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Article

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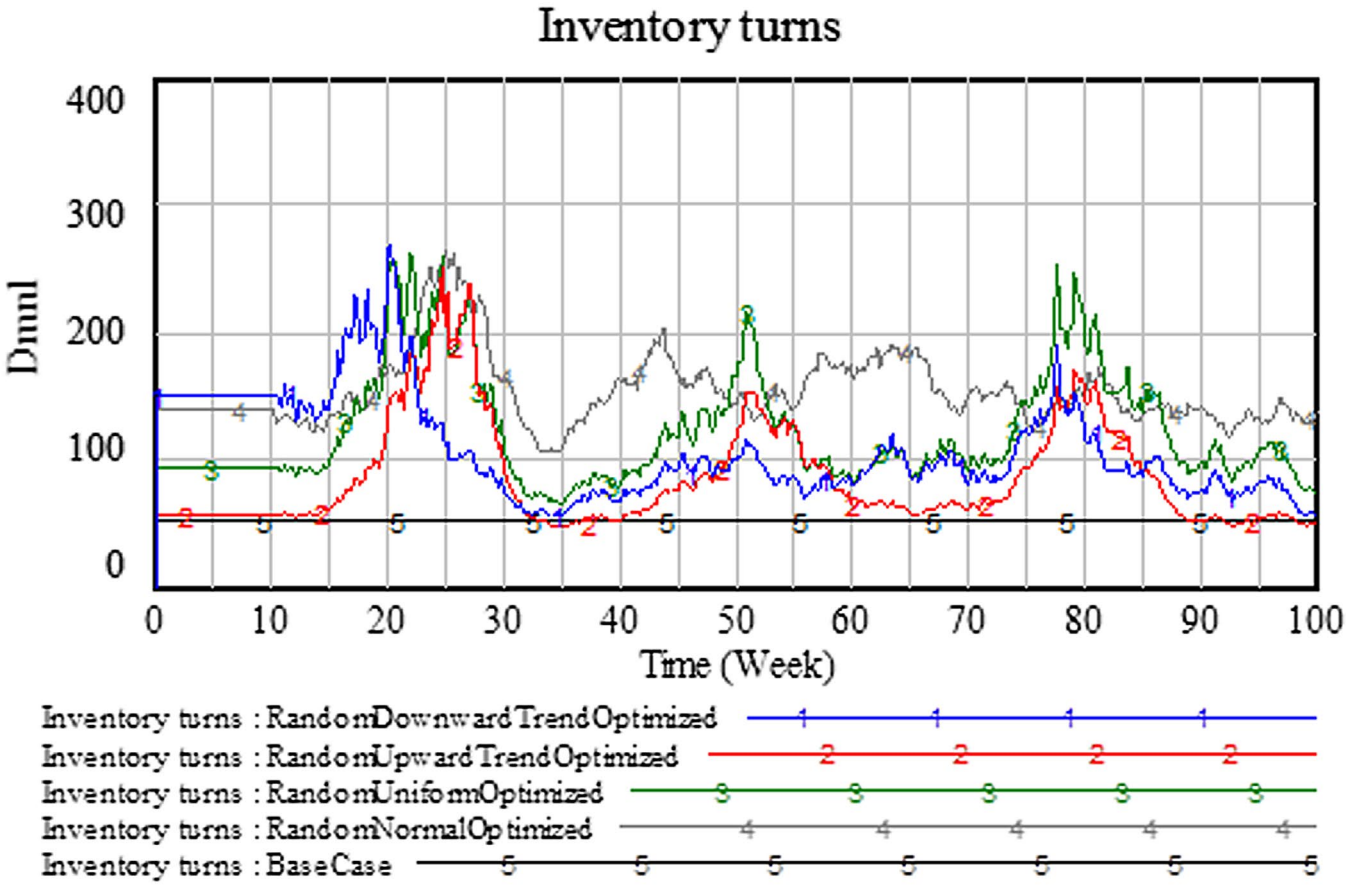

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Performance metric optimization advocates CPFR in supply chains: A system dynamics model based study

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Abstract: Background: Supply Chain partners often find themselves in rather helpless positions, unable to improve their firm's performance and profitability because their partners although willing to share production information do not fully collaborate in tackling customer order variations as they don't seem to appreciate the benefits of such collaboration. **Methods**: We use a two-player (supplier-manufacturer) System Dynamics model to study the dynamics to assess the impact and usefulness of supply chain partner collaboration on the supply chain performance measures. **Results**: Simulation results of supply chain metrics under varied customer order patterns viz., basecase, random normal, random uniform, random upwardtrend, and random downwardtrend under (a) basecase, (b) independent optimization by manufacturer, and (c) collaborative optimization by manufacturer and supplier, are obtained to contrast them to develop useful insights. **Conclusions**: Focus on obtaining improved inventory turns with optimization techniques provides some viable options to managers and makes a strong case for increased collaborative planning forecasting and replenishment (CPFR) in supply chains. Despite the differences in the inventory management practices that it was contrasted with, CPFR has proven to be beneficial in a supply chain environment for all SC partners.

Balaji Janamanchi

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PUBLIC INTEREST STATEMENT

Supply Chains are complex business systems. Supply chain dynamics are best studied using tools and techniques, capable of grappling with the dynamic complexity inherent in them, such as system dynamics simulation. This is a system dynamics simulation model based study to understand the pre-requisites for successful attainment of desired supply chain performance metrics. We conclude that when the customer orders are exhibiting either upward or downward trend, manufacturers should be focused on eliminating unfilled orders more than the stability in production schedules. Supply chain partners, both supplier and manufacturer, not only need share information in real time but also actively embrace and implement collaborative planning forecasting and replenishment (CPFR) for successful attainment of desired supply chain performance metrics.

Subjects: Optimization; Simulation & Modeling; Supply Chain Management

Keywords: supply chain performance metrics; CPFR; optimization; systems dynamics; simulation modeling

1. Introduction

Supply chains are complex business systems that exhibit nonlinear behavior of system variables. Typical managerial tools are deficient in coping with this nonlinear behavior of system variables, in providing decision support to managers. System dynamics simulation modeling can quite easily capture these nonlinear behaviors of system variables and can also provide useful managerial decision support to deal with such complex systems.

This study is part of a series of studies aimed at gaining a deeper and better understanding of supply chain dynamics using System Dynamics modeling methodology (Forrester, 1958, 1961; Sterman, 2000). In prior studies (Burns & Janamanchi, 2006; Janamanchi & Burns, 2007a, 2007b, 2008, 2010), effects of reductions in information delays and flow delays as well as forecasting/smoothing upon bullwhip effect and on supply chains have been explored. The focus of the current study is a simple two-player manufacturer–supplier supply chain to assess the options to improve supply chain metric of inventory turns and to understand the need for CPFR efforts between the supply chain partners (Russell & Taylor, 2011). In particular, we contrast the situation obtaining, with and without such collaborative efforts and provide persuasive evidence to support the case for increased CPFR by supply chain partners. The objective is to develop useful insights for forecasting, order filling, and stocking policies in order to maximize the inventory turns and to, possibly, minimize inventory carrying costs per unit of product sold; under different customer order pattern scenarios, while, not losing sight of eliminating unfilled orders at either of supply chain partners ends. Boone, Ganeshan, and Stenger (2001) researched the impact of CPFR on Supply Chain performance by comparing the CPFR with the traditional Reorder Point (ROP) system followed in supply chains and concluded that, CPFR increases the fill rate, decreases the supply chain inventories, reduces the supply chain cycle time, and increases the shareholders' wealth. The Voluntary Interindustry Commerce Solutions (VICS) developed and presented a report titled, "Linking CPFR and S&OP: A Roadmap to Integrated Business Planning."(VICS, 2010), while comparing Sales and Operations Planning (S&OP) with CPFR suggests, "S&OP is the best practice model for internal collaboration for a business entity" and in contrast, "CPFR is the best practice model for external collaboration between business entities." Fundamentally, the aim of CPFR is to convert the supply chain from a disjointed, ineffective, and inefficient "push" system to a coordinated "pull" system based upon end consumer demand (VICS, 2010).

The remainder of this paper is organized as follows. Modelling Methodology section discusses the modeling methodology and explains the general outline of a hypothetical supplier–manufacturer supply chain model set up. The results from the simulation of the base case and four sets of customer order patterns without and with collaborative efforts are presented in results from simulations, followed by discussion section containing discussion of insights that may be gained from these results. Finally, the last section lists the contributions/limitations of the current study and directions for future studies.

2. Modelling methodology

As its founder Dr. Jay Forrester would explain, System Dynamics research methodology comprises six steps depicted and succinctly captured in Figure 1.

The flows going back and forth indicate the iterative nature of the process. Model is revised and refined for known and observed behavior of the real-life system; accordingly, a simulation model that mimics the real-life system as closely as possible to provide actionable policy pointers evolves and emerges. As stated, this study is an extension of a series of studies (Janamanchi & Burns, 2007a, 2007b, 2008, 2010). As will be seen, we are simulating a variety of scenarios, as suggested in step 4 in Figure 1, to develop data to facilitate debate and discussion of step 5 in Figure 1, and eventually

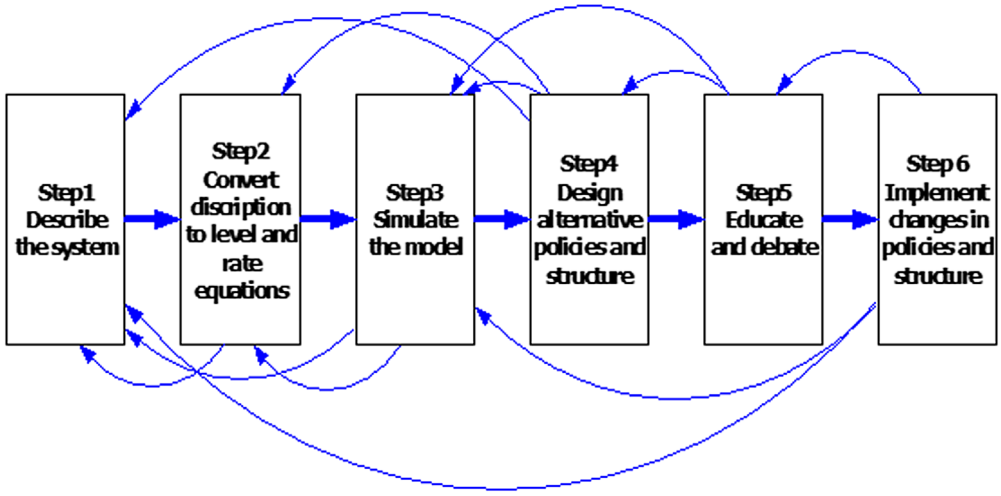


Figure 1. System dynamics methodology.

Source: MIT system dynamics literature collection—Dr. Jay W. Forrester.

lead to step 6 (of Figure 1) by way of contribution of the study findings to System Dynamics and Supply Chain literature and practice.

2.1. Brief overview of the supply chain set up

The supply chain set up considered under this study is fairly simple. Customers place orders for products with manufacturer who places orders with his supplier for the required input material. Both supply chain partners carry minimal finished goods inventories (enough inventory to fill current week order to start with) and have in place inventory policies for replenishment requisitions. Both supply chain partners carry "work-in-process" (WIP) inventories. Similarly, they have order forecasting policies in place using the "exponential smoothing" method with a smoothing alpha of 0.125 and 0.500, respectively, for manufacture and his upstream supplier.

2.2. Model structure

The model utilized in this study is a continuous-deterministic simulation model. The methodology utilized is known as System Dynamics and was developed by Forrester (1958, 1961) and advanced by Sterman (2000). The software implementation tool utilized is Vensim (*Ventana Systems Inc*, 2013). The founder of system dynamics, Dr. Jay W. Forrester, was the first to use system dynamics to study the firm and its interaction with suppliers (1958, 1961). More recently, system dynamicists have been studying supply chains using system dynamics methodology (Akkermans & Dellaert, 2005; Croson & Donohue 2003, 2005; Sterman, 2000).

2.3. Manufacturer's set up

Figure 2, shows the System Dynamics Model structure for the manufacturer's production set up. The basic constructs for the model structure are derived from state-of-the-art models presented in Sterman (2000, chapters 17, 18, and 19). Customer orders in the right of the figure initiate the action. This is the single most significant external input used to stimulate and test the model. Understandably this will ultimately determine the quantity sold. At the lower right hand side of Figure 2 is an exponential smoothing forecast mechanism that computes the "Forecast Order rate." This structure uses a SMOOTHING FACTOR ALPHA (set at 0.125 at start). The Forecast order rate is used to compute the "Desired Finished Goods inventory" and thereby the "desired production rate" based on inventory policies. In conjunction with the limiting factors of available material and workforce (and permissible flexibility of workforce with overtime working) practicable scheduled production rate for the next time period is determined. This practicable scheduled production rate drives the supplier's production setup in Figure 3. In both figures, the parameters (constants) are shown in all caps. A week is the unit of time in this model. However, in order to identify any leverage points for performance

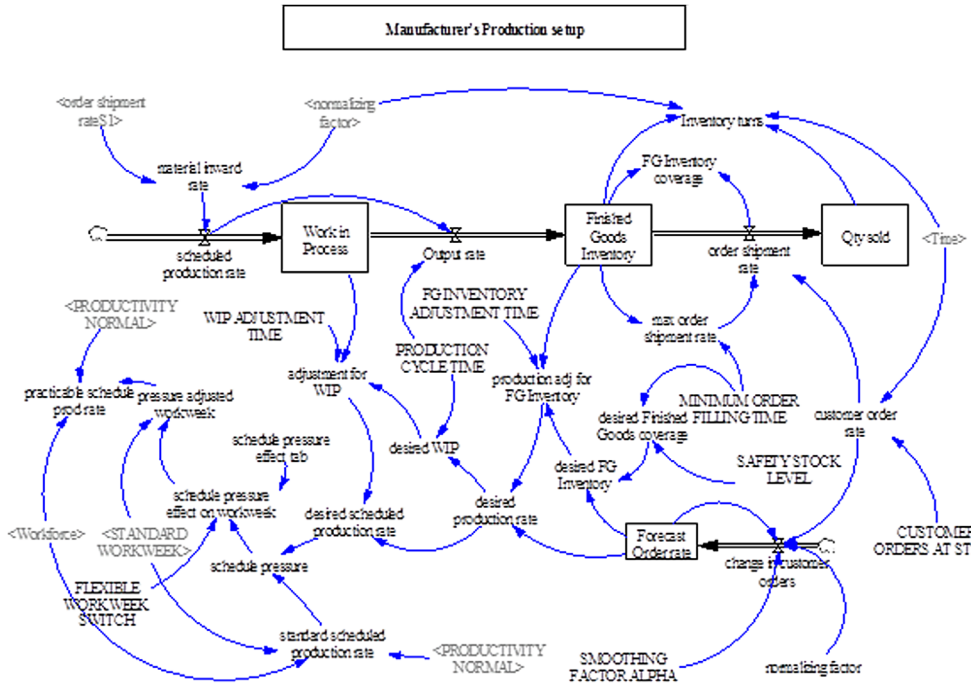


Figure 2. Manufacturer's production set up—finished goods, order filling, customer order forecasting, and inventory turns tracking.

optimization, 0.2 of a week (day) was used as smallest possible unit of time for customer order filling process. Figure 3 depicts the production set up for the supplier.

The sequence of operations begins with the "Forecast Order rateS1" on the lower right. The "desired Finished Goods coverage" is the sum of the SAFETY STOCK LEVELS1 (nil to begin with) and the MINIMUM ORDER FILLING TIMES1 (one week initially). Then "Forecast Order rateS1" per week is multiplied by the "desired Finished Goods coverage" yields the "desired FG InventoryS1." The "production adj for FG InventoryS1" (production adjustment for Finished Goods Inventory) is but a correction of the gap in "desired FG InventoryS1" versus actual "Finished Goods InventoryS1" over the FG INVENTORY ADJUSTMENT TIMES1; thus

"Production adj for FG InventoryS1" = ("desired FG InventoryS1" – "Finished Goods InventoryS1")/FG INVENTORY ADJUSTMENT TIMES1

Inventory turns is annualized by converting end-of- the-week data using the following formula.

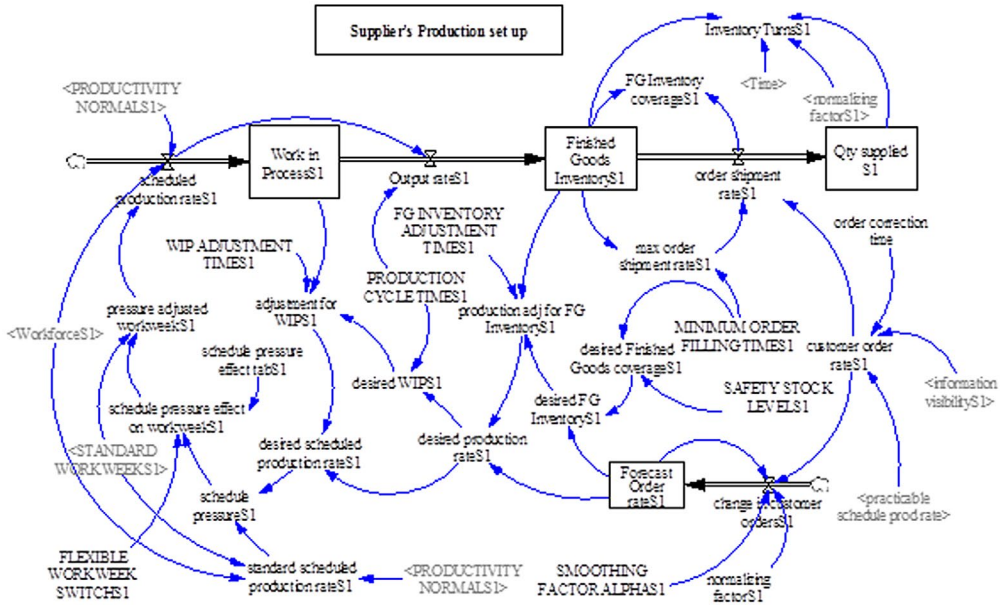
Inventory Turns S1 = (Qty supplied S1*52 weeks/Time in weeks)/Finished Goods InventoryS1

(Similar structure for capture of inventory turns may be noticed for manufacturer in Figure 2).

Further, in Figure 3, it may be observed that, "production adj for FG InventoryS1" is the rate at which FG safety stocks are replenished. Intuitively, it would seem that rapid replacement of safety stocks would be better than slow replenishment. Understandably, the "production adj for FG InventoryS1" is combined (literally added) with the "forecast order rate" to derive the desired production rate.

The desired production rate is multiplied by the PRODUCTION CYCLE TIMES1 to yield the desired WIPS1. This is just a direct implementation of Little's Law (1961). Analogous to the adjustment for Finished Goods, an "adjustment for WIP" is computed based on the following formula:

Figure 3. Supplier's production setup.



"Adjustment for WIPS1" = ("Desired WIPS1" – "Work in ProcessS1")/WIP ADJUSTMENT TIMES1.

Quite logically, the "desired production rateS1" and the "adjustment for WIPS1" yields the "desired scheduled production rateS1", that is:

"Desired scheduled production rateS1" = "desired production rateS1" + "adjustment for WIPS1".

But then, manufacturer's desired production plans are constrained by two main factors viz., availability of material inputs in the required quantity, and availability of the requisite "workforceS1". Based on the available "workforceS1," "standard workweekS1," and PRODUCTIVITY NORMALS1, the "standard scheduled production rateS1" is computed as the product of these. PRODUCTIVITY NORMALS1 is assumed at 0.5 unit per/person*hour, denoting half a unit of output per worker per hour. Based on "desired scheduled production rateS1" and "standard scheduled production rateS1", the "schedule pressureS1" is computed as the ratio of these. Specifically, "schedule pressureS1" = "desired scheduled production rateS1"/"standard scheduled production rateS1". As may be noted, a "schedule pressureS1" greater than "1", indicates a shortage of "workforceS1"; and on the other hand, a "schedule pressureS1" that is less than "1," indicates an excess of "workforceS1". Typically, such excess or shortage of "workforceS1", as is signaled by the "schedule pressureS1", triggers action for adjustment in workforce levelS1, either by way of decreases in the hiring/increases in the hiring of additional workforce.

Figure 4 depicts the supplier's workforce portion of the model structure, which is very similar to that of the manufacturer with the exception of a couple of parametric settings. Desired scheduled production rateS1, STANDARD WORKWEEKS1, and PRODUCTIVITY NORMALS1 yield the "desired workforceS1" to support the production operations. If there is no information visibility between functional areas, there exists a delay of one time-period (one week) in communicating the "desired scheduled production rate" to the personnel department. With information visibility, communication delays between the manufacture and supplier are removed (assuming that the manufacturer and supplier have in place, suitable information systems). One of the delays is the time required to perceive the need for changes in the workforce. Based on management's policy of adjusting the gap in workforce, desired versus actual, an "adjustment for workforce" is computed. "WorkforceS1" is regularly depleted by the "quit rate" of the workforce. The "expected quit rate" for the next period is equal to the current period's "quit rate". The "desired hiring rate" is the sum of the "expected quit

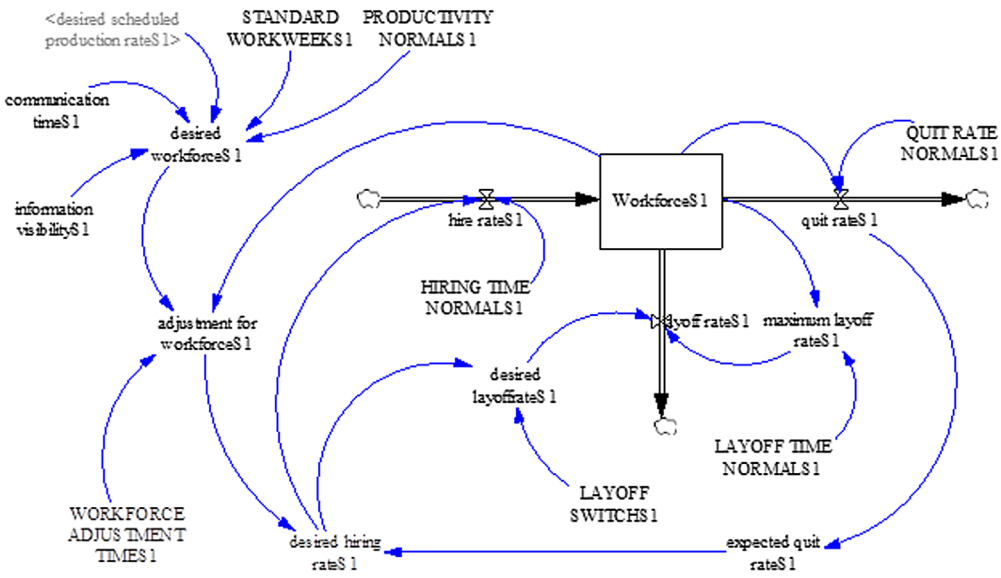


Figure 4. Workforce view of the supplier manufacturer.

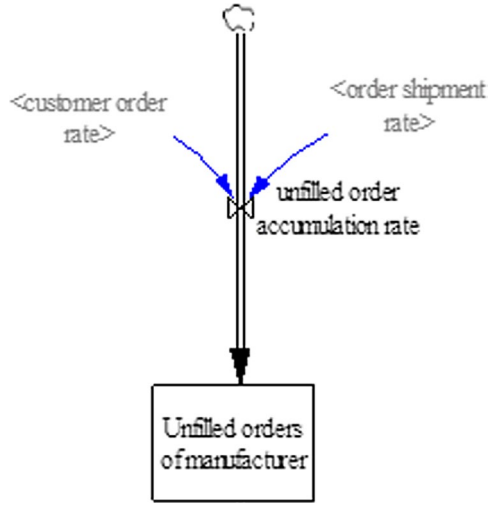


Figure 5a. Unfilled orders at manufacturer.

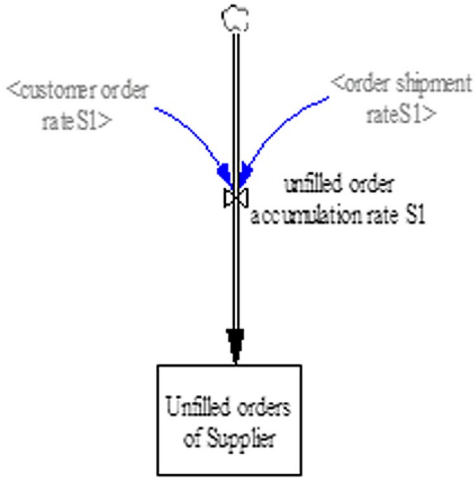


Figure 5b. Unfilled orders at supplier.

rate" and the "adjustment for workforce," to maintain an equilibrium level of "workforce". However, only positive values of "desired hiring rate" result in recruitment of "workforce". If "desired hiring rateS1" is negative, then such rate is used in computing the "desired lay off rate" depending upon management's policy on layoffs (LAYOFF SWITCHS1 value 1 = yes and 0 = no), "workforce" is laid off or is not laid off. For simplicity, we assume that the management of both manufacturer and supplier do not practice lay-offs in this study. Figures 5a and 5b depict the model structure that captures the unfilled orders of finished goods at the manufacturer facility and the supplier's facility.

2.4. Initial parameter/policy setting for manufacturer and his supplier

Table 1 given lists the initial values for the major stocks and policy parameters of the retailer and the supplier in the model. Running time for the simulation is 100 weeks.

Table 2 summarizes the various customer order scenarios simulated in this study.

Figure 6 depicts the customer order levels under each scenario. Under the base case scenario, there is no change in the steady rate of customer orders (10,000 per week). Under other scenarios,

Table 1. Initial parameter settings

Parameter	Unit	Manufacturer	Supplier
Production and inventory			
Simulation time	weeks	100	100
Customer orders at start	units/week	10,000	na
Orders from manufacturer	units/week	na	10,000
Order variation start time	weeks	11	na
Smoothing alpha	dimensionless	0.125	0.5
Min order filling time	weeks	1	1
Safety stock level	weeks	0	0
FG Inv adj time	weeks	4	4
Production cycle time	weeks	2	2
WIP adj time	weeks	4	4
Standard workweek	hours	40	40
Flexible workweek -max	hours	50	50
Flexible workweek-min	hours	30	30
Productivity normal	units/(hour*person)	25	25
WIP	units	20,000	20,000
Finished goods	units	10,000	10,000
Workforce view			
Workforce adj time	weeks	3	3
Communication time	weeks	1	1
Hiring time normal	weeks	1	1
Layoff time normal	weeks	5	5
Quit rate normal	dmnl/week	0.01	0.01
Workforce	person	10	10
Inventory/labor costs view			
Inventory cost normal	dollars/(unit*week)	0.1	0.1
Hourly rate normal	dollars/(person*hour)	12	12
Overtime wages	times normal wage	2	2
Hiring costs normal	dollars/person	100	100
Layoff costs normal	dollars/person	250	250

the customer orders vary as above. Random Uniform pattern is overlapping the Random Normal patterns since the variance in Random Uniform is typically larger than Random Normal when the Upper and Lower bounds of distributions are approximately same. Furthermore, both these patterns represent a level pattern of orders with a stationary mean.

3. Results from simulations and discussion

As discussed, we start the model simulation with the base case, where the system is in steady state and the customer orders are received steadily at 10,000 units/week. Inventory policies (One week stocks to cover order filling time and no additional safety stock) and forecast policies (exponential smoothing with alpha = 0.125) are working perfectly for the manufacturer. Similarly, with just one week of inventory (to cover order filling time), no additional safety stocks, and an exponential smoothing alpha of 0.50, the supplier is enjoying a steady state of production as well. Then we continue with the scenarios listed in Table 2.

Table 2. Customer order scenarios simulated

Scenarios	Description
Basecase	No changes in customer orders of 10,000 units/week Information visibility turned on and flexible work week is turned on (These are turned on in four scenarios described below as well)
Random normal	Starting week 11, customer orders vary between min of 8,000 and max of 12,000 with Mean of 10,000 and Std. Deviation of 500
Random uniform	Starting week 11, customer orders vary in a random uniform pattern between a low of 8,000 and high of 12,000
Random upward trend	Starting week 11, customer orders show a upward trend of 50 units/week Plus vary in a random uniform pattern of +/- 2,000 units on either side of trend line
Random downward trend	Starting week 11, customer orders show a downward trend of 50 units/week Plus vary in a random uniform pattern of +/- 2,000 units on either side of trend line

Figure 6. Customer order rates simulated in the study.

For obvious reasons, due the volatility in the orders, the inventory turns metric of the manufacturer starts to deteriorate. Figure 7A captures the inventory turns metric of the manufacturer under these five order situations. What was a steady 52 turns per year (given that average inventory holding is 1 week, to cover the order filling time), the metric falls down due to order variations resulting in increases in average stocking. Similarly, Figure 7B captures the inventory turns metric of supplier under these scenarios during the simulation time.

As a matter of fact, both manufacturer and his supplier also experience unfilled order under these volatile order scenarios. Unfilled orders are captured and computed with the assumption that they will not affect the future orders. At the same time, they are not carried forward as backordered. Figure 8 depicts unfilled orders of manufacture.

3.1. When the supplier is unable to collaborate

For a variety of reasons, the supplier may not be willing to collaborate with the manufacturer in the planning, forecasting, and replenishment efforts even though he may be willing to share production, order filling, and inventory information. The supplier may be part of a bigger organization where policy- and decision-making is done on a different review periods than the manufacturer. Or the manufacturer represents a small portion of supplier's business in that he is not too keen to collaborate. Or the supplier may not fully appreciate the benefits of collaboration. Under such circumstances, the manufacturer is left with no options but to explore for opportunities internally to maximize his performance metrics.

3.2. Manufacturer's independent optimization efforts

Given that the main goal of a business is to sell as much as possible, manufacturer would obviously choose to eliminate unfilled orders. For obvious reasons, the next most important focus is to improve operational efficiency denoted by the inventory turns and average inventory on hand. If the sales volume remains rather constant, then inventory turns and average inventory are inversely proportionately related. If average stock levels go up, the inventory turns fall, and if average inventory levels falls inventory turns improve. Senge (1990) asserts in his classic work Fifth Discipline dealing with systems thinking that the areas of highest leverage in systems are often least obvious. So in order to find possible avenues for improvement, we try and search for parametric settings of, order

Figure 7A. Inventory turns of manufacturer under different order scenarios.

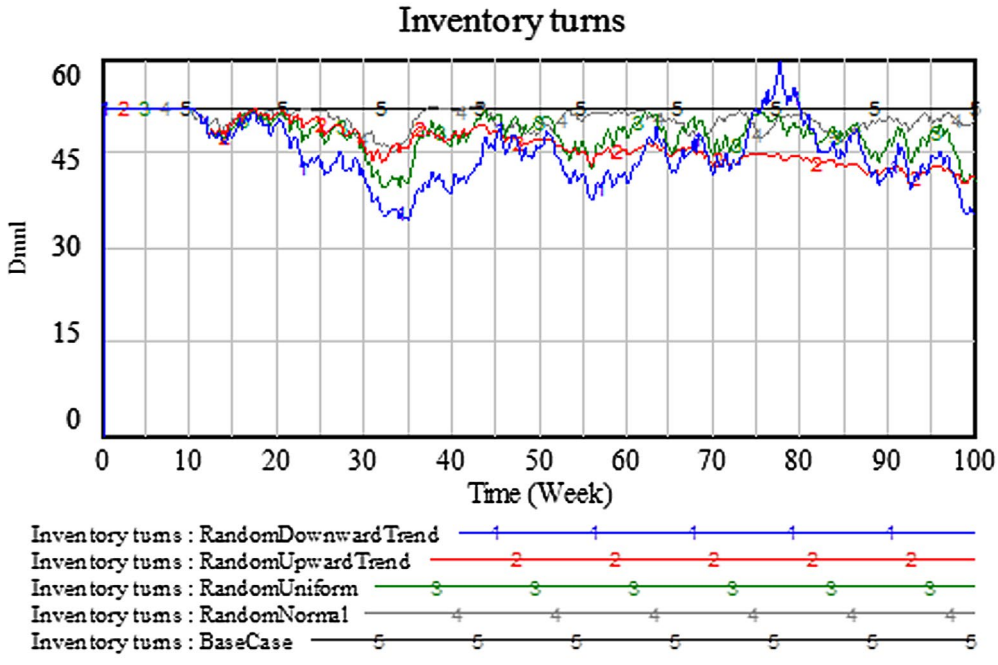
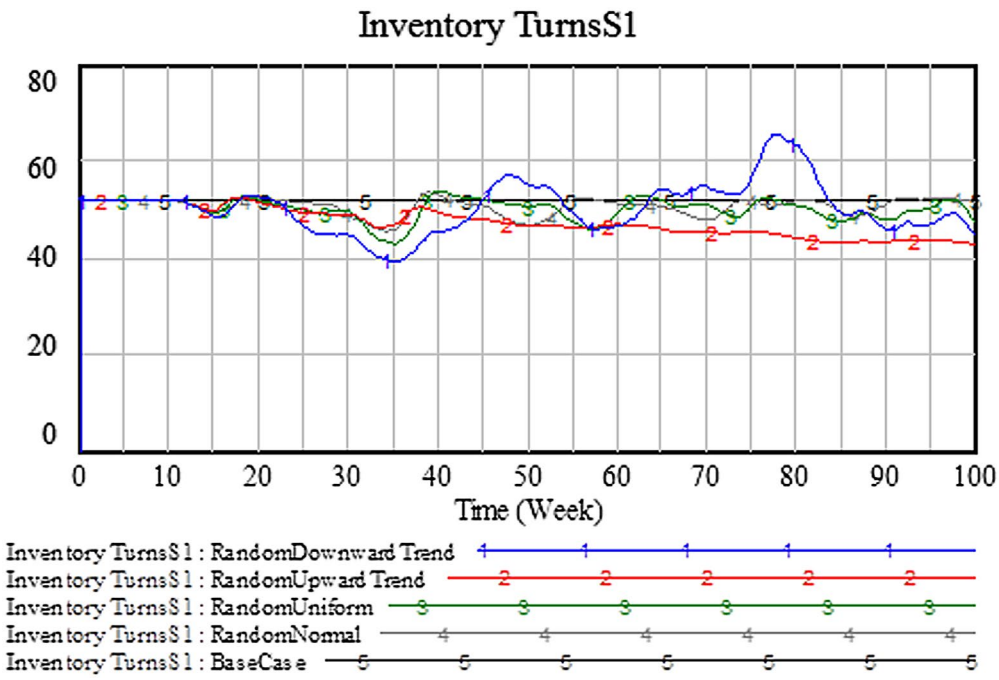


Figure 7B. Inventory turns of the supplier under different order scenarios.



filling time, safety stocks, and smoothing alpha for forecasting to maximize the inventory turns while holding unfilled orders to zero or minimal.

Objective function and search space constraints: Manufacturer's objective function is to, "Maximize inventory turns while simultaneously minimizing the unfilled orders." We attempt optimization under all four scenarios of customer orders from a **start point** of current settings, with following restrictions.

Figure 8. Unfilled orders of manufacturer under different order scenarios.

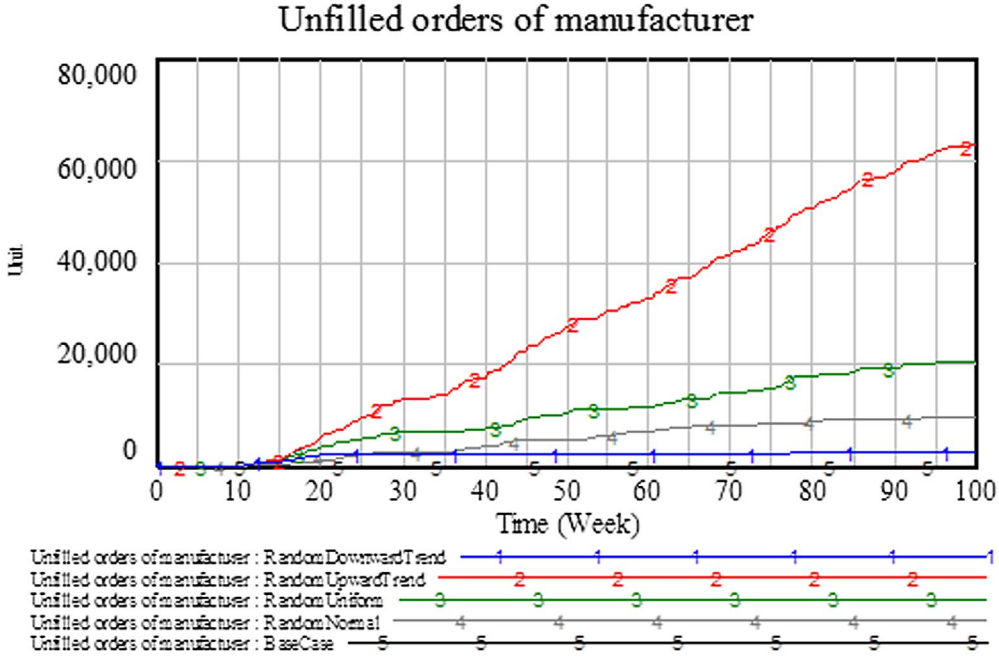
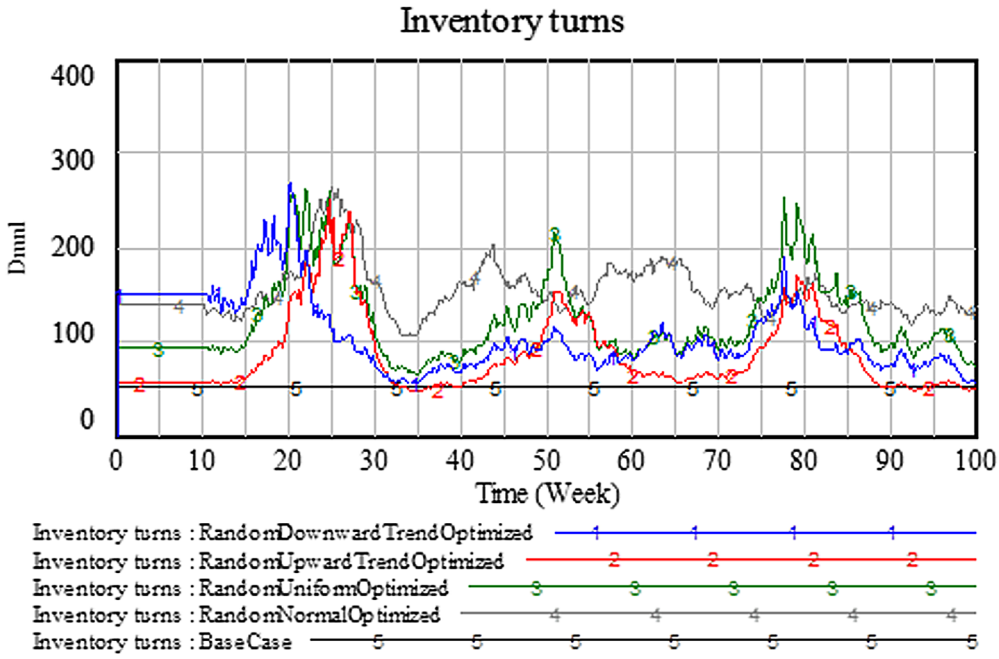


Figure 9. Inventory turns under optimization runs for manufacturer.



- Order filling time is currently, 1 week (or 5 days), to be realistic, we search for a parameter value in the range of 0.2 weeks (1 day) to 1 week (5 days) for this constant.
- Safety stock can be anywhere from 0 to 1 week, and finally
- Smoothing factor alpha can technically be anywhere from 0 to 1.

Powell's hill-climbing algorithm which is built into Vensim will explore on either side of the start point to move in the desired direction to optimize the objective function, in this case to maximize the inventory turns and minimize the unfilled orders. These optimization runs under different customer order scenarios generate the requisite parametric settings that will accomplish the desired objective function.

Figure 9 depicts the inventory turns of manufacturer under optimization for different scenarios compared with the base case scenario. As may be seen, there is a distinct possibility of improving the inventory turns with subtle changes made to system constants. Not surprisingly, the unfilled order drop back to zero under all scenarios under optimization as in base case. All unfilled orders are eliminated, inventory turns are improved. Inventory costs per unit sold also drop lower as may be seen in Figure 10 leading to improvement in profitability of the firm. These are, obviously, the best results that the manufacturer can obtain without any collaboration from his supplier in planning, forecasting, and replenishment efforts.

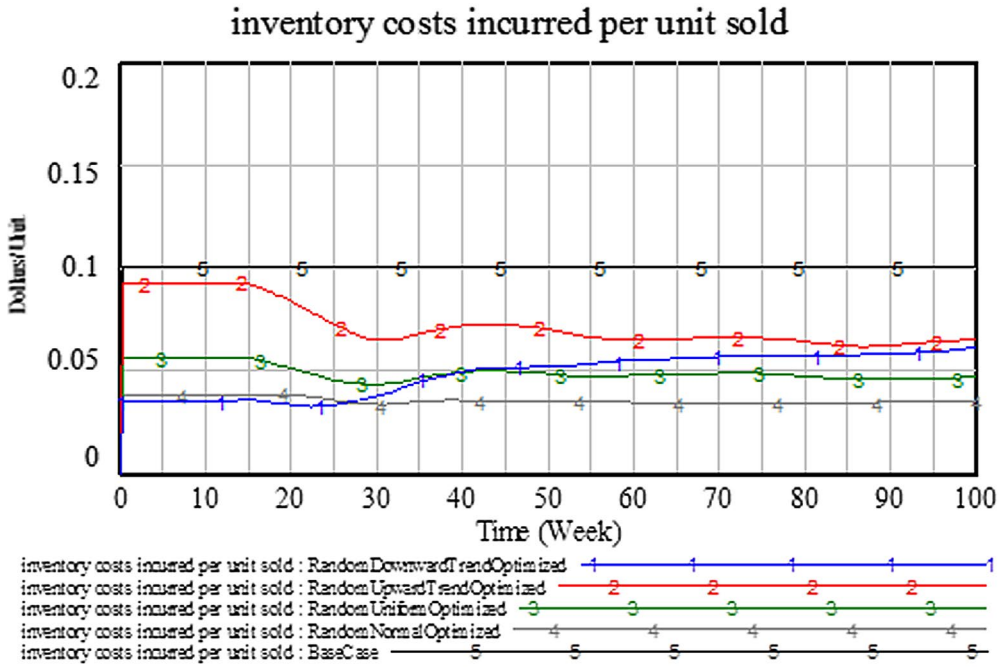
3.3. Collaborative optimization efforts

Assuming that supplier is able to collaborate, we define a more comprehensive objective function that combines the improvement in supply chain metric of inventory turns for both partners viz. supplier and manufacturer while eliminating all unfilled orders simultaneously, subject to the same set of constraints as before for the manufacture and rather similar range constraints for the parameter values for the supplier.

3.4. Objective function and search space constraints

The combined objective function is to, "Maximize inventory turns while simultaneously minimizing the unfilled orders for both manufacturer and supplier." We attempt optimization under all four

Figure 10. Inventory costs incurred per unit sold for manufacturer.

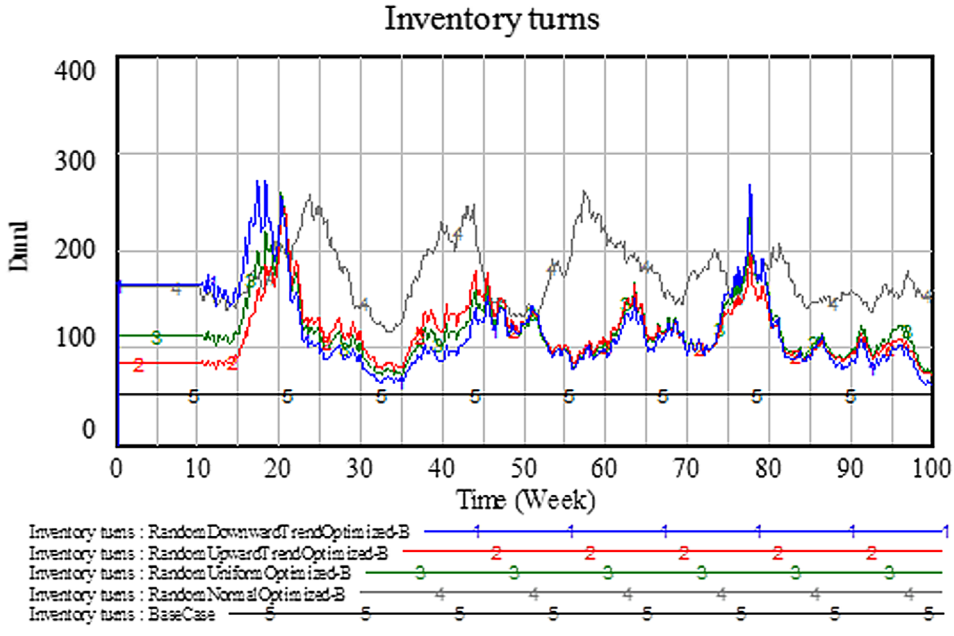


scenarios of customer orders from a **start point** of current settings, with the following restrictions for both supply chain partners.

- Order filling time in the range of 0.2 weeks (1 day) to 1 week (5 days),
- Safety stock anywhere from 0 to 1 week, and finally
- Smoothing factor alpha anywhere from 0 to 1.

Figure 11 depicts the improvement in inventory turns of manufacture under these collaborative optimization efforts.

Figure 11. Inventory turns under collaborative optimization runs for manufacturer.



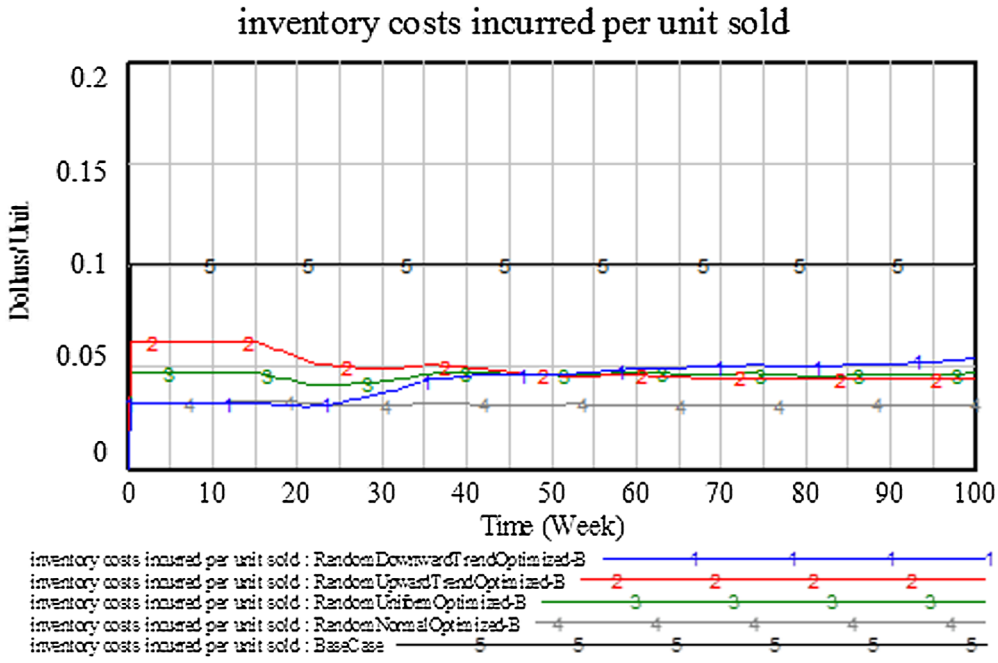


Figure 12. Inventory costs incurred per unit sold for manufacturer-collaborative efforts.

Furthermore, as may be seen from Figure 12, there is a further reduction in the inventory costs per unit sold for the manufacturer.

3.5. Supplier's metrics improve

Since supplier joins the collaborative planning, forecasting and replenishment efforts, his operational metrics improve. Consider the improvement in inventory turns before and after collaborative efforts as shown in Figures 13 and 14.

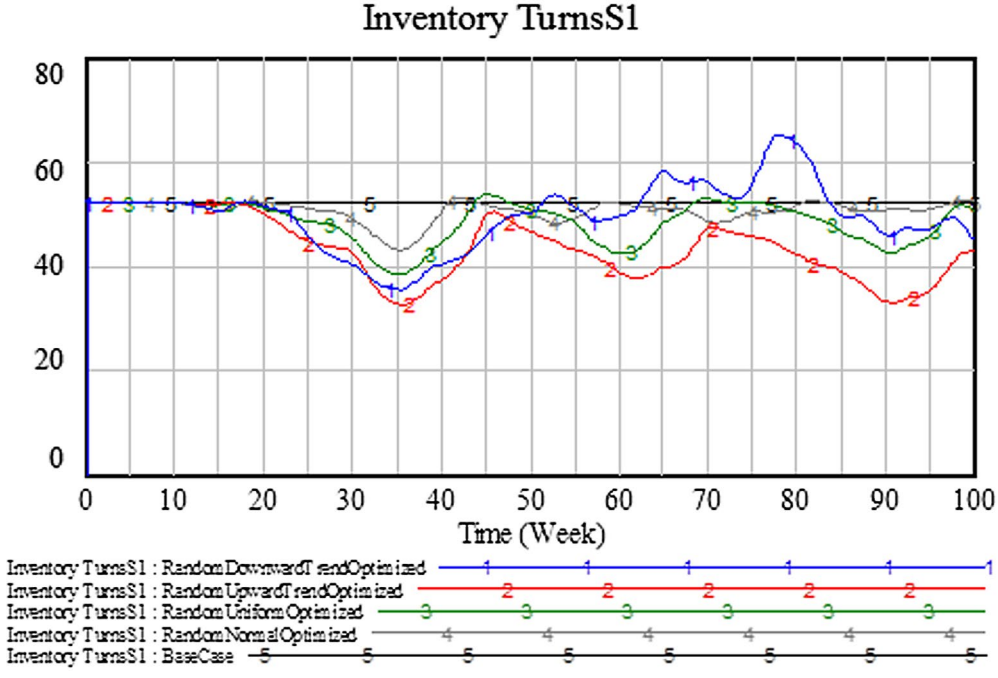


Figure 13. Inventory turns before collaborative optimization for supplier.

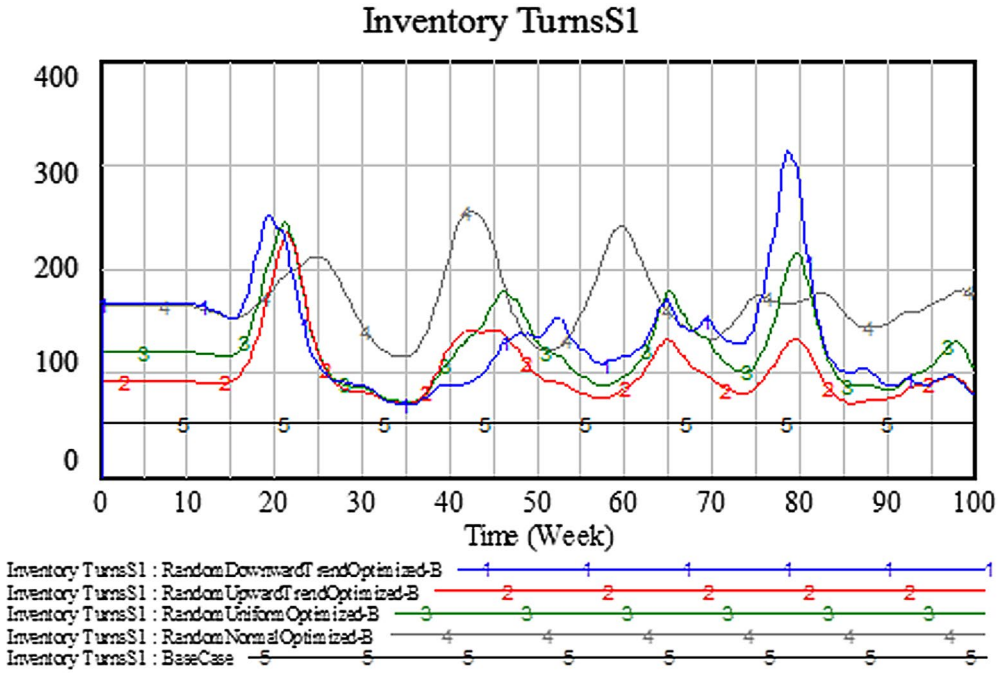


Figure 14. Inventory turns under collaborative optimization for supplier.

It may be seen from Figures 14 and 15, supplier stands to gain substantially by collaborating with his downstream partner in terms of improved schedules, reduced inventory and improved performance metrics and an overall improved profitability.

Figures 16 and 17 depicts the process of selecting the payoff variables and defining the range of parametric values to search in the built in optimization process of Vensim. As may be observed, these screen shorts represent the collaborative optimization setup. In Figure 16, the four components of the objective function are given equal weight of 0.25 each. However, since the inventory turns are to be maximized, coefficient sign is positive (+ve) and the unfilled orders are to be

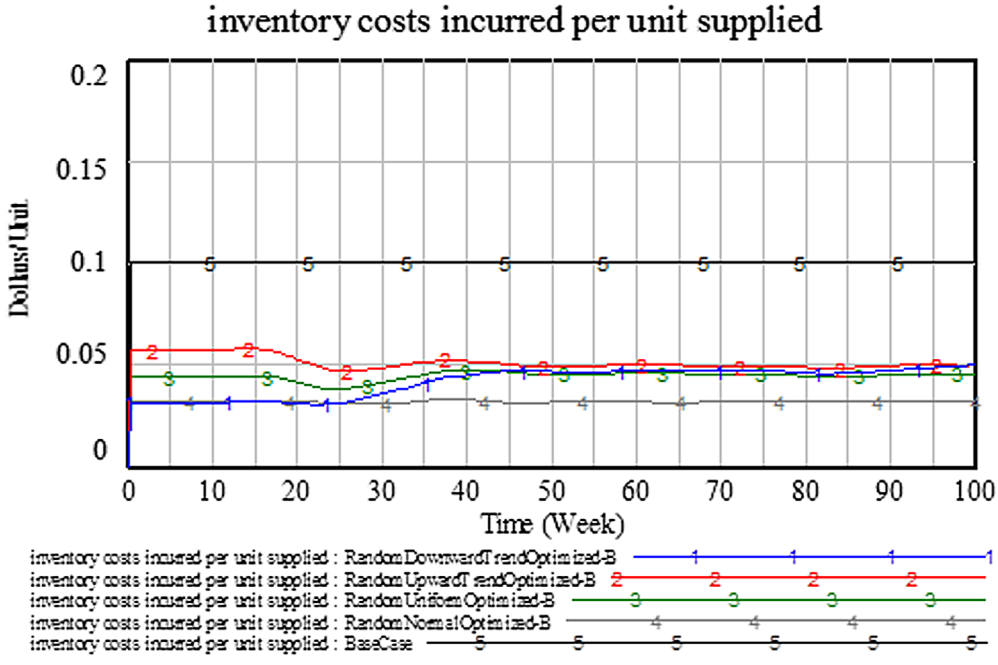


Figure 15. Inventory costs incurred per unit supplied by supplier collaborative efforts.

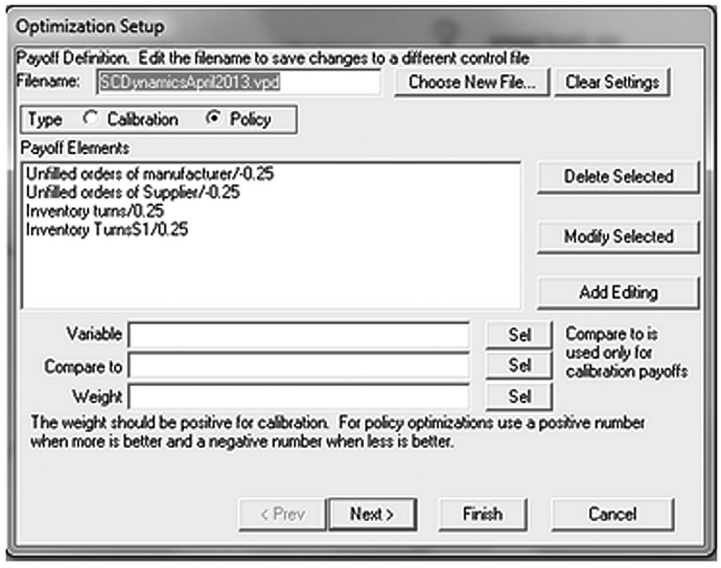


Figure 16. Selecting the payoff elements for optimization—objective function is to increase inventory turns and eliminate unfilled orders for both partners.

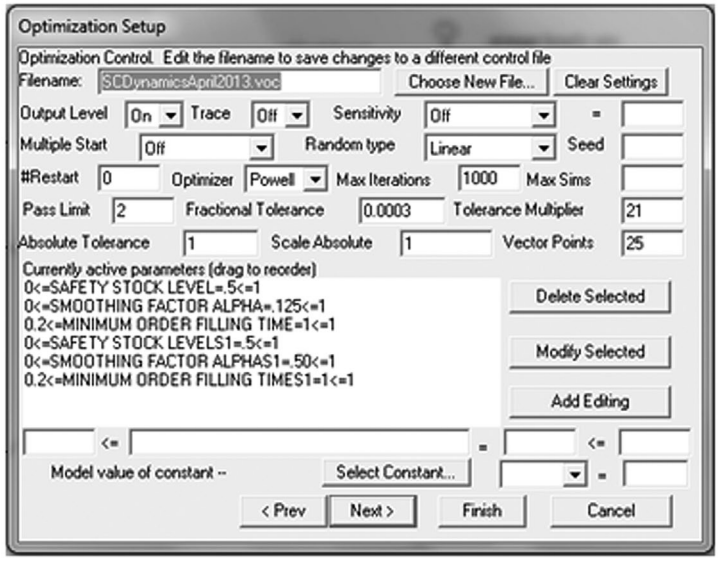


Figure 17. Selecting the search range for the parameters.

minimized the coefficient sign is negative (−ve). In Figure 17, the search space is being defined with permissible range values for each parameter besides denoting the starting point for search.

Obviously, by defining an objective function that would include a term for minimizing the control effort (i.e. minimize the departure of parametric values from their initial settings), we could find a more restrictive settings for the, order filling time, stocking levels, and the smoothing factors alpha for manufacturer and supplier.

3.6. Discussion

Results from these two sets of optimization runs and initial simulations are listed in Table 3.

Some simple and straight forward insights and inferences from the above table:

(a) Reduction in order filling times has beneficial impact on SC metrics

For obvious reasons, if the order filling time can be reduced below 1 week, it must always be so reduced under all scenarios. Notice the recommendation 0f 0.2 for order filling time under all optimization runs where the parameter was allowed to be manipulated.

(b) Collaborative Planning Forecasting and Replenishment (CPFR) benefits both supply chain partners in improving their respective firm performances.

While manufacture can get fairly improved performance metrics by his independent planning and scheduling efforts, collaborative efforts lead to more improved results for both partners. Notice the drop in safety stock requirements of manufacture from 0.1719 to 0.1219, from 0.3552 to 0.2654 and from 0.7206 to 0.4180 and finally from 0.1472 to 0.1153 under respective scenarios before and after collaborative effort.

(c) Supplier could simply follow the manufacturer's order signals without further moderation for better results in production scheduling

In all scenarios, supplier is well advised to adopt a rather higher smoothing alpha and in one case a smoothing alpha of 1. These findings suggest that supplier needn't moderate the downstream partner's orders as much as the downstream partner need moderate the customer orders in determining his production schedules.

(d) CPFR helps improve Supply Chain operational metrics.

Obviously, by paying attention to the stocking and order filling rates in a proactive manner, all unfilled orders can be eliminated. And by careful restructuring of operational setup, operations efficiencies in terms of improved metrics are possible.

(e) Improvement in inventory turns often automatically leads to improvement in reduction in inventory carrying cost per unit sold.

A more interesting finding has been the great reduction in the inventory carrying cost per unit sold, by increase in the inventory turns. As the inventory doesn't sit in the warehouse and moves out even as it comes out of production line, the carrying costs are reduced tremendously.

Any supplier who can review these likely benefits that he stands to gain from collaborating with his downstream supplier will not, we hope, hesitate to participate in such collaborative efforts. As such, we believe these *results provide a strong and irrefutable case for CPFR practice in supply chains*, more particularly from the supplier's point of view.

Some more simple observations:

(f) In a random normal order pattern setting, carrying a small amount of stock may suffice to maintain a steady and uniform level of operations in terms of constant level of production (see smoothing factor alpha is "zero" for manufacture). The same is true either with or without collaboration from supplier albeit with some varying levels of stocks (0.2654 vs. 0.3552).

(g) Random uniform order pattern appears easier to tackle than the upward or downward trend patterns given the minimal changes in parametric values and moderate levels of inventory requirements.

As we know, when dealing with a multi-dimensional search space, one may run into multiple local optimal solutions. For obvious reasons, it makes sense to move towards the local optimal that's beneficial to all stake holders and one which appears to serve additional objectives besides the stated objective function. Another not so obvious benefit of settling for a local optimal instead of

Table 3. Parameter settings and results from optimization runs

Parameters (M = Manufacture and S = Supplier)	Order filling time	Safety stocks (weeks)	Smoothing factor Alpha (S1)	Unfilled orders
Basecase - M	1	0	0.125	0
Basecase - S	1	0	0.5	0
Random normal - M	1	0	0.125	9,794
Random normal - S	1	0	0.5	5,147
Random uniform - M	1	0	0.125	20,289
Random uniform - S	1	0	0.5	6,793
Random upward trend - M	1	0	0.125	63,046
Random upward trend - S	1	0	0.5	20,869
Random downward trend - M	1	0	0.125	2,648
Random downward trend - S	1	0	0.5	1,482
Independent optimization efforts				
Random normal optimized - M	0.2	0.1719	0	0
Random normal optimized - S	1	0	0.5	5,306
Random uniform optimized - M	0.2	0.3552	0	0
Random uniform optimized - S	1	0	0.5	12,363
Random upward trend optimized - M	0.2	0.7206	0.1041	0
Random upward trend optimized - S	1	0	0.5	37,085
Random downward trend optimized - M	0.2	0.1472	0.1404	0
Random downward trend optimized - S	1	0	0.5	2,815
Collaborative Optimization efforts				
Random normal optimized-B - M	0.2	0.1219	0	0
Random normal optimized-B - S	0.2	0.1177	0.4926	0
Random uniform optimized-B - M	0.2	0.2654	0.1248	0
Random uniform optimized-B - S	0.2	0.235	0.4971	0
Random upward trend optimized-B - M	0.2	0.418	0.122	0
Random upward trend optimized-B - S	0.2	0.3695	0.4852	0
Random downward trend optimized-B - M	0.2	0.1157	0.2332	0
Random downward trend optimized-B - S	0.2	0.1153	1	0

searching for a global optimal in a multidimensional search space would be that, a local optimal may result in a minimal variations in SC setting from where we begin as opposed to a global optimal which has the potential to recommend a drastically difficult to accomplish parametric setting; for instance, a global optimal may recommend compression of lead time to 1/10 of a week or less which may be practically impossible, unless the supplier is a sub-contractor located on the premises of the manufacturer with a demarcated area for his operations.

One must recognize that stocks are serving one of the fundamental objectives of providing cushion against material flow delays in the production cycle and/or unforeseen fluctuations in orders. As we have seen here, in a seemingly straightforward supply chain, the fluctuations in orders have caused multiple feedback effects on the variables involved. Use of System Dynamics modeling allows the user to capture the resultant behavior over time of the variables involved so that suitable corrective action may be taken while focusing on the desired objective function or combinations of objective functions.

4. Contributions and limitations

As is evidenced in this study, information sharing alone is not enough to obtain improve results. If supply chain partners implement CPFR in their operations, they stand to realize substantial gains in operations results. Results of this study suggest that just in time inventory policies are not feasible solutions in production environments with considerable cycle times. Careful selection of a forecast mechanism and a good grasp of how one's forecasts are to be factored into production plans is essential for manufacturers and suppliers in supply chains.

Stability in production schedules is less important than obtaining improved performance metrics like, increased inventory turns, and reduced inventory costs. This is true, when the environment in which the business is operating is constantly changing, then attempting for equilibrium or steady state operations is less important than adjusting to the turbulence to accomplish objective functions. Particularly, when the customer orders are exhibiting a trend (either upward or downward) manufacturers should be more focused on eliminating unfilled orders. As has been seen here, supply chain partners not only need share information in real time but practice CPFR.

Our findings support the finding of Boone et al. (2001) in that, while they found CPFR when compared to ROP system increases the fill rate, decreases the supply chain inventories, reduces the supply chain cycle time, and increases the shareholders' wealth; our findings from optimization of SC performance metrics strongly advocates the adoption of CPFR.

Boone et al. (2001) established that, CPFR is a better approach than ROP for accomplishing the objectives of increased fill rate, decreased SC inventories, reduced SC cycle time, and increased shareholders' wealth. Whereas our finding establish CPFR as a preferred pre-condition to accomplish substantially, similar SC objectives of elimination of unfilled orders, reduced inventory levels, increased inventory turns, and reduced inventory carrying costs which automatically leads to increased shareholder wealth. It may also be noted that in our model, the reorder quantity is estimated based on exponential smoothing forecast supported by minimal safety stock levels in contrast to ROP used by Boone et al. (2001). Despite the differences in the inventory management practices that it was contrasted with (ROP vs. Exponential Smoothing), CPFR has proven to be beneficial in a supply chain environment for all SC partners lending credibility to the findings.

4.1. Limitations of the model

Although the model captures the two-tier supply chain behavior observed in the real world, it must be admitted that the model is simplified compared to the complex real world. Also certain constructs in the modeling environment make these models more suitable for policy formulation rather than day to day tactical decision support. As such the results from the study must be viewed more broadly to identify the patterns rather than to study minute details. Further, the model is parsimonious in that it captures the dynamic essence of the generic manufacture–supplier two-tier supply chain with minimal structure. The following explicit assumptions helped simplify the model. a) uniform shipping cost per unit, b) uniform ordering costs, c) permitting decimal values in the workforce numbers, d) assuming that supplier is servicing a retailer, and e) assuming availability of sufficient surplus capacities at manufacture as well as supplier.

4.2. Future studies

Further studies will focus on obtaining more useful insights into other possible scenarios involving other performance metrics and parameters and order scenarios. Like multiple downstream partners served by single upstream supplier and vice versa.

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Correction
Information contained in the About the Author section was incorrectly attributed to the wrong author. This has been amended in the corrected article.

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