Using Simulation Modeling and Analysis to Assess the Effect of Variability and Flexibility on Supply Chain Lead Time

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Abstract In today's highly competitive marketplace, enterprises are in constant need to improve and sustain their existence. Two key supply-chain performance measures are lead time and variability in lead time, both of which affect sustainability of manufacturing and logistics systems. One way that has been proposed to improve both measures is to increase supplier flexibility. Our research focuses on defining the effects of various manufacturing and logistics flexibility-related factors on lead time and its variability. We use simulation modeling and analysis as the basis for studying the impact of both design and system factors on performance. In this chapter, we present our findings on the effect on lead time of supplier flexibility level, proportion of process time that is production and transportation time, and level of variability in process time. We also discuss briefly our flexibility-factor framework and conceptual model for the simulation, as well as its implementation in *FlexSim* simulation software.

Keywords Flexibility • Supply chain • Framework • Conceptual model

1 Introduction

The concept of a flexible supply chain (FSC) is gaining more and more importance since it provides a means to absorb system disturbance or dynamics. In general, the system dynamics comes from uncertainty and variability in operations in the supply chain. This chapter investigates the effect of this variability on FSC performance. It is apparent that supply chain design and analysis that incorporates the consideration of variability is more complicated than the deterministic case. The "best" level

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of flexibility in a supply chain depends on the supply chain structure, the level of variability in the various components of the supply chain, and the operation of key processes. Flexibility can be obtained both internally—e.g. shift arrangements, additional resources (personnel and equipment)—and externally through policies and relationships between suppliers. In this study our focus is on external flexibility where multiple suppliers serve a number of buyers. However, the approach we have developed can be used to address internal factors as well.

Many of the factors we consider in our framework, such as lot size, distance between suppliers, mode of transportation, etc. can be used to make operational and strategic decisions, that consider environmental effects. Also, flexibility provides responsiveness to market dynamics and thus enhances business sustainability.

In this chapter, we consider a supply chain where a number of suppliers perform work for a number of buyers. The basic structure of this flexible supply chain is from Chan at al. (2009) where they considered a cluster of six suppliers supported a single buyer. Their research considers three factors: Supplier Flexibility Level (SFL), Change in Physical Characteristics (CPC), and Time Delay (TD). SFL allows multiple suppliers the opportunity to perform operations on a product. CPC increases the process time for alternative, or non-primary, suppliers. They apply a common percentage increase in process time for the alternative suppliers; however, a more realistic approach is to individually adjust the process times based on user input. This is the approach we have taken in our model—process times depend on the supplier and the product. TD represents the supplier's delay in updating their production information in their online information system. While Chan at al. (2009) use simulation modeling and analysis to analyze the effect of changes in these factors on lead time, they use deterministic process times and consider only a single system configuration.

In order to effectively design flexible supply chains, a number of factors must be considered. Jannat and Greenwood (2014a) identify and define a framework of important factors for flexible supply chain design and analysis. They divide the factors into two broad categories: system factors and design factors. System factors are used to describe the system and provide the foundation for the simulation model. They define the relationships among buyers and suppliers, order characteristics, internal supplier operations, etc. Design factors include decision variables that can be controlled and are used to improve the system; they are divided into two main categories, those internal to a supplier and those internal to a buyer. These, along with other key elements of the modeling and analysis process, are shown in Fig. 1. As shown in the figure, the analyses that are employed to identify and assess ways to improve the operation of a system (e.g. the best level of supplier flexibility) are based on results obtained from experiments performed with a discrete-event simulation (DES) model of the buyer–supplier system.

Figure 1 also shows experimentation factors (e.g. number of replications, stopping criteria) are key inputs to any simulation model. Specification of the variability in the system is also a key input to simulation. It is shown as a major component of the system factors. For the purpose of experimentation and analysis all process times are assumed to be triangularly distributed. We use an approach for specifying the parameters of the triangular distribution that is described in Jannat and Greenwood (2012).

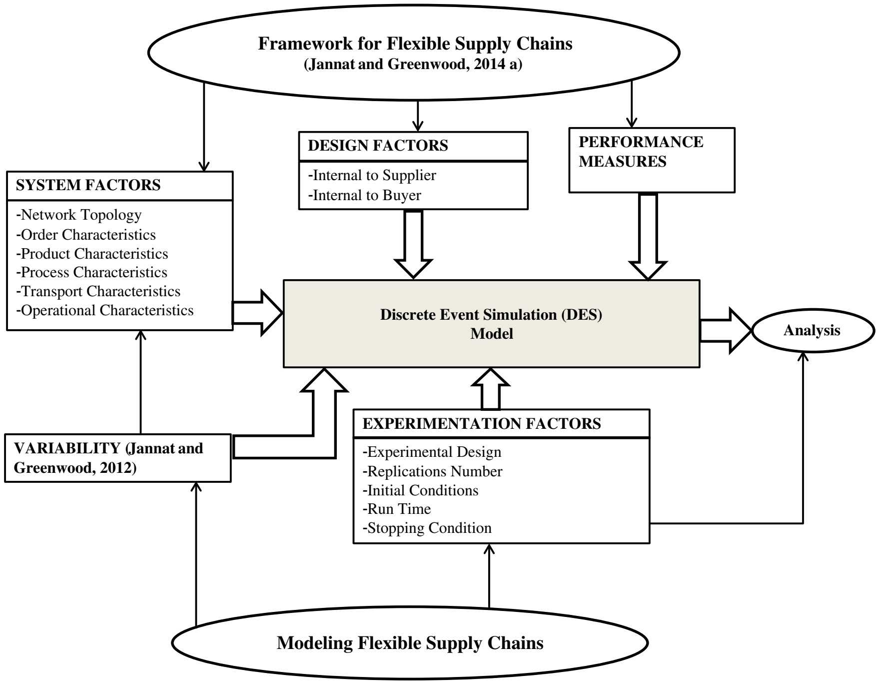

Fig. 1 Process for using simulation modeling and analysis to design flexible supply chains (*Source* Own study)

Jannat and Greenwood's (2012) approach provides an effective means to specify and control variability for experimentation purposes. In this chapter process times are modeled as triangularly distributed random variables with different levels of variation and skewness. The level of variability is specified by the coefficient of variation, denoted as $Cv = \sigma/\mu$, where μ is the mean of the distribution and σ is the standard deviation. Skewness (Sk) measures the symmetry of a distribution and may be positive or negative. In positively skewed distribution, the distribution has a long tail to right; i.e. Mean > Median > Mode. In a negatively-skewed distribution, the distribution has longer tail to the left of the distribution; i.e., Mean < Median < Mode.

As indicated earlier, the basic structure of the supplier–buyer system is as described in Chan at al. (2009). However, we have developed a more comprehensive, flexible, and open model of the system. In general, a cluster of suppliers work together for a buyer. Suppliers receive orders from buyers and process them based on a specified flexibility level. For every operation on every product, up to five suppliers have the capability to perform that operation, thus making the system flexible. Process time for each operation on each product type varies from 40 to 100 time units. Chan at al. (2009) assume transportation time is embedded in the operation time. We believe that to be an overly restrictive assumption; therefore, in this chapter we separate the process time into operation time and transportation time. Also, instead of assuming deterministic process times, we consider variability, specified by the triangular distribution.

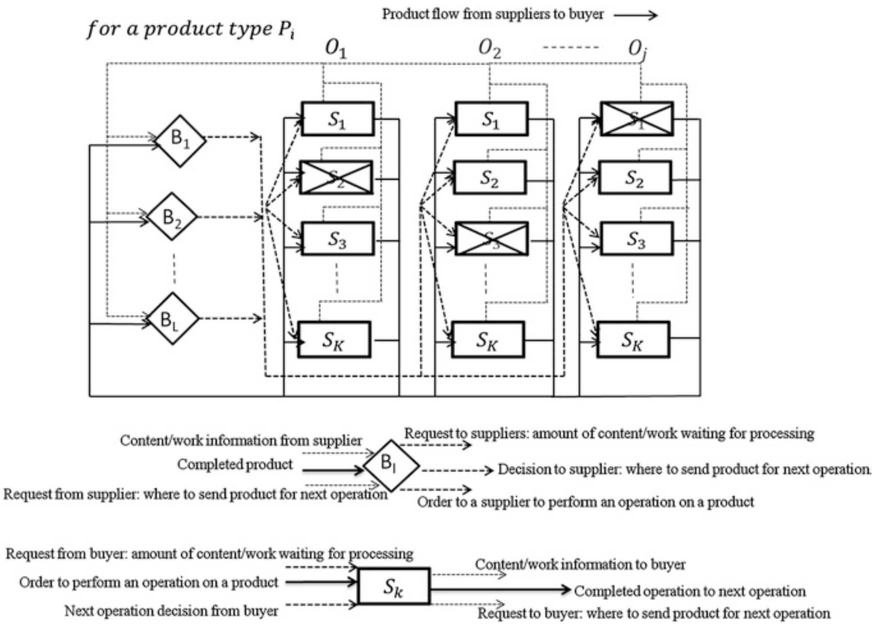

Fig. 2 Product and information flows between buyers and suppliers (*Source* Own study)

2 Conceptual Model and Model Validation

This section provides the conceptual model for developing a simulation of a flexible supply chain. While this generic representation allows the flexible supply chain system to be modeled in any simulation software model, we have developed the model using *FlexSim*. It is briefly described in the next section and further in Jannat and Greenwood (2014b). The model is available from the authors upon request. The conceptual model is presented in Figs. 2 and 3.

Figure 2 provides a high-level representation of the buyer–supplier relationships. The solid lines represent the physical flow of products and the dashed lines represent communication among the elements. (Heavy dashed lines represent information flows from a buyer to a supplier and light dashed lines represent information flows from a supplier to a buyer.) Buyers send orders for products to suppliers. Products vary by the number and sequence of operations required and the process time of the operations. Each operation can be performed by a subset of the suppliers. Initially, product orders (product characteristics and quantity) are generated based on the input parameter values that are supplied by the user. The buyer decides, after each operation, which supplier performs the next operation based on the number of units or the amount of work awaiting processing at each supplier. That is, when an operation O_j needs to be performed on a product P_i a buyer B_i decides which supplier S_k is to perform the operation. The decision process is triggered when a supplier completes an operation—the supplier informs the buyer that it needs to know where to send a product for the next operation. Upon receiving that request, the buyer queries all

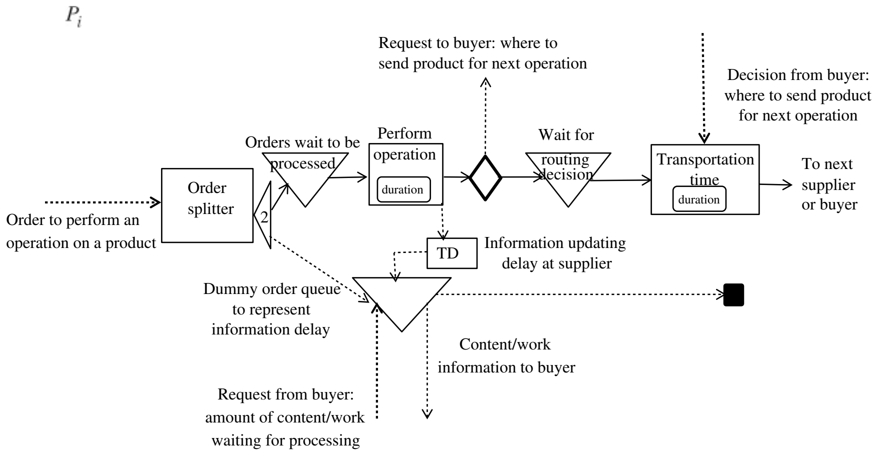

Fig. 3 Conceptual model of the operations within a supplier (*Source* Own study)

suppliers and chooses the one that either has the fewest number of products waiting to be processed or the one with the shortest wait time

The flow of activities that occur within a supplier is shown in Fig. 3. As soon as an order is received at a supplier it is split into two parts—one represents the physical product that is to be produced and the other is a dummy order that is represents an updating delay in the supplier's information system (TD in Fig. 3). This way, when a buyer queries a supplier to obtain information on the number of products waiting or the amount of work waiting to be processed, the information that is obtained is not current. This accounts for delays in updating production information at the supplier and the time to respond to a buyer's query. There may also be a time lag at the buyer to make and respond with the routing decision (TDB in Fig. 3).

3 Application Example and Simulation Results

This example is based on the problem presented in Chan at al. (2009). The six products, their order quantity, number and sequence of operations, mean process times, and supplier preferences are the same. However, we consider two buyers (rather than one), various levels of variability in process times (rather than deterministic), and various operation and transport time ratios (rather than a single all-inclusive process time). Thus, our objective is to assess the effect on mean lead time and lead time variability of four factors from the Jannat and Greenwood's (2014a) framework: Supplier Flexibility Level (SFL), Proportion of Production and Transportation Time (PPTT), and variability in process time (as measured by the coefficient of variation C_V).

We have validated our model with the one described by Chan at al. (2009) and have extended their representation into a more general, flexible, and open simulation model. *FlexSim* simulation software is used to model and analyze flexible supply chains. The model is available from the authors upon request.

Table 1 Product and supplier data for the example

Product	Order quantity	Operation (mean process time)	Suppliers at each flexibility level				
			1	2	3	4	5
P1	50	O1 (40)	S1	S2	S4	S5	S3
		O2 (50)	S3	S5	S2	S1	S4
		O3 (60)	S4	S1	S5	S2	S6
		O4 (70)	S6	S3	S1	S2	S5
P2	50	O1 (40)	S4	S3	S5	S6	S1
		O2 (55)	S2	S1	S3	S4	S5
		O3 (54)	S6	S4	S2	S1	S3
		O4 (95)	S5	S2	S4	S3	S6
P3	50	O1 (60)	S5	S6	S2	S1	S4
		O2 (45)	S1	S4	S6	S5	S2
		O3 (48)	S3	S5	S4	S6	S1
		O4 (65)	S2	S1	S6	S5	S4
		O5 (75)	S4	S6	S1	S2	S3
P4	50	O1 (40)	S2	S1	S3	S4	S5
		O2 (50)	S5	S3	S4	S6	S1
		O3 (50)	S6	S2	S1	S3	S5
		O4 (45)	S3	S6	S5	S4	S1
		O5 (85)	S1	S5	S2	S4	S6
P5	50	O1 (40)	S6	S5	S1	S3	S2
		O2 (45)	S4	S6	S5	S2	S3
		O3 (45)	S2	S3	S6	S4	S5
		O4 (40)	S5	S4	S3	S1	S6
		O5 (55)	S1	S2	S3	S6	S5
		O6 (100)	S3	S1	S6	S5	S4
P6	50	O1 (35)	S3	S4	S6	S2	S5
		O2 (45)	S5	S2	S1	S3	S6
		O3 (100)	S4	S1	S3	S4	S5
		O4 (50)	S1	S5	S2	S6	S3
		O5 (52)	S6	S3	S4	S1	S2
		O6 (75)	S2	S4	S5	S3	S1

Table 1 provides information on each product: quantity ordered, process steps and mean times, and the buyer's supplier preference at each flexibility level. For example, for Product 1 (P1) Operation 1 (O1), the buyer would use Supplier 1 (S1) if Supplier Flexibility Level (SFL) is 1, Suppliers 1 and 2 for SFL = 2, Supplier 1, 2, and 4 (S1, S2, S4) for SFL = 3, etc. In this case all suppliers have the same mean process time, 40 time units. However, our model allows the process time for each product operation to be dependent upon supplier.

Table 2 summarizes the experimental factors that are considered in this example. Our simulation model is capable of handling most of the factors in the framework from Jannat and Greenwood (2014a). However, since the purpose of this example is to illustrate the capability of the model and the value of the analyses that can be performed with the model, we limit the number of factors considered.

Table 2 Experimentation factors and level

Factor name	Factor level	Factor's level explanation
Supplier flexibility level (SFL)	1	1 supplier is available for the operation
	2	2 suppliers are available for the operation
	3	3 suppliers are available for the operation
	4	4 suppliers are available for the operation
	5	5 suppliers are available for the operation
Proportion operation/transportation time (PPTT)	1	100 and 0 % of process time considered as operation and transportation times respectively
	2	75 and 25 % of process time considered as operation and transportation times respectively
	3	50 and 50 % of process time considered as operation and transportation times respectively
	4	25 and 75 % of process time considered as operation and transportation times respectively

		Distribution properties		Triangular distribution location parameters		
		C_v	S_k	Minimum, a	Maximum, b	Mode, m
Process time	1	0.0	0	N/A	N/A	N/A
Distribution	2	0.1	0	0.7551	1.2450	1.0000
Level of variability	3	0.1	0.4	0.8000	1.2732	0.9268
	4	0.1	−0.4	0.7268	1.2000	1.0732
	5	0.2	0	0.5101	1.4899	1.0000
	6	0.2	0.4	0.6000	1.5464	0.8536
	7	0.2	−0.4	0.4536	1.4000	1.1468
	8	0.3	0	0.2652	1.7349	1.0000
	9	0.3	0.4	0.4000	1.8196	0.7804
	10	0.3	−0.4	0.1804	1.6000	1.2196

Each level of each factor is considered a simulation scenario. Each scenario is replicated 10 times in order to obtain a measure of variability in lead time. Lead time is the time for all products to be delivered to the buyer. In this case, 300 products, 50 each of six products. In terms of the starting conditions for each replication, we assume the supplier cluster provides immediate service to the buyer and thus the model starts, and ends, with all work queues at the suppliers empty and all supplier processes idle. This approach is used for simplicity; however, alternative approaches to starting the simulation model include:

1. start with dummy orders at each supplier queue.
2. inject dummy orders to the suppliers at regular intervals but only capture statistics on the set of orders of interest. This reduces the start-up and ending biases.
3. create an initial load at each supplier, with dummy orders, that represent the supplier typical utilization, if it is known.

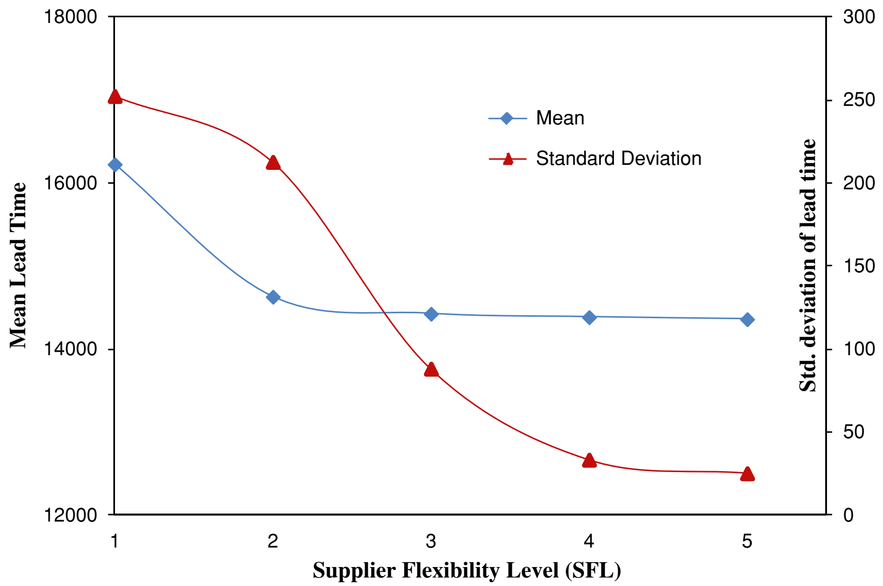

Fig. 4 Mean and standard deviation of lead time at various levels of SFL (PPTT = 0 % transportation time $C_v = 0$) (*Source* own study)

Since the number of factors and levels are relatively few, we use a full-factorial experimental design (Montgomery 2000; Ruiz et al. 2006). This methodology is usually utilized when number of factors and their levels are small or moderate.

4 Simulation Results

One objective of this chapter is to assess the effect of the following factors on lead time and variability in lead time: supplier flexibility level (SFL), proportion of process time that is operations time and transportation time, and the level of variability in process time as specified by a triangular distribution's coefficient of variation C_v and skewness S_k. Based on initial experimentation, it was found that skewness did not have a significant effect on lead time and the variability in lead time. Therefore, the results provided here are all based on symmetric ($S_k = 0$) triangular random variables.

4.1 Effect of SFL on Lead Time

The effect of SFL on lead time is shown in Fig. 4. In this case, all process times are 100 % operations time (0 % transportation time) and have no variability ($Cv = 0$) in process times. As can be seem from the figure, lead time is significantly reduced as SFL increases from 1 to 2, but shows small improvement

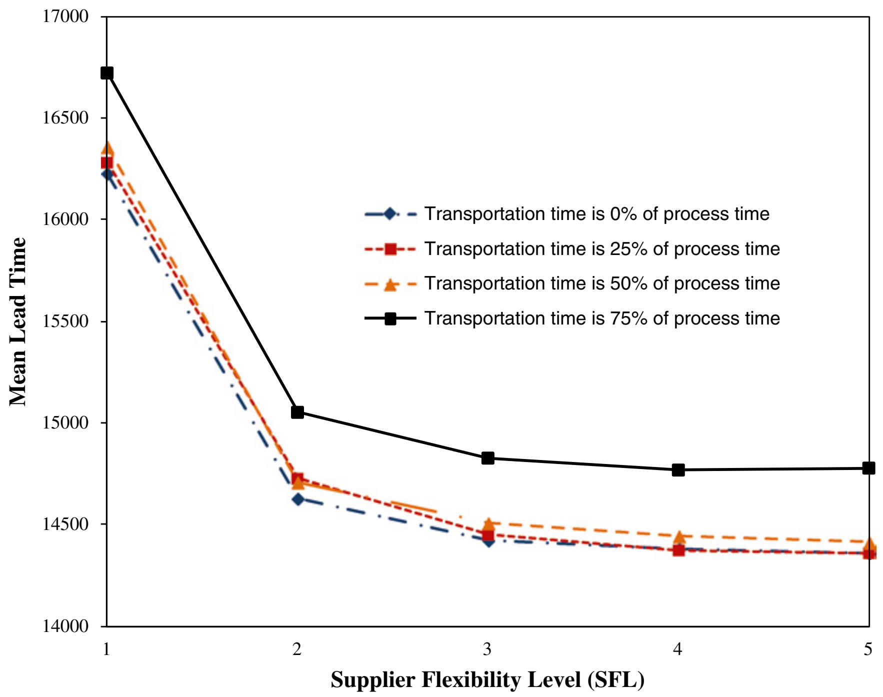

Fig. 5 Mean lead time at various levels of PPTT ($C_V = 0$) (*Source* Own study)

for SFLs above 2. However, variability, as measured by the standard deviation of lead time, continues to drop significantly up to SFL = 4. Therefore, if lead time risk is important to the decision maker, then measures other than the mean need to be considered. Of course, this measure is easy to obtain from simulation model results.

4.2 Effect of PPTT on Lead Time

Figure 5 shows the relationship between SFL and mean lead time at various levels of PPTT (percent of process time that is transportation time). The relationship exhibits a similar pattern to the previous figure, with the largest impact being SFL. However, as the PPTT increases, lead time increases. Recall, the buyer's decision as to which supplier is to produce the next operation is made at the end of the current operation. If PPTT = 0 then the next supplier receives the order immediately and its status (in terms of work in the system) is the same as when the decision is made. However, if there is a long lag between the decision and the arrival of the order, due to transportation time, the supplier status can be quite different when the order actually arrives. For example, if the supplier has a low work content when several buyer decisions are being made, the supplier may receive several orders, but by the time the orders actually arrive there

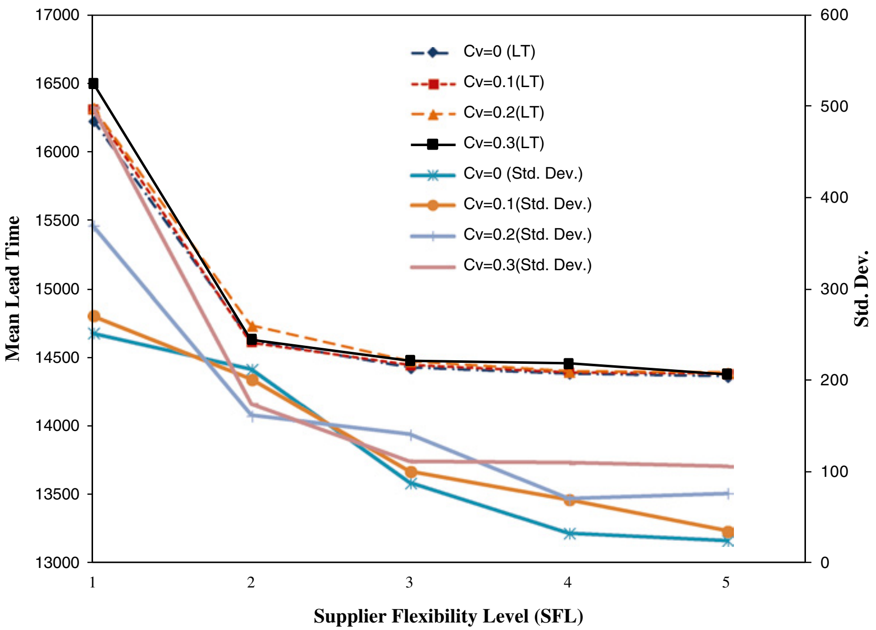

Fig. 6 Mean and standard deviation of lead time at various levels of C_v (PPTT = 0) (*Source* Own study)

could be a lot of work in the supplier's system. A future version of the model may need to include an extension that accounts for this by having the buyer's query based on the content of the orders and not on the work actually in the system.

4.3 Effect of Operations Time Variation on Lead Time

Figure 6 illustrates the effect of variability in operations times, as measured by the coefficient of variation C_v, on lead time. Recall process time is composed of operations time and transportation time and that it is assumed that there is no variability in transportation times. Also, operation time distributions are symmetric triangular distributions with $C_v = 0.0$, 0.1, 0.2, and 0.3. Note that mean lead time follows a similar pattern to that shown in Figs. 4 and 5. However, we also plot the variation in lead time, as measured by the standard deviation of lead time. Generally variability continues to decrease as SFL increases. Of course, within each SFL variability in lead time is affected by the level of variability in operation times. It appears that the effect is quite high when SFL = 1. That is, when SFL = 1, as expected the lowest mean lead time is when $C_v = 0$ and it is highest when $C_v = 0.3$; however, there is considerable affect in the variability of lead time as operation variability increases. Therefore, increasing SFL from 1 to 2 not only greatly reduces mean lead time, but reduces variability in lead time as well.

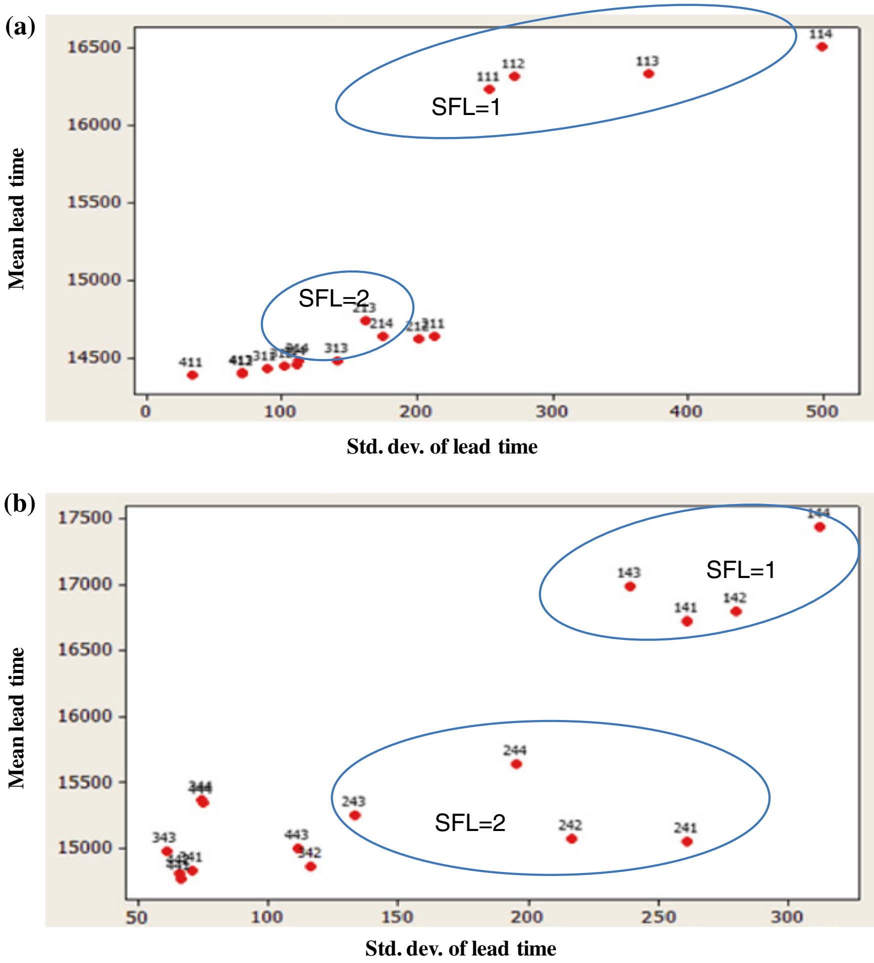

Fig. 7 Scatter plot of mean and variability of lead time considering all factors at all levels (*Source* Own study). **a** Process time = 100 % operation time. **b** Process time = 25 % operation time

4.4 *Effect of Factors on Mean Lead Time and Variability in Lead Time*

Since Figs. 4 and 6 show that changes in system factors affect both mean lead time and variability in lead time, we examine plots that consider both concurrently at various factor levels. Figure 7 is an example. The notation at each plot point is the factor settings at that point, SFL-PPTT-C_V. For example 143 is SFL = 1, PPTT at level 4 (process time is 75 % transportation time), and C_v at level 4 (C_v = 0.3). Panel (a) is for PPTT = 0 (process times are all (100 %) operations times, no transportation times) and Panel (b) is for PPTT = 0.75 (process times are only 25 % operations time, 75 % transportation time). The improvement in lead time is again evident as SFL increases, as is the diminishing returns in improvement.

These plots also illustrate factor effects when other factors are held constant. For example, in Panel (a) the points highlighted by the oval for SFL = 1 show the effect of increasing operation time variability when process time is all operation time. A similar comparison can be made by considering the points within the oval for SFL = 2. In both cases, when process time is all operation time, increasing the variability in operation time has a similar effect on changing mean lead time, but the effect on lead time variability is much less when SFL = 2 (compared to SFL = 1).

5 Conclusions

This chapter demonstrates that simulation provides an effective means to design and analyze flexible supply chains. The simulation model can address the effect on performance of a number of system and design factors. Those factors and measures are based on a comprehensive framework for modeling and analyzing flexible supply chains. The framework is intentionally general so that it can be used to address a variety of manufacturing and logistical issues. However, the factors and simulation model built considering those factors can be used to address sustainability issues especially regarding transportation.

While the results derived from the example problem considered in this chapter just pertain to its specific problem structure and the values of its system parameters, the example clearly illustrates the value of the approach and the type of insight that can be gleaned. It also clearly illustrates that:

- designing flexible supply chains in a dynamic, stochastic environment is complex and requires the use of sophisticated modeling and analysis tools. Simulation is an effective tool for such analyses.
- a number of system and design factors affect performance and need to be addressed concurrently, not separately or just one at a time. Again, simulation modeling and analysis, along with a good experimental design, provide an effective means to do this.
- in order to design effective flexible supply systems, one must consider not just the mean performance measure, e.g. lead time, but its variability as well, when comparing alternative design and system scenarios.
- there are diminishing returns in increasing supplier flexibility level, but the degree, will vary by measure.

References

Chan FTS, Bhagwat R, Wadhwa S (2009) Study on suppliers' flexibility in supply chains: is real-time control necessary? Int J Prod Res 47(4):965–987

Jannat S, Greenwood A (2012) Estimating parameters of the triangular distribution using non-standard information. In: Proceedings of the 2012 winter simulation conference

Jannat S, Greenwood A (2014a) A conceptual framework for developing a flexible supply chain. Working Paper, Mississippi State University

Jannat S, Greenwood A (2014b) A conceptual model for developing the flexible supply chain simulation models. Working Paper, Mississippi State University

Montgomery DC (2000) Design and analysis of experiments, 5th edn. Wiley, New York

Ruiz R, Maroto C, Alcaraz J (2006) Two new robust genetic algorithms for the flow shop scheduling problem. Omega 34(5):461–476