (Table 12).

Operational cost	Rs. 21,20,398
RM 1 unit cost	Rs. 900
RM 2 unit cost	Rs. 850
RM 3 unit cost	Rs. 1100
RM 4 unit cost	Rs. 920

Table 12 Cost Data

As can be seen in Table 13, Ws3 and Ws4 are the constraints in the system because the minutes required to process weekly demand levels for all products on these workstations (7,040 minutes on Ws3 and 6,200 minutes on Ws4) exceed available minutes for each workstation (5,100 minutes).

	Demand	Ws1	Ws 2	Ws 3	Ws4	Ws 5	RM 1	RM 2	RM 3	RM 4
A	300	0	1800	3300	0	2700	300	0	0	300
B	240	0	1440	0	1920	2160	0	240	0	0
C	340	2040	0	3740	2720	0	0	340	340	0
D	195	1170	1170	0	1560	0	0	0	0	195
Total		3210	4410	7040	6200	4860	300	580	340	495
Available		5100	5100	5100	5100	5100	350	600	350	450
OK?		Y	Y	N	N	Y	Y	Y	Y	Y

Table 13 Constraint Analysis

Material availability is not a constraint; to exploit the process time constraint by loading workstations in a way that maximises net margin, selling price, cost data and material consumption rates were used. The profit/constraint-minute for each product is calculated by utilising all contribution margins and required workstation processing times. The results of these calculations are shown in Table 14.

Products	A	B	C	D
Profit	2,880	4,350	2,350	4,980
Total time on Ws3 & Ws4	3300	1920	6460	1560
Profit/min	0.87	2.27	0.36	3.19

Table 14 Margin per Product per Constraint Time

Product D is the most profitable product per minute of constraint time, then to maximise overall net margin, the facility needs to maximise product D throughput. If product D is produced to the maximum of market demand (195 units), then 240 units of product B should be manufactured; additionally, weekly demand of product A (300 units) can be satisfied successfully. 163 units of product C can be made if the remaining time available on the constraint is utilised. This product mix, which fully utilises the constraint resource with the most profitable product first followed by the lesser profitable products, results in a weekly gross margin for the facility of Rs. 32,62,150 and, after subtracting operating expenses, a net margin of Rs. 11,41,753 per week.

V.   Conclusion

Supply chain analytics can provide greater supply visibility and improved forecasting will also lead to lowering the inventory levels, thereby saving money. Analytics has the potential to change the way our supply chains work resulting in cost-cutting and efficiency increment. The issue of securing the data flow and its analysis will remain as the major concern. Among other benefits, supply chain analytics has the potential to improve demand forecasting methods, detect disruptions in supply chain, and improve global communications. This paper is based on a project with an aim of targeted improvement on multiple levels of XYZ supply chain – strategy, design and execution. R programming and Excel is used to discover insights and observe key constrains; simulation models are provided along with detailed financial analysis and recommendations.

VI.   Declaration

VII.   References

[1] J. Sharma, A text book on Operations Research; Theory Applications. 4th Edition. ,, Macmillan publishers, 2009.

[2] S. S. J. H. B. L. K. a. C. C. (. Zhu, "How supply chain analytics enables operational

supply chain transparency: An organizational information processing theory perspective," *International Journal of Physical Distribution & Log, Vol. 48,* pp. 47-68, 2018.

[3] B. (. Chae, D. Olson and C. Sheuto, "The impact of supply chain analytics on operational performance: a resource-based view," *International Journal of Production Research, Vol. 52, Issue 16,* pp. 4695-4710, 2013.

[4] M. M. O. Kembe, "A Study of Waiting And Service Costs of A Multi- Server Queuing Model In A Specialist Hospital," *International Journal OF Scientific & Technology Research Vol. 1, No. 8,* pp. 19-23, 2012.

[5] U. Amakom, *How large is the Opportunity Cost of Queuing in Service Centres? Evidence from Eastern Nigeria,* 2008, pp. 1-18.

[6] M. Kohl, Introduction to statistical data analysis with R, Bookboon, 2015.

[7] P. W. Robertson, Supply Chain Analytics - Using Data to Optimise Supply Chain Processes, London: Routledge, 2020.

[8] P. Lemenkova, "Factor Analysis by R Programming to Assess Variability Among Environmental Determinants of the Mariana Trench," *Turkish Journal of Maritime and Marine Sciences ,* vol. 4, no. 2, pp. 146-155, 2018.

[9] R. G. M. M. Sridhar Tayur, Quantitative Models for Supply Chain Management, Springer Science & Business Media, 2012.

[10] M. K. G. S. O. I. Waheed Babatunde Yahya, "Profit Maximization In A Product Mix Company Using Linear Programming," *European Journal of Business and Management ,* vol. 4, no. 17, pp. 126-131, 2012 .

[11] W. B. Yahya, "Determination of Optimum Product Mix at Minimum Raw Material Cost, Using Linear programming," *Nigerian Journal of Pure and Applied Sciences,* vol. 19, pp. 1712-1721., 2004.

[12] J. R. &. R. Ortt, "A multi-variable approach to supplier segmentation," *International Journal of Production Research,* vol. 50, no. 16, pp. 4593-4611, 2012.

[13] T. a. H. J. Choi, " An exploration of supplier selection practices across the supply chain" *Journal of Operations Management,* vol. 14, no. 4, pp. 333-343, 1996.

[14] Robert Kee, Charles Schmidt, "A comparative analysis of utilizing activity-based costing and the theory of constraints for making product-mix decisions", International Journal of Production Economics, Vol. 63, No. 1, pp. 1-17, 2000.

[15] Vedpal Arya, Pankaj Sharma, Ashwani Singh, P.T.M. De Silva, (2017) "An exploratory study on supply chain analytics applied to spare parts supply chain", Benchmarking: An International Journal, Vol. 24 Issue: 6, pp.1571-1580.

[16] Gilvan C. Souza, "Supply chain analytics", Business Horizons, Vol. 57, Issue 5, pp.595-605, 2014.

[17] Sahay, B.S. and Ranjan, J. (2008), "Real time business intelligence in supply chain analytics", Information Management & Computer Security, Vol. 16 No. 1, pp. 28-48.

[18] Sarkis, J. and Talluri, S. (2002), "A model for strategic supplier selection", The Journal of Supply Chain Management, Vol. 38 No. 1, pp. 18-28.

Figures

```
> pnorm(q=29, mean = mean(MyDataFrame$Dur
[1] 0.9689372
```

Figure 1

Output when pnorm() is Executed

Company's	High		Captive buyer	Strategic
Level of Investment	Low		Non Critical	Captive Supplier
			Low	High

Suppliers' level of Investment

Figure 2

As-Is Supplier Segmentation

As-Is Supplier Segmentation Result

Company's	High		4		1
Level of Investment	Low		10		3
			Low	High	

Suppliers' level of Investment

Figure 3

As-Is Supplier Segmentation

Recommended Supplier Segmentation

Company's	High		2		4
Level of Investment	Low		4		3
			Low	High	

Suppliers' level of Investment

Figure 4

Recommended Supplier Segmentation

```
MyDataFrame$APH (integer)

  length         n     NAs  unique      0s   mean  meanCI'
     120       120       0      11       0   5.90    5.52
             100.0%    0.0%             0.0%          6.28


     .05       .10     .25  median     .75    .90     .95
    2.95      3.00    4.75    6.00    7.00   8.00    9.05


   range        sd   vcoef     mad     IQR   skew    kurt
   11.00      2.12    0.36    1.48    2.25   0.72    1.54
```

Figure 5

Desc() Output on Truck Arrivals Data

```
"Probability that X is less than"
7
0.7549
"Probability that X is less than"
8
0.8546
"Probability that X is less than"
9
0.92
"Probability that X is less than"
10
0.9586
"Probability that X is less than"
11
0.9793
```

Figure 6

dpois() Output on Truck Arrivals Data

	Product	Material needed/unit	Material Availability/week	Mfg Capacity(units/week)	Demand/week	Profit/unit		Current Customer contracts(units/week)	
X1	Accessary 1	100	260000	2300	2550	3200		1500	
X2	Accessary 2	55	99000	2200	1998	3500		1250	
X3	Accessary 3	72	270000	4000	3700	2700		2900	
X4	Accessary 4	68	145000	2500	2200	3700		1425	

Figure 7

As-Is System Parameters

Figure 8

Excel Solver for LP

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- a4.xlsx