Supply Chain Structure Design for a Short Lifecycle Product: A Loop Dominance Based Analysis

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Abstract

Designing a supply chain structure for a volatile market can be tricky. This is more so for products with a short lifecycle. A capacity constrained supply chain in such a setting impedes the product's market acceptance by limiting product availability and thereby frustrating customers. This paper presents an experimental method, which can be used by channel designers for this purpose. We use a two-echelon supply chain system to elucidate the method. The supply chain structure is represented using system dynamics formalism. Experiment on the model leads to an indication of the cost that the system would incur. Using this cost and through loop dominance analysis we identify feedback loops that primarily determine system behavior. We show that by strengthening the dominant feedback loop, significant improvement in performance can be achieved. The method we claim can easily be deployed in supply chains of other products and can also be used to justify information technology investment decisions.

1. Introduction

Supply Chain Management is a field of growing interest for both companies and researchers. It deals with the management of materials, information and financial flows in a network consisting of suppliers, manufacturers, distributors, and customers. For a long time the supply chain was considered as a linear system where raw material entered at one end and finished goods exited from the other. Each member of this supply chain used to work in isolation and hold large inventories and excess capacity to insulate themselves from variability and volatility. However, in recent times this sequential view of supply chains is being replaced by a more modern view where the supply chain is seen as a value constellation or networks centered around the customer. By this view supply chain can be defined as a network of organizations which develop new ideas, source raw materials, produce goods or deliver services, stock those goods and deliver them to the consumers. The supply chain of Dell computers and Nike shoes are excellent examples of this concept. There is little doubt that the advancement of communication technology and Internet has catalyzed this dramatic transformation of supply chains.

In this networked form the importance of designing appropriate supply chain in the success of a product cannot be overemphasized. Design of supply chain can be defined as the set of activities that lead to a structure, among different agents, in a manner that supply chain objectives get fulfilled. Conceptual framework and analytical formulation of the supply chain structure is provided by [25,26]. Structure refers to how the information available within the system is shared by the different agents, utilized for decision making (e.g. the forecasting techniques deployed and the different policy decisions formulated) to optimize the responsiveness of the supply chain. Thus it can include everything from designing of products and processes, to building supplier/customer contracts, formation of strategic alliances with supply chain partners etc. Fischer [22] argues that problems of supply chain are associated with mismatches between the types of supply chain (demand-pull versus supply-push) and the type of product (innovative versus functional). Functional products have stable, predictable demands, long lead times and low margins (e.g. groceries). These need supply chains that are efficient logistically. Innovative products in contrast require consumers to change some aspect of their life style and are associated with short lifecycle (e.g. microprocessor chips). For an innovative product, Fischer recommends, the mismatch can be minimized by adopting strategies that reduce uncertainty, cut cycle time and improve flexibility. Continuous time differential equations, discrete time difference models, discrete event simulation and operational research techniques are some of the commonly used quantitative modeling techniques to evaluate supply chains.

One of the major difficulties in designing supply chain for an innovative product is deciding strategy for capacity augmentation. Clearly, under uncertainty of market acceptance of the product in such cases, manufacturers adopt a cautious approach by making low capacity investment at start up. The idea is to run the plant at maximum utilization, reducing per unit production cost and invest in capacity as and when the need arises. Due to the variation in demand there exists a trade off between inventory holding and capacity investments. It is known that the variations in demand increases as one moves up

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the supply chain. The fluctuation and amplification, of orders and inventory, is mainly due to lack of timely sharing of production information caused due to delays and feedback in the decision rules among the enterprises of the supply chain. Lee *et al.* [15] have studied this phenomenon extensively and termed it as the bullwhip effect. Even when the retailer demand is arriving at a rate, which is much lower than the capacity of the manufacturer, due to the variation and stock in pipeline the manufacturer feels that the capacity is a constraint during certain demand periods. The "Beer Game" assumes that there is no restriction on the capacity of manufacturer and the transporter. There are few other studies [11,14] that take capacity constraint into consideration. We move a step forward in determining how the manufacturer can utilize information available at the retailer to make the decision about capacity augmentation, so that the total cost of the supply chain is minimized.

In this paper we propose a method for deriving a good supply chain structure. The supply chain here consists of one retailer, one wholesaler and one distributor. The abstraction is done based on aggregation, which is defined as the level of detail with which a specific sphere of activity is represented. The supply chain is aggregated to a simple linear structure based on similar structure and behavior. In other words, it is the study of capacity augmentation for a single-product, single-manufacturer, single-retailer supply chain in which the manufacturer invests so that a very high service level and plant utilization is achieved. We have used the case of an 'Innovative' product but we believe that the same method can be applied to 'Functional' product as well.

The supply chain is modeled based on system dynamics modeling techniques. System dynamics models explicitly represent physical flows and information flows along with their respective delays, in an information feedback control type of setting. The main focus rests on the feedback loops that control the flows and in turn determine the dynamics of a system. Simulation of the model, under various parametric and structural variations leads to policy formulations and in turn results in design of better systems. System dynamics has been used widely to study dynamics of supply chains [2,10,11,13].

The supply chain decisions are mostly interdependent and usually the management decision follows microscopic view due to scarcity of effective design strategies and tools. We have overcome these ad hoc decisions by performing loop dominance analysis which helps in determining the key variables, their interactions and determining how the information can be better managed so as to increase the utility of the entire supply chain. We feel that our proposed method can be a useful tool for channel designers who need a way to hedge market risk of a new product. The model has a wide range of real world applications, ranging from fashion goods, health care services, apparel industry and high-tech products that have the characteristics of rapid obsolescence, volatile markets and utilizes significant production time. This helps companies to cope with uncertain changes in market demand over the product life cycle. It can also be used to justify information technology investment for supply chain management, because the structural changes that lead to better system performance are mostly in the form of alterations in the information flows.

This paper is organized as follows. Section 2, provides the literature survey. The problem is defined and a system dynamics model of the supply chain is constructed in section 3. The simulation result over a wide range of supply chain structures is provided in section 4. Loop dominance analysis is performed in section 5. Section 6 discusses methodological considerations, limitations of the study and provides managerial implication. Finally we have given concluding remarks and directions for future research in section 7.

2. Literature Review

Companies are required to cope with uncertain changes in production volume, product mix, and product life cycle. Cost, time and uncertainty are among the key challenges faced by any supply chain. One of the objectives of supply chain is to meet the customer needs and maximize the profit. For this, we need to determine manner in which information is shared and utilized so that mutual benefits of the individual players and the supply chain as a whole is maximized. Inventory, lead-time and capacity are common strategies used in supply chains facing uncertain or variable demand. Each provides a buffering mechanism to absorb the uncertainty.

The retailer places the order with the manufacturer based on sales, expected demand and replenishment lead time. In each period, the retailer would ideally like to hold inventory that exactly meets the demand requirements. As the demand is uncertain and the manufacturer consumes time to produce and ship, retailers must determine how much inventory to build. A large inventory enables the retailer to fulfill demand most of the time. The manufacturer has a nominal capacity that enables him to produce only a certain quantity each period. Inventory information is usually categorized as on-hand, backlog and work in process inventory. If no inventory exists in the system, lost sales or backorders occur in periods in which demand exceeds capacity. By carrying inventory, a supply chain can meet some of the excess demand. Inventory can be used to smooth the demand process.

Lead time, or the delay of the process, is one of the major factors that contribute to the bullwhip effect [10,15]. Decreasing the lead time, which is the actual time between order placement and delivery, is another way of reducing the demand uncertainty. The general result is that, longer the lead time, smaller the benefit of information sharing. Finished goods service time, defined as the time allowed between customer order placement and actual delivery, has a large impact on the supply chain's ability to deal with demand uncertainty. If the service time is small, and the demand exceeds the supply chain capacity, then a shortfall will occur if there is insufficient inventory. As the service time increases, the supply chain will be in a better position to absorb demand uncertainty. Customer orders in periods of high demand may take longer to fill, due to capacity constraints, but as long as this increase does not cause the customer lead time to exceed the finished goods service time, demand can still be fulfilled. The increase in finished goods service time comes at the expense of decreased customer satisfaction.

The nominal capacity of the various entities of the supply chain is another way to cope with demand uncertainty. Demand can be fulfilled as long as the capacity is not exceeded. The larger the capacity, higher is the probability of meeting the demand. When the manufacturer is unable to meet the high demand due to capacity constraint, capacity allocation is usually followed. Capacity allocation is an assignment of available capacity in production sites to confirmed and forecasted orders. Cachon and Lariviere [3] studied the sharing of demand forecast to supplier in order to secure capacity. Capacity is costly and therefore one should be mindful of the tradeoff between cost and customer service when the capacities of the various supply chain entities are chosen.

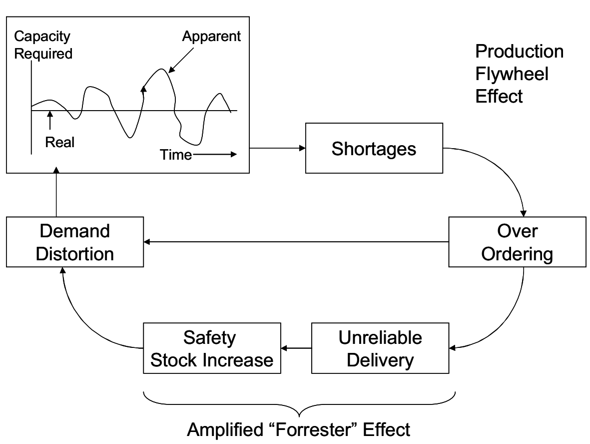


Fig. 1: The Forrester Effect (Source [12])

Forrester [10] analyses and explains issues evolving around supply chain management. It has been shown by him that the factory production rate often fluctuates more widely than the fluctuation in the retail consumption rate. He went on to develop a continuous time mathematical model of the dynamic production and distribution process. Towill [20] has developed various industrial dynamic models in the supply chain arena and has shown that the best results are obtained by adopting a holistic approach.

Upstream behavior is triggered by downstream decision making. Often times these (upstream) units have poor global information (like retail customer demand pattern, information held at different points of supply chain) and have to depend on local information like capacity utilization of self, inventory of self, orders placed by downstream units etc. False seasonal demands are induced by random market sales operating on the system's dynamics, which is extremely confusing for all upstream resource planners and decision makers. Furthermore, the time for the waveform to move upstream is beyond the comprehension of most managers. Croson and Donohue [4] through their experiments have demonstrated that sharing point of sale data reduces the order of oscillations at higher levels of the supply chain and leads to significant savings where the decision maker is prone to decision bias. Riddalls *et al.* [16] have addressed the modeling issues of supply chain and have shown that OR techniques are good for local tactical problems whereas dynamic simulation is the only way to go for evaluating the global behavior of the entire supply chain.

Angerhofer [2] provides taxonomy of research and development on system dynamics modeling in supply chain management. Our problem of designing structure to minimize the supply chain costs falls under the research area of supply chain design. Huang *et al.* [13] provides a rich review on supply chain dynamics literature, investigating the impacts of information sharing and supply chain structure. Riddalls and Bennett [17] have modeled the aggregated production-inventory system by assuming pure production delays. The dynamics was also evaluated on supply chains by cascading such production-inventory systems. Tomlin [19] has analyzed capacity investments in single-product supply chains in which the participants make investments to maximize their individual expected profits. The solution approaches to capacity decisions in multiple products, multiple stage supply chain is also described. But the method works under demand patterns that assure an upper bound stock out. Helo [11] deals with demand magnification, capacity surge effects, tradeoff between capacity utilization and lead times under capacity constraints and concludes that capacity utilization is an important factor and can be used as a substitute for inventory. Helo [11] however does not consider capacity augmentation.

It is known that Bullwhip effect distorts retail sales information reaching upstream unit, which has to make capacity investment decision. Simchi-Levi and Zhao [18] have shown how the manufacturer can effectively use the demand information from the retailer over a finite time horizon. Chen *et al.* [5] have considered a simple supply chain consisting of a single retailer and a single manufacturer and have shown that demand forecasting and order lead times are the two main causes for bullwhip effect. This effect can be reduced by sharing information but cannot be eliminated. Dejonckheere *et al.* [7] have proved that the bullwhip effect is guaranteed in the order-up-to level model irrespective of the forecasting method employed. They have used the matched filter [6] to adjust the smoothing constant of the exponential smoothing algorithm within inventory controlled feedback systems. Aviv [1] has shown that collaborative forecasting has an edge over local forecasting in a two-echelon supply chain system, when the different players bring something unique to the table. Zhang [21] shows that forecasting methods play an important role in determining the impact of lead time and demand autocorrelation on the bullwhip effect.

Our work proposes to expand the literature on dynamic simulation methodology of supply chain analysis and design. It focuses on short lifecycle product and capacity augmentation policies that result in favorable supply chain performance.

3. The Model

We consider a two-echelon supply chain consisting of a retailer and a manufacturer. The two standard models available in literature have been integrated and the necessary modifications made to suit the problem under consideration. The first model is the market growth model provided by Jarmain [24], which is used as a proxy for modeling capacity augmentation decisions. The other model is the standard production inventory control model [8,10]. The objective is to design a supply chain structure that can achieve high service level at least cost.

For the supply chain under consideration, the retailer faces demand from the customer for the product that is met from the inventory. The orders are placed with the manufacturer who takes a certain processing time and transportation time to replenish the order. Stock-outs result in lost sales. Lost-sales have a cost attached to it. The model has the provision of incorporating partial/full backlogging of demand but is not used in this paper. As the customers order increase, the capacity at the manufacturer is not sufficient to meet the demands of the retailer. The tradeoff between information sharing and different cost components is evaluated before going in for capacity augmentation, which takes a certain amount of time before being realized. Our interest lies in analyzing whether the capacity constraint is real or apparent and in determining the kind of information sharing required among the retailer order, inventory position and manufacturing capacity so as to minimize the cost of the system over the product lifecycle.

The investment in production capacity must usually be made based on forecast so that the capacity is ready before the demand has grown to that proportion. The demand forecast may take the form of a probability distribution. This uncertainty in the product demand complicates the capacity investment decision and any reduction in the uncertainty would be desirable. In some circumstances, the manufacturer may have the ability to make capacity investments over a number of periods. Sales in prior periods may contain valuable information that can then be used to update and refine the forecast for future period sales. We are interested in knowing when the manufacturer should augment his capacity based on the information obtained from the retailer.

System dynamics has been widely used to model and analyze supply chain problems [2,10,11,13]. We have modeled a generic structure of the supply chain. The traditional supply chain issue does not address the capacity issue. Different researchers under different contexts have analyzed supply chains. It is widely known that incorporating order backlog in retail orders can dampen the oscillations. We have introduced the same in our model. Our interest lies in determining the behaviour of production capacity. We know that the feedback loops are the main causes of dynamics. Here we perform the loop dominance analysis and come with policy decisions that make the supply chain structure more responsive to uncertain market changes. The stock and flow structure for the capacity augmentable supply chain structure is given in Figure 2.

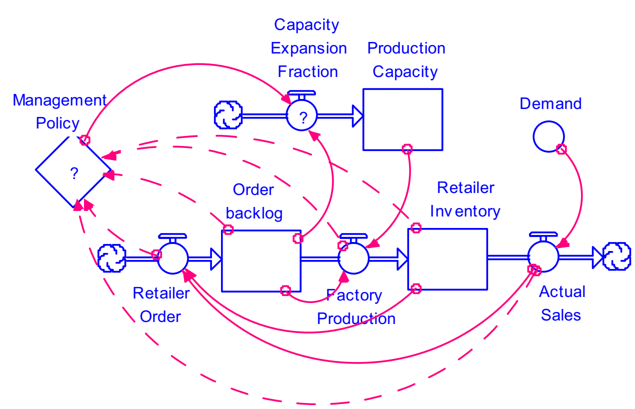


Fig. 2: Capacity constrained supply chain structure

Demand and retailer inventory determines the actual sales at the retailer. Retailer orders are placed taking into consideration the trend in the demand and the inventory level. Factory production is restricted by the production capacity availability, which is augmented based on the information available in the system.

Firms must forecast demand because it takes time to adjust production to changes in demand, and because it is costly to make large changes in production. They do not want to respond to temporary changes in demand but only to sustained new trends. A good forecasting procedure should filter out random changes in incoming orders to avoid costly and unnecessary changes in output (setups, changeovers, hiring and firing, overtime, etc.) while still responding quickly to changes in trends to avoid costly stockouts and lost business. To do so, firms constantly revise their forecasts as conditions change.

Consider the stream of successive forecasts rather than any particular forecast. Even though the firm is trying to anticipate the future order rate, the only information available upon which to base a forecast is information about the current or past behavior of the system. Since it takes time to gather the information necessary for forecasting, and since it consumes time to decide whether a change in the current order rate heralds a new trend or presents a random variation that will rapidly reverse, changes in the forecast will lag behind changes in actual conditions: a delay. The challenge is to respond to changing rates without overreacting to noise, to predict which change in demand is the beginning of a new trend and which one is a mere random blip.

4. Simulation Results

4.1. Demand Patterns

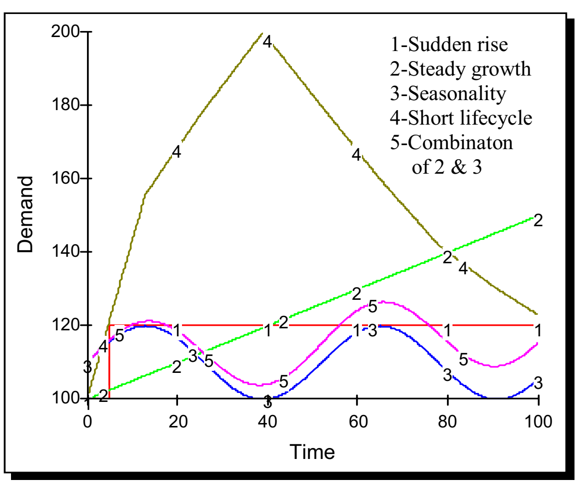


Fig. 3: Input Demand Patterns

The difference equations corresponding to the model given above (vide equations given in Annexure) were numerically evaluated with the different types of demand pattern, as given in Figure 3, as input. Initially the system was assumed to be performing at 100% utilization. The short lifecycle demand pattern follows a bell shaped curve and has a 100% demand increase as its peak requirement.

4.2. Supply Chain Capacity Structure

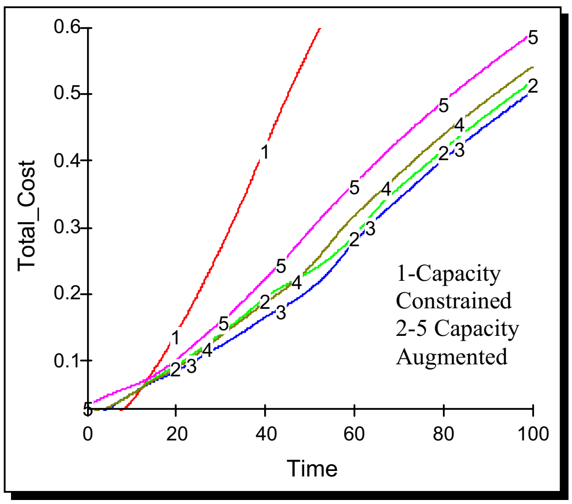
Table I gives the performance metrics for the initial supply chain structure under three strategies namely (a) Unlimited capacity; (b) Limited capacity and no capacity augmentation; (c) Limited capacity and with capacity augmentation. These are evaluated for the short lifecycle demand pattern.

Table I: Performance of the supply chain under different capacity structure strategies

Strategy	Shortage (%)	Retailer Inv. Value	Total Cost
Unconstrained Capacity	0	72742	92263
Limited capacity and no capacity augmentation	57	26196	169905
Limited capacity with capacity augmentation	2.22	61287	86696
Strategy	**Extra Capacity**	**Capacity Gap**	**Final Prod. Capacity**
Unconstrained Capacity	∞	0	∞
Limited capacity and no capacity augmentation	0	-25.31	100
Limited capacity with capacity augmentation	0.252	3.94	195.32

There is a huge shortage if the company does not go for capacity augmentation. This results in a loss of brand image of the company and this scenario provides the upper bound on the cost of the supply chain system. The other extreme case is to build sufficient capacity at start up. This results in under utilization of the plant and blockage of capital investment. The table above clearly depicts that a good strategy would be to start of with a limited capacity and go in for capacity increments when needed.

An important question that needs to be answered is what should be the initial capacity of the plant? Figure 4 provides a trade off between the start up investments and the capacity build up costs. The costs are normalized with respect to the costs that would have to be incurred if the company did not go in for capacity augmentation. The observed least cost curve is (3), which has an initial capacity of 125. This is because the supply chain structure takes certain time to build the capacity. Shortages occur in this period if capacity is not sufficient to replenish the stock at the retailer at that particular rate. So an efficient forecasting technique is necessary to make capacity augmentation decisions so that the cost of the supply chain structure is minimized.



Initial Capacity: (1) 100 (2) 100 (3) 125 (4) 150 (5) 200

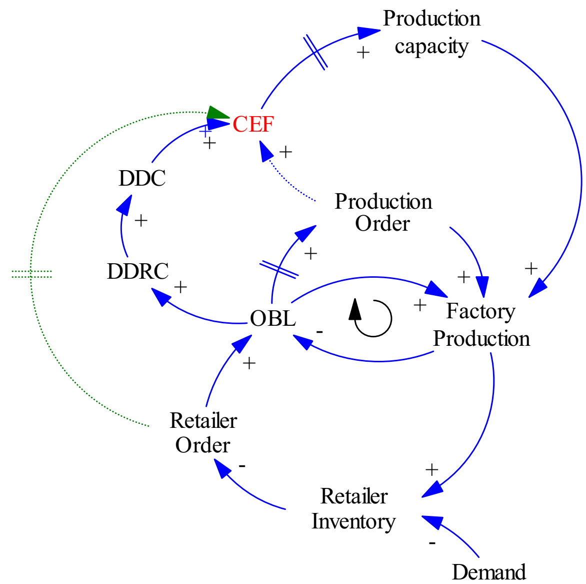
Fig. 4: Tradeoff between initial investment and buildup

5. Loop Dominance Analysis

In an information feedback controlled system, feedback loop dominance explains how structure drives behavior. This can help to determine which loops affect the behaviour in a major way. For example it is known that responsiveness of supply chain means that it should be able to achieve the desired service level (backorders should be minimum). Loop analysis can show us which loops contribute to the tardiness of the system.

In this paper our objective is to find out which loops can help us to augment the capacity only to the desired level while keeping the costs incurred at a minimum. Additionally, the objective is to derive a structure that exhibits desired dynamics. That is, it adjusts the capacity as fast as possible initially and then slowly to reach desired level and attain equilibrium. As the demand for the product in an uncertain market is highly unpredictable our structure need to be robust to work well with different types of demand patterns.

A simplistic representation of our problem without compromising on the structure is given in Figure 5.



OBL – Order backlog
DDRC – Delivery delay recognized by company
DDC – Delivery delay condition
CEF – Capacity expansion fraction

Fig. 5: Simplified causal loop diagram

The retailer orders are back logged at the manufacturer and take certain time before being produced and shipped to the retailer. With increase in demand, the production order also increases. The decision to augment the capacity is determined by the policy formulated by the management about the delay recognized, inventory held and the demand forecast. The performance of the system is determined by the feedback loops.

Out of the many different feedback loops, the six important feedback loops that were studied in detail are

L1: OBL – Production order – Factory production
L2: OBL – DDRC – DDC – CEF – Production capacity – Factory production
L3: OBL – Production order – CEF – Production capacity – Factory production
L4: OBL – Production order – Factory production – Retailer inventory – Retailer order
L5: OBL – DDRC – DDC – CEF – Production capacity – Factory production - Retailer inventory – Retailer order
L6: OBL – Production order – CEF – Production capacity – Factory production – Retailer inventory – Retailer order

Production capacity is the variable of interest and we perform the loop dominance by considering the six feedback loops given above. The time interval over which this is evaluated is two years. The system performance is demonstrated for a bell shaped input. Each loop is made inactive without affecting the dynamics of the other loop. The change in behaviour is observed for loop L3 and the main contributor is the link between production order and CEF. We change the structure of decision making by removing that link and installing a forecasting technique between retail order and CEF. This leads to better dynamics of the system.

System dynamists have traditionally used experimental model exploration, model reduction or both with their understanding of the behavior patterns typically generated by positive and negative feedback loops to identify dominant loops. These informal approaches can lead to errors and hence there is a need for rigorous feedback loop dominance analysis. We have used the behavioral approach [9] to perform the feedback loop dominance.

Detail discussion on [9] is beyond the scope of this paper. Only the following points are described for the sake of completeness.

- A feedback loop is said to dominate the behaviour of a variable during a time interval in a given structure and a set of system conditions when the loop determines the atomic pattern of variable's behaviour.
- Atomic behaviour pattern can be one of three types (a) linear (the rate of change remains constant over time); (b) exponential (the absolute rate of change increases over time); and (c) logarithmic (the absolute rate of change reduces over time)
- The method starts of by identifying a variable of interest and identifying time intervals in which the simulated behaviour of the variable demonstrate one of the three atomic behavioral patters. In subsequent steps for each time slot, all loops that are expected to dominate are deactivated, first individually and then in groups, to see if the deactivation causes any change in the atomic behavioral pattern.

The atomic pattern indicator, which is the first order derivate of the production capacity, the variable of interest, is shown in Figure 6. Analysis show that for the given supply chain structure, loop L3 is the dominant loop and CEF acts as the major contributing factor towards the loop dynamics. When there is a need for higher production capacity (due to increase in retail sales), the loops L2 and L3 shadow each other and act in such a manner so as to adjust the production capacity to that of steady state retail sales. In our proposed structure, the loops L2 & L3, L1 & L3 shadow each other at different time intervals and determine the behavior of the system.

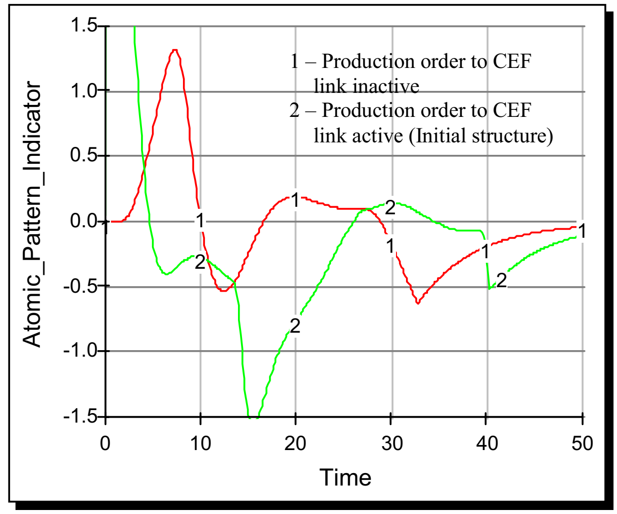


Fig. 6: Atomic behaviour pattern of production capacity to determine the dominant feedback loops in different time intervals

5.1. Proposed Supply Chain Structure – Modified Information Flow

The analysis was performed for the product with short lifecycle (demand pattern as in Figure 3). Initially the system was in steady state with production capacity in level with the retail sales. During the growth period it is seen that loop L2 and L3 shadow each other and timely CEF adjustment is crucial for capacity augmentation. Once the capacity is augmented the loops L1 and L3 contribute significantly to the dynamics of the system.

The performance of the system before and after the incorporation of the changes to the supply chain structure is presented in Table II. 'Initial' refers to the structure when the link between production order to CEF is present. The 'Proposed' structure eliminates this link and incorporates a forecasting technique of retailer orders to obtain CEF.

Table II: Comparison of the supply chain performance under different information processing policies

Strategy	Shortage (%)	Retailer Inv. Value	Total Cost
Proposed	2.22	61287	86696
Initial	2.33	71519	102637
Strategy	Extra Cap.	Cap. Gap	Final Prod. Cap.
Proposed	0.252	3.94	195.32
Initial	13.450	36.73	236.73

Around 15% reduction in cost can be achieved by adopting the new structure. The shortage and capacity gap are also reduced. The capacity is augmented, and Figure 7 shows the available capacity of the system.

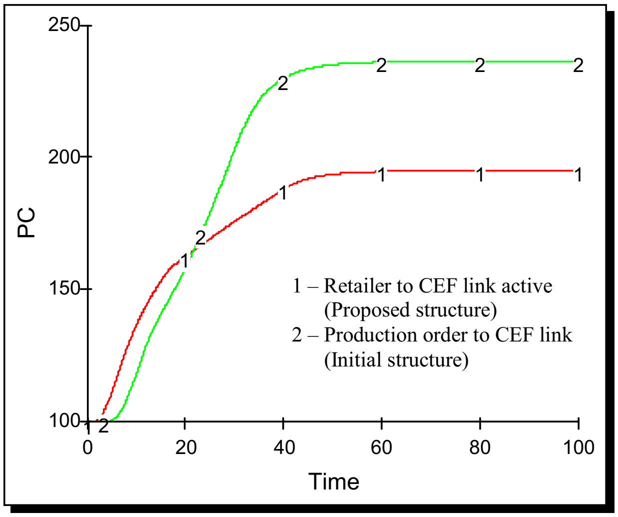


Fig. 7: Production Capacity Augmentation over time under different policies

5.2. Forecasting Techniques

Forecasters consider a wide array of factors to arrive at the forecast. The software packages usually provide the basic forecasting techniques for undertaking the analysis. The historical data is usually smoothed over a certain time period to arrive at the forecast. The longer the time, the lesser is the overshoot and fluctuation. The proposed supply chain structure is evaluated for different types of demand patterns and evaluated for four types of forecasting techniques. The results are tabulated in Table III. As expected delay1, the first order delay in updating the information provides the least capacity gap but results in highest shortage. It is known that single order exponential smoothing underestimates demand. As a result it builds capacity in a conservative way.

Table III: Supply Chain Performance w/o factory inventory, different forecasting techniques, different demand patterns

Capacity gap				
	Forecast	Trend	Delay1	Delay3
Step	44.38	28.83	6.93	12.20
Ramp	0.38	0.34	0.23	0.23
Seasonality	9.38	3.23	4.76	6.10
Short lifecycle	3.94	1.38	0.06	0.07
Comb (2&3)	3.65	3.17	1.89	2.38
Shortage (%)				
Step	0	0	0.33	0.34
Ramp	0.11	1.24	6.65	6.68
Seasonality	0	0	0	0
Short lifecycle	2.22	4.52	13.10	13.00
Comb (2&3)	0	0	0	0

5.3. Effect of Factory Inventory Buffer

Extra inventory usually acts as a buffer against demand variations at the retailer. A factory inventory buffer is added to the supply chain structure and the performance of system is tabulated in Table IV.

Table IV: Performance of the supply chain with factory inventory, different forecasting techniques, different demand patterns

	Forecast	Trend	Delay1	Delay3
Capacity gap				
Sudden rise	37.29	22.40	-0.14	1.84
Steady growth	0.74	0.67	0.47	0.47
Seasonality	6.64	3.10	3.24	5.43
Short lifecycle	8.00	2.26	0.08	0.12
Comb (2&3)	4.15	-0.43	-0.44	0.86
Shortage (%)				
Sudden rise	0	0	0.34	0
Steady growth	0.16	0.14	6.68	6.53
Seasonality	0	0	0	0
Short lifecycle	1.40	3.85	12.60	12.10
Comb (2&3)	0	0	0	0

Clearly in this structure the benefit of having the factory inventory does not come out. It is easy to see that this is due to the inability of the model to represent discrete capacity buildup, which allows for proactive inventory buildup. By using an appropriate discrete structure this problem can be eliminated.

6. Discussion

6.1. Methodological Consideration

System dynamics is a widely used approach to bring out structural peculiarities and macro level behavior of supply chains. This tool aids in effective management of the system resources so as to improve the performance of the entire system. However modeling supply chain at an operational level does not yield desired insight.

6.2. Limitation and Links

Obviously, there are many limitations to our study. It is assumed that the information is readily available and the manufacturer is able to augment the capacity in a continuous manner and not in discrete jumps as would be the case in reality. There is no doubt that the entire model should be validated with real world data. Our research is progressing in that direction but here we have restricted ourselves to present the supply chain structure and provide the analysis mechanism.

It may also be pointed out here that methods of loop dominance analysis differ in their definition of loop dominance. Richardson [23] for example defines a dominant loop as one that is primarily responsible for model behavior over some time interval. By this, only one loop can dominate the behaviour during any time interval. The definition by Ford [9], discussed in this paper, in contrast, does allow for multiple loop dominating in a single time interval. The definition is different from the one used in this paper. As the outcomes of analysis depends on the definition of the loop dominance, patterns of behaviour, the results of various loop dominance analysis methods are bound to be different.

6.3. Managerial Implication

The limitations not withstanding, the study gives insight into the factors that dominate the dynamics of supply chains. For effective management these structures need to be monitored by means of appropriate information systems. The efficacy of different forecasting techniques for different types of demand and the way in which capacity augmentation needs to be done are also indicated.

7. Conclusion

This paper presents a supply chain structure analysis and design method. Specifically this shows how effective decision can be made for capacity augmentation to achieve high service levels. As illustration we have used the case of products, which have short lifecycle. This kind of products has become particularly important because of the advent of Internet. But similar analysis can as well be used in other types of products. The analysis is based primarily on loop dominance. This brings out the dominant loops and enables structural changes. The cost figures show that the capacity is built only to the required level and at the required time. The model is evaluated for different demand patterns and forecasting techniques demonstrating its robustness. The limitation of this study is the validation on actual data. A good work would be to collect this data for different industries and perform the tuning of supply chain parameters to obtain better results. Effective forecasting techniques within the decision making model will also be an interesting work. Another study could focus on why the retailer should provide the factory with real time data or determine how the net benefit generated from efficient supply chain management is redistributed among members. Finally one can think about achieving an optimized supply chain with minimum cost, and least order and shipment fluctuations.

8. References

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Annexure

System equations for the supply chain

init	OBL = 200
flow	OBL = -dt*factory_production +dt*retail_orders
init	PC = 200
flow	PC = +dt*PCAR
doc	PC = Production capacity
init	PCOO = 0
flow	PCOO = -dt*PCAR+dt*PCO
doc	PCOO = Production capacity on order
init	RINV = 200
flow	RINV = +dt*factory_production - dt*retail_sales
init	rinv_value = 0
flow	rinv_value = +dt*rinv_r
init	tot_ret_sale = 0
flow	tot_ret_sale = +dt*sales
init	tot_shortfall = 0
flow	tot_shortfall = +dt*shortfal
init	Total_cap_value = 0
flow	Total_cap_value = +dt*capvalrate
init	Total_Cost = (PC-100)*50
flow	Total_Cost = +dt*Cost_Chng
doc	Total_Cost = PC*50
aux	capvalrate = PCO*50
aux	Cost_Chng=(Shortfall_Ret*20+MAX(RINV,0)*2.5 +PCO*50+Total_Cost*0.18/52)
aux	factory_production= MIN(production_capable, Production_Order,OBL)
aux	PCAR = DELAYMTR(PCO,6,1,0)
aux	PCO = CEF
doc	PCO = production capacity ordering
aux	retail_orders=MAX(average_retail_sales+(DINV-RINV)/2+(average_retail_sales*WOBD-OBL)/2,0)
aux	retail_sales = MIN(Demand,RINV)
aux	rinv_r = -MIN(0,RINV)*5+MAX(RINV,0)*2.5
aux	sales = retail_sales
aux	shortfal = Shortfall_Ret
aux	API_cef = DERIVN(ABS(DERIVN(CEF,1)),1)
aux	API_Conv=IF(Atomic_Pattern_Indicator<-1e-6,-1, IF(Atomic_Pattern_Indicator>1e-6,1,0))
aux	Atomic_Pattern_Indicator= DERIVN(ABS(DERIVN(PC,1)),1)
aux	average_retail_sales=DELAYINF(Demand, time_to_average_retail_sales,3)
aux	cap_gap = PC-high_rs
aux	CEF=MAX((PCDP-PCOO-PC)*DDC,0)
doc	CEF = capacity expansion fraction
aux	DDC = MAX((DDRC/DDOG)-DDB,0)
doc	DDC = delivery delay condition
aux	DDOG = DDT*DDW+DDMG*DDWC
doc	DDOG = delivery delay operating goal
aux	DDRC = (OBL)/(factory_production)
doc	DDRC = delivery delay recognised by company for augmentation
aux	DDT = DELAYINF(DDRC, TDDT, 1)
doc	DDT = delivery delay traditional
aux	DDWC = 1-DDW
doc	DDWC = Delivery delay weight complement
aux	Demand= GRAPH(TIME,0,13,[100,156,179,200, 180,160,142,130,120,102,0"Min:100;Max:200"])
doc	Demand= Different types of input 1)110+RAMP(0.1,0)+SINWAVE(10,52) 2)GRAPH(TIME,0,13,[100,156,179,200,180,160,142, 130,120,102,0"Min:100;Max:200"]) 3)100+RAMP(0.5,0) 4)100+STEP(20,5) 5)110+SINWAVE(10,52)
aux	DINV = average_retail_sales*Coverage
aux	extracapacity = PC-highvalueproduction
aux	high_rs = HIVAL(retail_sales)
aux	highvalueproduction = HIVAL(factory_production)
aux	PCDP=FORECAST(retail_orders, 2, 2,100)
doc	PCDP = capacity desired; 1)FORECAST(retail_orders, 2, 2,100) 2)TREND(retail_orders, 3,100) 3)DELAYINF(retail_orders, 3,1) 4)DELAYINF(retail_orders, 3,3)
aux	production_capable = PC
aux	production_indicated = OBL/WOBD
aux	Production_Order=DELAYINF(production_indicated, time_to_adjust_production,1)
aux	shortage = tot_shortfall/tot_ret_sale
aux	Shortfall_Ret = MAX(Demand-retail_sales,0)
const	Coverage = 2
const	DDB = .3
doc	DDB = delivery delay bias
const	DDMG = 2
doc	DDMG = delivery delay management goal
const	DDW = .3
doc	DDW = Delivery delay weighting
const	TDDT = 12
doc	TDDT = time for delivery delay tradition
const	time_to_adjust_production = 4
const	time_to_average_retail_sales = 1
const	WOBD = 2
doc	WOBD = weeks of backlog desired

