

Improving lead time visibility in import export operations

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Summary: This research aimed at identifying the key segments, sub segments and associated lead times for the import export delivery process of a global chemical conglomerate for ten different countries. To define these segments and their lead times allowed us to design a PERT model that supports more accurate prediction of delivery lead times for any given route. To perform our study, we worked with two different types of lead time data; standardized (fixed) and historical (variable). Standardized lead time(fixed) data was obtain through interviews and creation of delivery time lines with each country's representatives. The other type of data (variable) was delivery lead time historical data and was provided by the data service department of the sponsor. To improve our model, modern artificial intelligence techniques were applied to get better most likely values for PERT model analysis. The results obtained from the methodology have been used to generate the lead time distributions to be used for different scenarios to be used by the sponsors to get the associated probabilities.



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KEY INSIGHTS

- A critical path model for the overall order to delivery lead time process.
- A PERT based model of overall order to delivery lead time distribution to get the preliminary level of visibility and improve the delivery lead time prediction accuracy.
- A Multilayer perceptron method based on artificial neural network to enhance the accuracy of the distribution. The methodology was applied for the company's two most frequently used routes.

Introduction

The thesis objective is to solve the issue related to the visibility and accuracy of lead time prediction in import-export operations for a global chemical conglomerate in the Asia Pacific region. The study focused on providing guidelines to sponsoring company's managers on their delivery operation processes with their respective lead time and lead time variability across ten countries. The thesis also

discussed the application of modern deep learning algorithm to predict the lead times of certain sub processes and suggests ways to incorporate it to increase the lead time visibility. The literature regarding supply chain visibility covers a broad spectrum ranging from demand forecasting, ordering, product supply, inventory to transportation and the status of events and milestones that occur prior to and

in transit. The research question for our thesis is as follows.

- 1- What are the sub processes that account for the order to delivery cycle and the lead times associated with them?
- 2- How to improve the order to delivery lead time visibility by accounting for lead time variability present in the different delivery segments and suggest methods or techniques to further improve the lead time visibility?

Literature review

Lead time variability and associated uncertainties affect organizational performance. The management of any given organization faces challenges when lead times are uncertain. Since it could jeopardize good relations with business partners, lead time requirements should be explicitly specified. If long lead times are paired with high lead time variability, then the result is catastrophic. Consequently, to ensure product delivery within a certain and acceptable time window is a must. The organization's performance and even its survival is at stake when lead time are not on point. Lead time variability, if not under control, will deteriorate the supply chain performance of the organization. Simchi-Levi and Zhao (2005) revealed that the total inventory cost and the stock levels in the supply chain will markedly increase as lead time variability increases

The first "visibility" definition that we provided in our study is the one offered by Heaney (2014): *"Supply chain visibility is the awareness of, and control over, specific information related to product demand forecast, orders and product supply and inventory plus physical shipments, including transport and other logistic activities, and the status of events and milestones that occur prior to, and in transit."* The supply chain visibility defines the awareness of the supply chain. For any given points in the supply chain, one can generate data and information that will lead to useful insights for the company, and help to explain the past, observe the present and predict the future. Visibility is an important competitive advantage because it provides knowledge that can make an organization more competitive than its rivals.

The PERT chart is a project management tool used to evaluate the probability that the project will successfully be completed in a given

timeframe. In this case, the project can be anything that has a time variability and data to support it. This approach was developed by Malcom and others in 1959 and it uses optimistic lead time, pessimistic lead time and most likely lead time for every segment of a process or flowchart in the critical path and finally the probability of success. (Omar, 2009) This technique assumes that the uncertainty associated with the overall process duration is normal in nature. The assumption is based on the central limit theorem and thus reasonable for processes where the exact lead time distribution of each sub process is unknown. It fits well for our analysis as the extent of information we had was limited (order to delivery using specific route).

Current literature provides many insights on the application of artificial intelligence technique for lead time estimates in complex engineered products with different attributes. (Mourtzis, Doukas, Fragou & Efthymiou, 2014). The artificial neural network was used for formulating standard lead time estimates for textile industry. (Susanto, Indra Tanaya, & Sudadi Soembagijo, 2012). Our problem was similar in nature. We had to estimate the most likely lead time of a sub process and the lead time depended on various attributes. Hence, this tool was utilised to estimate the most likely lead time in a sub process (point of loading to the point of sailing lead time) in the order to delivery lead time process.

Methodology and Results

The research methodology starts with understanding and mapping the process of order to delivery for every country under the scope of our research. That meant documenting the processes and getting the specifics related to each country's processes. Simultaneously, we cleaned and prepared the historical data to receive multiple analysis. After preparing all the lead time data(fixed and variable), we designed a PERT model to increase the delivery lead time prediction accuracy. The model was generic to a large extent but it was modified to country specific requirements. Respective steps, sub processes and the division of responsibilities were found out. Finally, neural network was used to improve our actual PERT model and increase its accuracy.

Overall order to delivery lead time depends on many factors. Full container load(FCL)/Less than

container load(LCL), Dangerous goods cargo (DG cargo)/ Non DG cargo, bulk cargo transported through parcel tankers, isotanks and flexibags, and temperature controlled cargos transferred through reefers are the factors that affects the order to delivery lead time.

Lead time data was collected through multiple points and sources in the company. The data collected was classified into two types. The first type contains the data mainly related to internal order processing in the company. This data included the lead time and the division of responsibility of a particular sub process. This data was collected from country representatives of the company. The company presently did not have any process in place to monitor the lead times of these steps and hence the data collected was perceptual and based on the experience of the representatives. The second type contains the lead time data of the sub processes that were actually monitored by the company. This data collected was semi structured in nature and was cleaned up before analysis. This included the correct mapping, removal of duplicates and incomplete data points.

Bases on the data collected, a critical path model was developed for the order to delivery process was developed for the ten respective countries in the Asia Pacific region in which the company operated. The critical path model can be divided into four parts. The first two parts contains steps or sub processes related to internal order processing. The third part starts from the moment when the goods are loaded and issued until they leave the port of origin. The fourth and last part is the segment that focuses on the transportation from the port of origin, in the country where the product has been manufactured and loaded, to the port of destination. Figure 1 shows one such model of a particular route R1.

Delivery process time line from Purchase order to arrival to the port of destination														
Lead time classification	1Standard					2Standard					3Variable		4Variable	
Segments	Order processing (PO to DO)					Inland (DO to Loading)					Inland (Loading to departure from port)		Sea (Port to port)	
Sub segments	Create PO	Create SO	Check SO & release blocks	Check trade compliance (applicable for new products)	Check product avail.	Create delivery & finalize qty & loading date	Place booking with carrier & prepare DG declaration form	DG Permit	Carrier process final booking and issues confirmation	Plan stuffing/ loading & arrange pre-leg	Complete shipment, Create & compile all export docs including those needed for CTF and Port	Pre-leg movement to plant, load and transfer to port	Declare customs (Export)	ETD to ETA Port to port
	1.1	1.2	1.3	1.4	1.5	1.6	2.1	2.2	2.3	2.4	2.5	3.1	3.2	4.1
Lead time (working day)	X	X	X	X	7	1	0.5	5	0.5	0.5	1	2	0.5	15

Figure 1: The figure shows different segments of order to delivery lead time process

A PERT based model was developed to get the overall order to delivery lead time distribution. The PERT based model fits well for analysis. It assumes that the variability associated with the overall process is normal in nature (basis central limit theorem). It requires three lead time values for each variable sub processes in the overall process. The optimistic lead time which is the least time required for completion, the most likely lead time and the pessimistic lead time. The lead times for first two part of the overall process, as described above, were considered standard (because of the data limitations). The variability in the last two processes were taken into account as we had data to support the same. This model was route specific in nature. The optimistic and the pessimistic lead time for the third sub process was taken from the historic data from the company and the most likely lead time was initially taken to the one provided by the country representatives. The most likely lead time for port to port sailing (fourth part) was taken from open sources while the optimistic and the pessimistic values were taken from the data historic data. An excel based tool as presented to the company to get the probability distribution of their order to delivery lead time for routes. Figure 2 Shows the probability distribution obtained for Route 1.

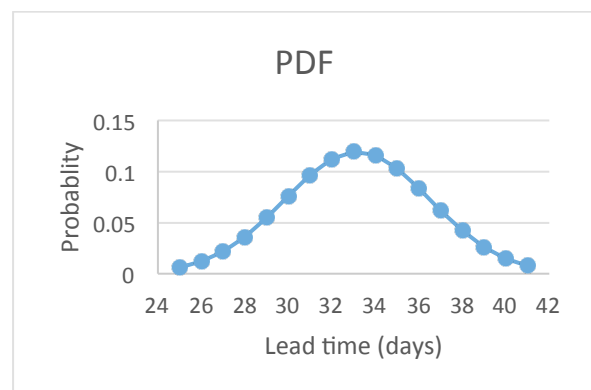


Figure 2: The probability distribution obtained using PERT based model for R1

It was realised that using one value for most likely lead time in the third leg does not go well with the historic data. In order to come up with a more accurate model, an artificial neural network model was used to get the most likely lead time of third leg. The lead time in this segment would depend on six different factors as identified by the experts in the company. The six factors were used as the input node in the neural network. Figure 3 shows the neural network. A multi-layer

perceptron model with two hidden layers and one output were used in the model. Each hidden layer contained six nodes. The selection of the number of layers and nodes in each layer were done after multiple iterations. The training of the model was done on seventy-five percent of the historical data of this leg and rest twenty-five percent data was used to test the model accuracy. This model gave input for the most likely lead time of the third leg based on the identified factors and finally this input was used in the PERT based model to get the overall order to delivery lead time distribution. Thus, changing the associated factors changes the order to delivery lead time distribution. Figure 4 and Figure 5 shows two such modified lead time distributions of route R1 obtained based on values obtained from the neural network.

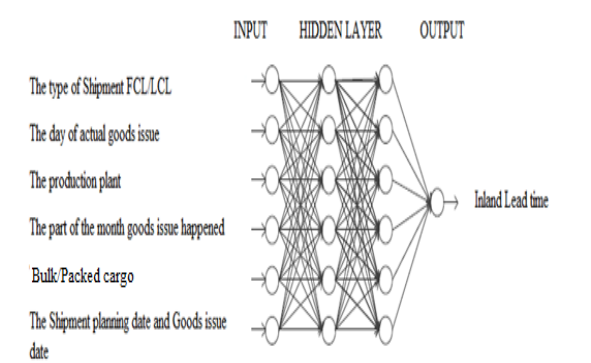


Figure 3: The neural network to get the most probable lead time for the third leg

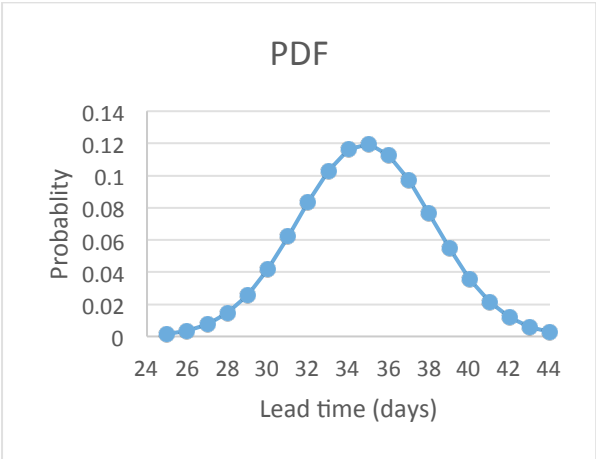


Figure 4: The probability distribution of lead time for R1 obtained from neural network using one set of factors as input

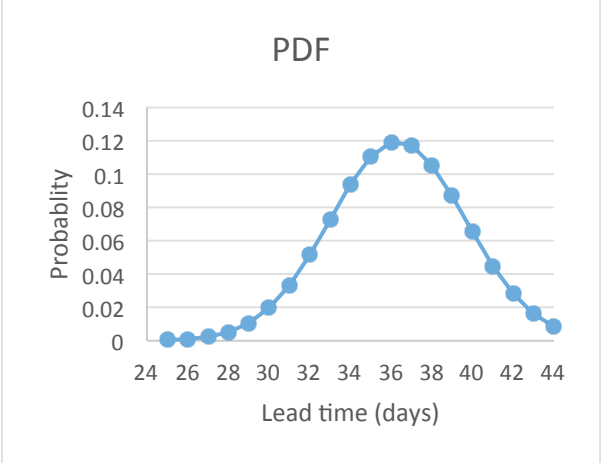


Figure 5: The probability distribution of lead time for R1 obtained from neural network using different set of factors as input

Recommendations and Future research

The methodology and tools are a good starting point for the organization to start looking into and to measure the lead time in its order to delivery cycle. However, our analysis is limited by the information. The method used by the company is not enough to have a good over all visibility of the lead time. The company lacks the overall monitoring of all the sub processes in the order to delivery lead time cycle. Suggestion regarding process lead time monitoring were given for improvement in the lead time visibility. Intradepartmental blockades arise due to division of responsibility between different departments. Information sharing could help to overcome this blockade.

A lot of avenues of future research exist in this domain. Order processing in the company is not documented and therefore sub process lead times are not captured. It is difficult to have a complete control over the process especially if the sub processes are outsourced. But the right methodology to collect, document and measure the lead time associated with these processes would significantly increase the visibility of this sub process. Our research is based on the data provided by the company only. Analysis made on the highly variable sub process with company data only could not be enough for full analysis and for effective learning using artificial intelligence. A much more elaborate data set with all factors could provide a much more accurate portrayal of the lead time associated with this sub process. Furthermore, effects of seasonality and disruptive events on lead time could also serve to be a good scope for future research.

Conclusion

This research was a great opportunity to explore delivery lead time visibility and delivery lead time variability in a global context for a chemical company. To familiarize ourselves with the related body of knowledge, we performed a thorough literature review that provided us insights and guidance on how to approach company's delivery lead time visibility and delivery lead time variability issue. It allowed us to lay a strong foundation to build upon and design our two research questions.

With clear research goals, and with the support of company, we developed the order to delivery process timelines of ten countries and therefore increased their lead time visibility. With the delivery lead time data-based PERT model that we designed, company now has a distribution of lead time considering the variability in the sub processes for any given delivery routes. This distribution provides the probability to successfully deliver within a given time and improves subsequent supply chain decisions. In this sense, we answered our two research questions and achieved to generate significant results for company X.

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