Four Echelon Retail Supply Chain Optimization-insights from Experimenting with Powel's Hill-climbing algorithm in Vensim©

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Abstract

This study focuses on developing useful and interesting insights into the functioning of four-echelon retail supply chains consisting of Supplier- Manufacturer- Distributor- Retailer utilizing a System Dynamics (SD) model developed with Vensim software (Ventana, 2015). The objective is to understand the response behavior of the supply chain to various changes in customer order patterns and to discern what inventory policies and forecasting policies will help accomplish the retail supply chain goals of "eliminating unfilled orders," "increase inventory turns," and "reduce inventory carrying costs," simultaneously. For obvious reasons, elimination of unfilled orders at the retailer should receive the top priority as that would be the ultimate objective of typical retail supply chains. Our experimentation with the Vensim built-in optimization function provides quite interesting and intriguing results.

Keywords: Supply chains, unfilled orders, inventory turns, carrying costs, optimization, Vensim

1.0 INTRODUCTION

Retail supply chains appear to be simple but are complex to manage due to the behavioral complexity of the stocks being managed. Typical management policies from other business activities when applied to these supply chains seem to fail in delivering the expected outcomes. Managers typically blame these failures on so-called, 'side effects' of managerial decisions. Stakeholders seem to accept this explanation as a feature of reality that one needs to learn to live with. However, in the words of Sterman (2000), "Side effects are not a feature of reality but a sign that our understanding of the system is narrow and flawed." Given the phenomenal explosion in these retail supply chains spanning the globe, there is an urgent need for improving our understanding of such dynamically complex supply chain systems.

This study is an extension of a series of studies aimed at gaining a deeper and better understanding of supply chain dynamics using system dynamics modeling methodology. While, the past studies were limited to "two-player" and "three player" supply chains, the focus of the current study is a four-player, viz., a "Supplier," "Manufacturer," "Distributor" and "Retailer" supply chain. In previous studies, effects of: 1) reductions in information delays, 2) operational / material flow delays and 3) forecasting / smoothing, upon supply chains have been explored

(Burns and Janamanchi, 2006; Janamanchi and Burns, 2007a; Janamanchi and Burns, 2010). Further, the effect of inventory policies as well as optimization of supply chain performance have been studied (Janamanchi and Burns, 2007b; Janamanchi and Burns, 2008; Janamanchi, 2009; Janamanchi, 2011).

Beginning with the founder of System Dynamics, Dr. Jay W. Forrester (1958; 1961) considerable research on supply chains has been contributed by him and by Sterman (2000), Akkermans and Dellaert (2005), and Croson and Donohue (2003; 2005). "Dynamic complexity" and "feedback loops" present in them, lend supply chains to a study in system dynamics. From a system dynamics perspective, "Supply chains consist of a stock and flow structure for the acquisition, storage, and conversion of inputs into outputs and the decision rules governing the flows," according to Sterman in **Business Dynamics** (2000).

Two types of delays viz., information and flow delays are present in most SD models. It's common knowledge amongst business managers that these two types of delays are quite intricately intertwined. Advances in Information and Communication Technologies (ICT) over past couple of decades have effectively addressed information delays but the perception and computational delays implicit in demand forecasts/tools used in such forecasts persist as do the physical flow delays inherent in certain industries.

Information visibility and real-time data sharing between SC partners can't guarantee that the Supply Chain (SC) partners will be able to use such information effectively because of 'perception delays' or on account of their organizational policies that are based on their own "perceptions" of the business operations.

While many flow delays can be reduced substantially by careful planning and redesigning efforts, they can't altogether be eliminated. Supply Chain partners have to learn to live with such minimal flow delays that are rather impracticable, if not impossible, to eliminate. For example, resources in terms of labor and production capacities require time for adjusting to reach the desired levels from the current levels be it on account of hiring/firing or acquiring required infra-structure, etc. Moreover, there are shipping, transportation, inspection, and storage delays that cannot be completely eliminated.

The remainder of this paper is organized as follows. Section 2 discusses the modeling tool, the general outline of a Supplier-Manufacturer--Distributor--Retailer Supply Chain set up. Results from the simulation of a basecase scenario (initial equilibrium state) and several sets of alternative scenarios, optimization efforts and policy formulations are presented in section 3, followed by the discussion of insights that may be gained from these results. Finally, section 4 lists the contributions / limitations of the current study and directions for future studies.

2.0 MODEL DESCRIPTION

As stated earlier, in this study, we employ system dynamics modeling to capture the production system of a Supplier-Manufacturer engaged in moderately labor-intensive and of considerable production cycle time involved manufacturing of a final product for supply to downstream Distributor who in turn supplies it to his retailers. Retailers sell it to end-users. The simulation model is developed using Vensim application software (Ventana, 2015).

2.1 Brief over view of the supply chain set up: Customers place orders for products with the Retailer who places orders with his 'upstream partner' who is a Distributor. The Distributor in turn places orders for supply to his upstream-partner who is a Manufacturer, who then places orders for the required input per his production plans from his supplier. All four SC partners carry Finished Goods inventories and relative policies. However, the Manufacturer and Supplier, carry 'work-in-process' (WIP) inventories denoting the presence of manufacturing cycle times. All four SC partners have order forecasting policies in place using the "exponential smoothing" method with a smoothing alpha of 0.25 (for retailer and distributor) and (0.125) for Manufacturer denoting a conservative approach and a (0.50) for his supplier demonstrating the trust in downstream partners forecast policy.

This set up mimics the case study of the supply chain of a shoe Manufacturer as presented in APICS journal (Gupta and Cox, 2012) in so far as it relates to the production cycle times, lead time for supply from Manufacturer to Distributor and from Distributor to retailer. Further, it is well known that the total cycle time of three-to-four weeks is the typical cycle time for many products like leather goods, mobile phones, LCDs, LEDs, and DVDs etc.

2.2 Model Structure: Figure 1 shows the System Dynamics structure for the Retailer's finished goods and customer order forecasting setup. The basic constructs for the model structure are drawn from the state of the art models presented in Sterman (2000, chapters 17, 18 and 19). The model structure for the Distributor is similar to that of Retailer except that Distributor receives orders from retailer and not directly from an external customer. So if the entire SC is visualized as a system, the single most significant external input to the system is the customer order rate. All other information flows are internal to the system.

The Manufacturer and his Supplier's finished goods and production structure is rather similar to that of retailer and Distributor only so far as it relates to finished goods and order filling process. For obvious reasons, Manufacturer's and his Supplier's setup is quite elaborate in that it includes production setup, it contains work-in-process and input coming from upstream supplier, a workforce set-up including hiring rate, quit rate, production normal, and overtime production when required, etc.

Brief descriptions of Retailer's, Distributor's and Manufacturer's setups follow.

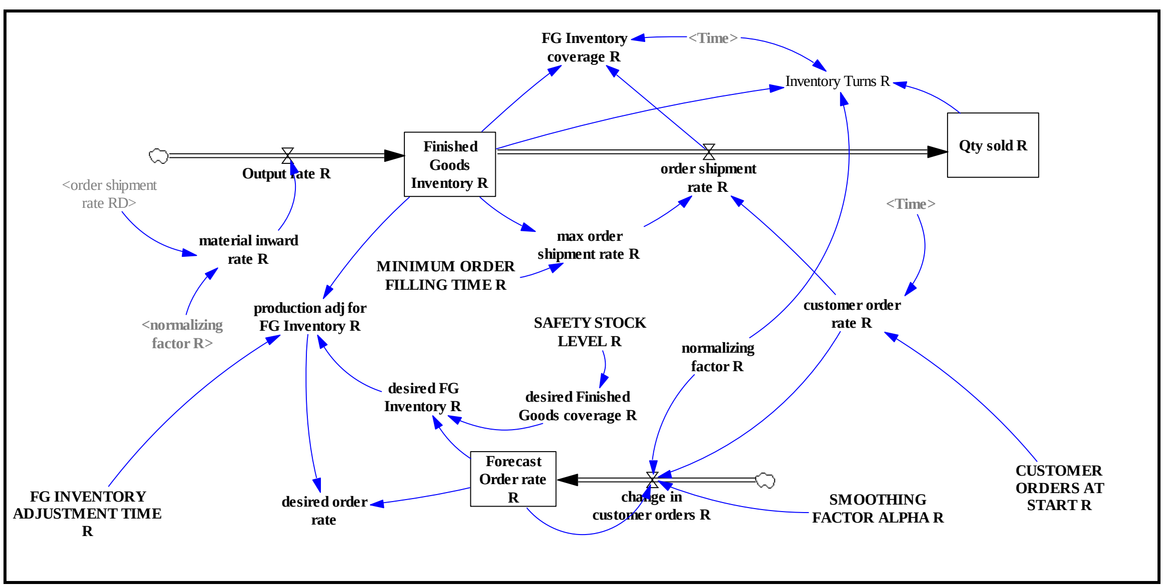

Figure 1: Retailer's facility setup- finished goods, order filling, and customer order forecasting

2.3 Retailer's set up: A week is the unit of time in this model. Variables that are duplicated across the supply chain partners' structures are given suitable suffixes, R- for retailer, D- for Distributor, M-for Manufacturer and S for Supplier. As mentioned before, customer orders at start, initiate the action. The retailer is employing a "single exponential smoothing" forecast. Model structure is fairly well known in SD circles and the basic constructs are drawn from Sterman (2000, chapters 17, 18 and 19).

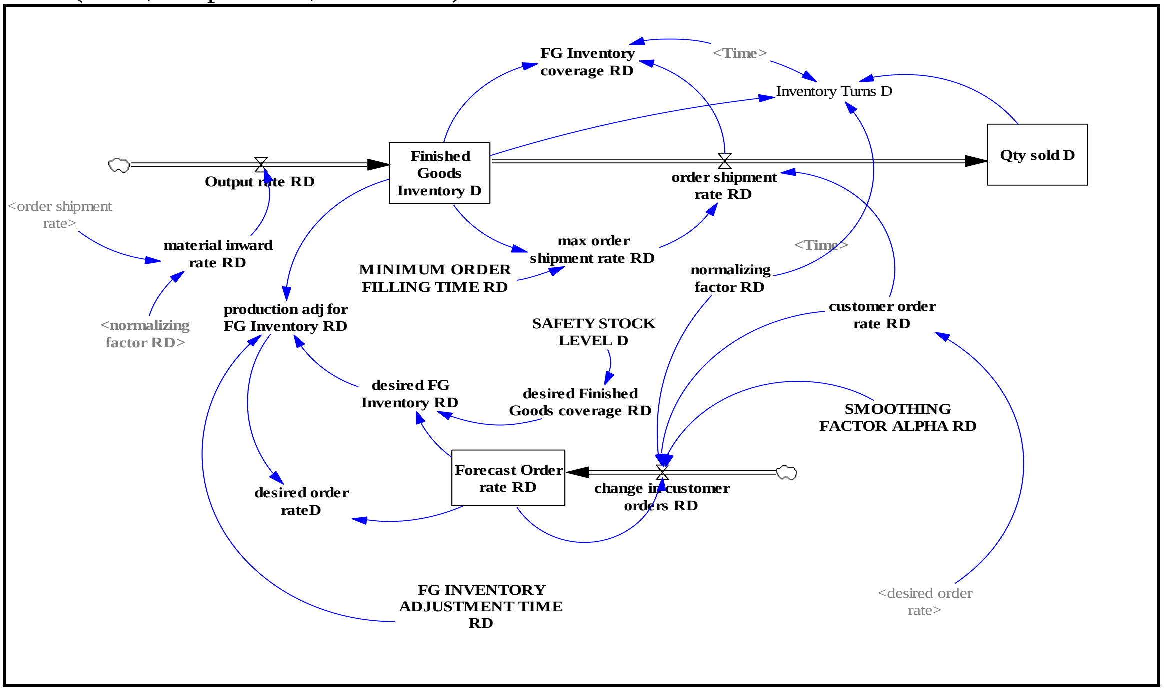

Figure 2: Distributor's facility setup- finished goods, order filling, and customer order forecasting

Figure 2 above depicts the Distributor's Finished Goods and Customer Order Forecasting structure which is pretty much similar to that of the Retailer's with the exception that orders from Retailer are the customer orders for Distributor.

Manufacturer's structure: Figure 3 below depicts the Manufacturer's setup.

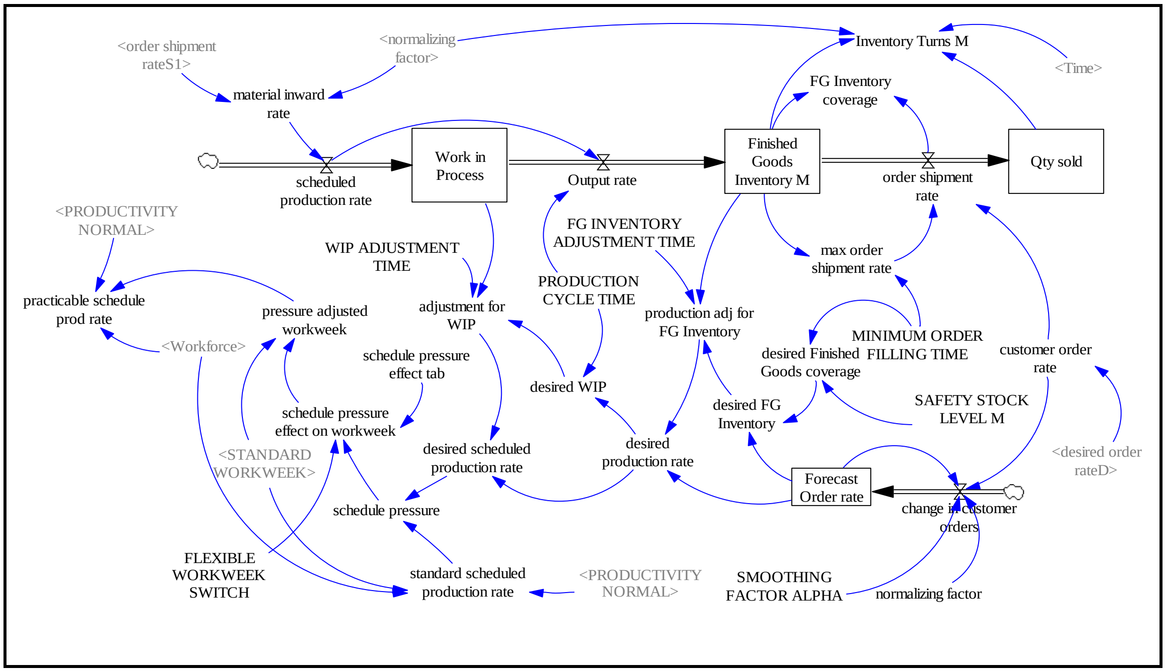

Figure 3: Manufacturer's setup- production and inventory view.

We have incorporated several features to bring our model closer to real-world behavior. Take for instance the flexible workweek switch showing in the lower left corner of the figure. Each week, the desired scheduled production rate is compared with standard scheduled production rate (based on available workforce and productivity normal) to compute a "Schedule pressure" which determines, when the "flexible workweek switch is turned on," if a departure from the normal work week of 40 hours is desirable. If the pressure is higher, the workweek is extended to anywhere up to a maximum of 50 hours and likewise, when the schedule pressure slacks off, workweek is compressed down to 30 hours. When the flexible workweek switch is turned off, workweek remains steady at 40 hours.

The following structure of the workforce in Figure 4 explains how the desired scheduled production rate influences the workforce adjustments. In this study, information visibility is presupposed. We also incorporated a lay-off switch, but for simplicity here, we assume that management does not practice lay-offs. Figure 5 depicts the Supplier's structure. Supplier workforce structure is similar to that of the manufacturer.

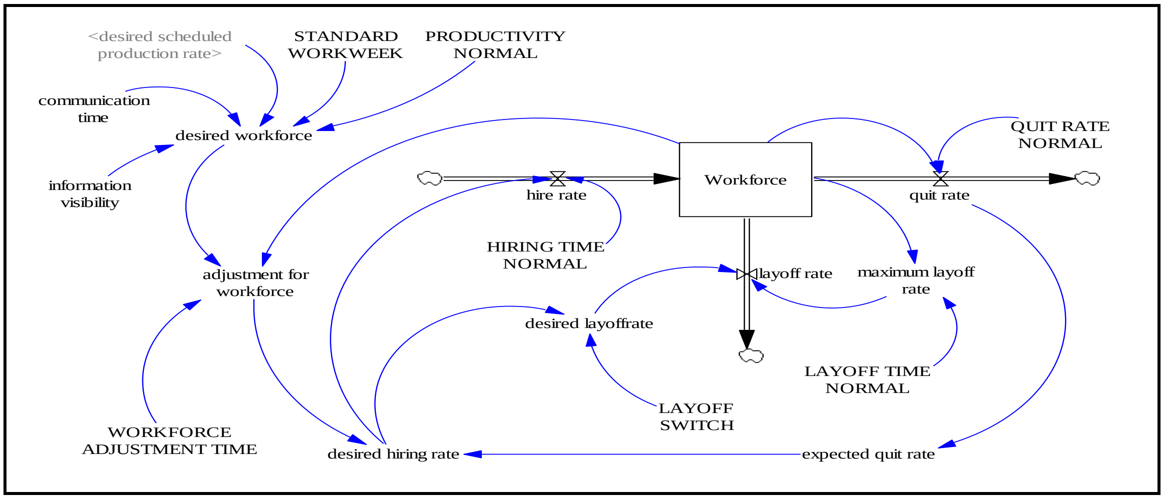

Figure 4: Workforce view within the Manufacturer Setup

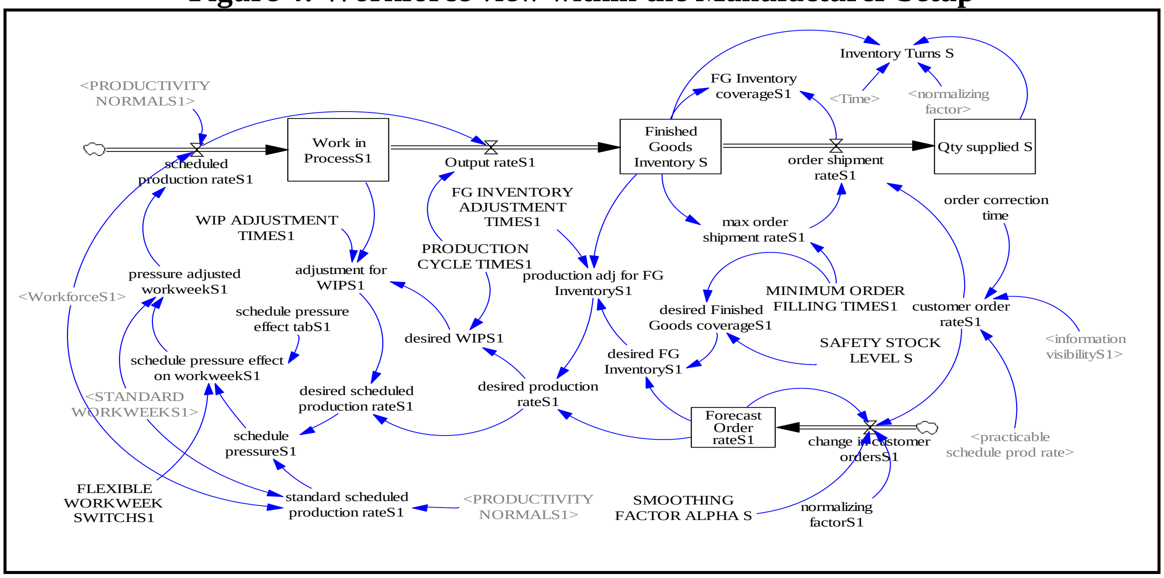

Figure 5: Supplier's setup- production and inventory view.

Table 1 given below lists the initial parametric values of the supply chain partners.

Parameter	Unit	S	M	D	R
Production and Inventory					
Simulation Time	weeks	100	100		
Customer Orders at start	Units/week	n.a.	n.a.	n.a.	10000
Orders from SC partner	Units/week	10000	10000	10000	n.a.
Start time of variation	Week				13
Smoothing Alpha	dimensionless	0.5	0.125	0.25	0.25
Min Order Filling Time	weeks	1	1	1	1
Safety Stock level	weeks	0	0	1	1
FG Inv Adj Time	weeks	4	4	n.a.	n.a.
Production Cycle Time	weeks	2	2	n.a.	n.a.
WIP Adj Time	weeks	4	4	n.a.	n.a.

Standard Workweek	hours	40	40		
Flexible workweek –max	hours	50	50	n.a.	n.a.
Flexible workweek –min	hours	30	30	n.a.	n.a.
Productivity Normal	units/(hour*person)	25	25	n.a.	n.a.
WIP	units	20000	20000		
Finished Goods* (represents order filling time qty for M and S- Safety stock for D and R)	units	10000	10000	10000	10000
Workforce View					
Workforce Adj Time	weeks	3	3	n.a.	n.a.
Communication time	weeks	1	1	n.a.	n.a.
Hiring Time Normal	weeks	1	1	n.a.	n.a.
Layoff Time Normal	weeks	5	5	n.a.	n.a.
Quit Rate Normal	dmnl/week	0.01	0.01	n.a.	n.a.
Workforce	person	10	10	n.a.	n.a.
Inventory/Labor Costs View					
Inventory Cost Normal	dollars/(unit*week)	0.1	0.1	n.a.	n.a.
Hourly Rate Normal	dollars/(person*hour)	12	12	n.a.	n.a.
Overtime wages	times normal wage	2	2	n.a.	n.a.
Hiring Costs Normal	dollars/person	100	100	n.a.	n.a.
Layoff Costs Normal	dollars/person		250	n.a.	n.a.

Table 1: Initial parameter settings

Table 2 below summarizes the various customer order scenarios simulated in this study. We chose the alternate order scenarios to assess the system variables' response and to discern possible patterns and to develop useful insights into the system behavior to formulate possible policy alternatives.

Scenarios	**Description**	**Equation for customer Order rate**
Basecase	No changes in customer orders of 20,000 units/week Information visibility turned on and flexible work week is turned on	IF THEN ELSE(Time>112, RANDOM UNIFORM(9000 , 11000 , 1) , CUSTOMER ORDERS AT START R) Note: since simulation time is 100 weeks, the above results in std. orders

Random Uniform	Starting week 13, customer orders vary in a random uniform pattern between a low of 18,000 and high of 22,000	IF THEN ELSE(Time>12, RANDOM UNIFORM(9000 , 11000 , 1) , CUSTOMER ORDERS AT START R)
RandomUpwardTrend	Starting week 13, customer orders show an upward trend of 50 units/week plus vary in a random uniform pattern of +/- 2000 units on either side of trend line	IF THEN ELSE(Time>12, RANDOM UNIFORM(9000 , 11000 , 1) + RAMP(50 , 13 , 100), CUSTOMER ORDERS AT START R)
RandomDownwardTrend	Starting week 13, customer orders show a downward trend of 50 units/week plus vary in a random uniform pattern of +/- 2000 units on either side of trend line	IF THEN ELSE(Time>12, RANDOM UNIFORM(9000 , 11000 , 1) - RAMP(50 , 13 , 100), CUSTOMER ORDERS AT START R)
Spiked Orders	Starting 13th week, every 13th week(one quarter approximately) customer orders spike up by 20% (13th , 26th , 39th, 52nd week etc)	IF THEN ELSE(Time>12, IF THEN ELSE(MODULO(Time , 13) , CUSTOMER ORDERS AT START R, CUSTOMER ORDERS AT START R*1.2), CUSTOMER ORDERS AT START R)
Dipped Orders	Starting 13th week, every 13th week(one quarter approximately) customer orders dip down by 20% (13th, 26th , 39th, 52nd week etc)	IF THEN ELSE(Time>12, IF THEN ELSE(MODULO(Time , 13) , CUSTOMER ORDERS AT START R, CUSTOMER ORDERS AT START R*0.8), CUSTOMER ORDERS AT START R)

Table 2: Customer order scenarios

Besides the above alternate scenarios, optimization runs were conducted on the system to obtain system-recommended optimal settings in respect to chosen variables—safety stock settings and smoothing factor alpha in this case. Table 3 below summarizes the optimization runs and policy runs in this study.

Run name	Description
OPT (All OPT suffix data sets)	Optimization run: Where the system is optimized to minimize unfilled orders (0.39 weight retailer + 0.19 weight Distributor + 0.19 weight for Manufacturer+0.19 weight for supplier) together with minimizing the FG holding costs of all four SC partners (0.01 + 0.01 + 0.01 +.01 weights) to find the lowest Safety Stock levels + Smoothing Factor Alpha for all four SC partners. Note: It is more important to minimize unfilled orders than to minimize inventory costs (hence proportionately less important to minimize) in value to unfilled order units.

POLICY1 (All Policy1 suffix data sets)	Policy 1: Where the results from the OPT datasets are reviewed and the Max level, of all scenarios, of Safety stocks for each of four supply chain partners as obtained from the OPT runs is adopted to check if that would suffice eliminating all unfilled orders at the retailer or not.
OPTB (All OPTB suffix data sets)	Optimization run: Where the system is optimized to simultaneously maximize the inventory turns (0.25 weight retailer + 0.25 weight Distributor + 0.25 weight for Manufacturer+0.25 weight for supplier) and minimize unfilled orders (0.249 weight retailer + 0.249 weight Distributor + 0.249 weight for Manufacturer+0.249 weight for supplier) together with minimizing the FG holding costs of all four SC partners (0.001 + 0.001 + 0.001 +.001 weights) to find the lowest Safety Stock levels + Smoothing Factor Alpha for all four SC partners. Note: It is more important to minimize unfilled orders than to minimize inventory costs (hence proportionately less important to minimize) in value to unfilled order units.
POLICY2 (All Policy2 suffix data sets)	Policy 1: Where the results from the OPTB datasets are reviewed and the Max level, of all scenarios, of Safety stocks for each of four supply chain partners as obtained from the OPT runs is adopted to check if that would suffice eliminating all unfilled orders at the retailer or not.

Table 3: Optimization and Policy formulation runs

Figure 6 below depicts the model structure necessary to capture the unfilled orders at all supply chain partners. These stocks are used as a means to define the "minimization of unfilled orders" portion of optimization objective.

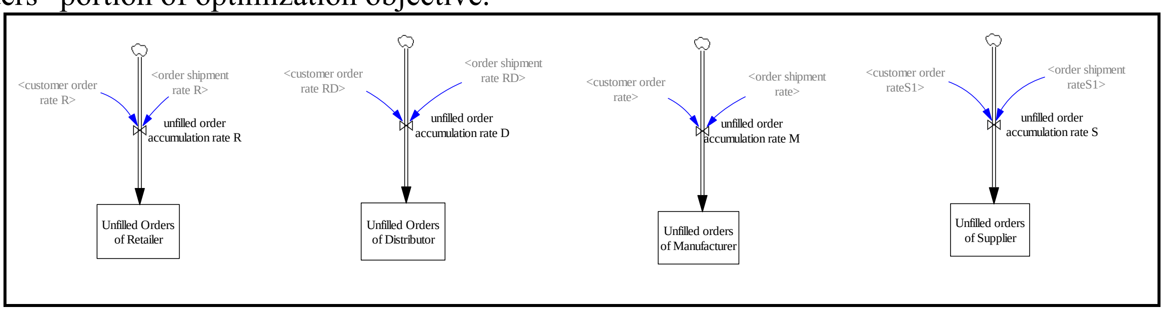

Figure 6: Unfilled orders at Retailer, Distributor and Manufacturer

3.0 RESULTS FROM SIMULATIONS

Under the base case scenario, there is no change in the steady rate of customer orders and as such the schedules of all supply chain partners run like clockwork. Under other scenarios the customer orders vary as described in Table 2. As stated earlier, the objective in choosing these variations in customer orders is to develop insights into resultant response behavior of the system under alternate scenarios. Figure 7 below depicts the various customer order patterns simulated in this study.

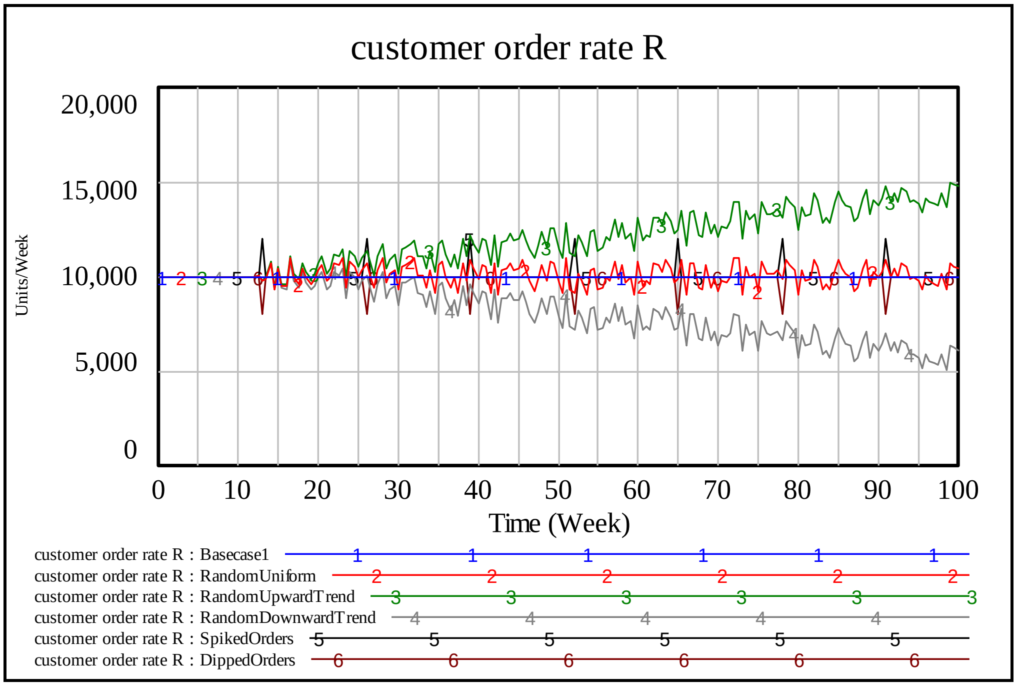

Figure 7: Customer Order Scenarios simulated in this study

As stated, we start the simulation with the base case, where system is in steady state and the customer orders are received steadily at 10,000 units/week. All customer orders are filled without fail and there are no fluctuations in stocks or schedules. Then we continue with the scenarios listed in Table 2. Figures 8 and 9 capture the finished good inventory at Distributor's and Manufacturer's facilities respectively under the various scenarios. As may be observed, the inventory policies and forecast practices that were working very well in a steady state (curve marked 1) are of little help when the customer orders are changed (curves labeled 2 to 6). These fluctuations in stocks are experienced despite absorbing some of the shock by providing real-time information sharing and by practicing flexible workweek policy. Figure 10 captures the unfilled orders status at the Retailer's under these customer order scenarios.

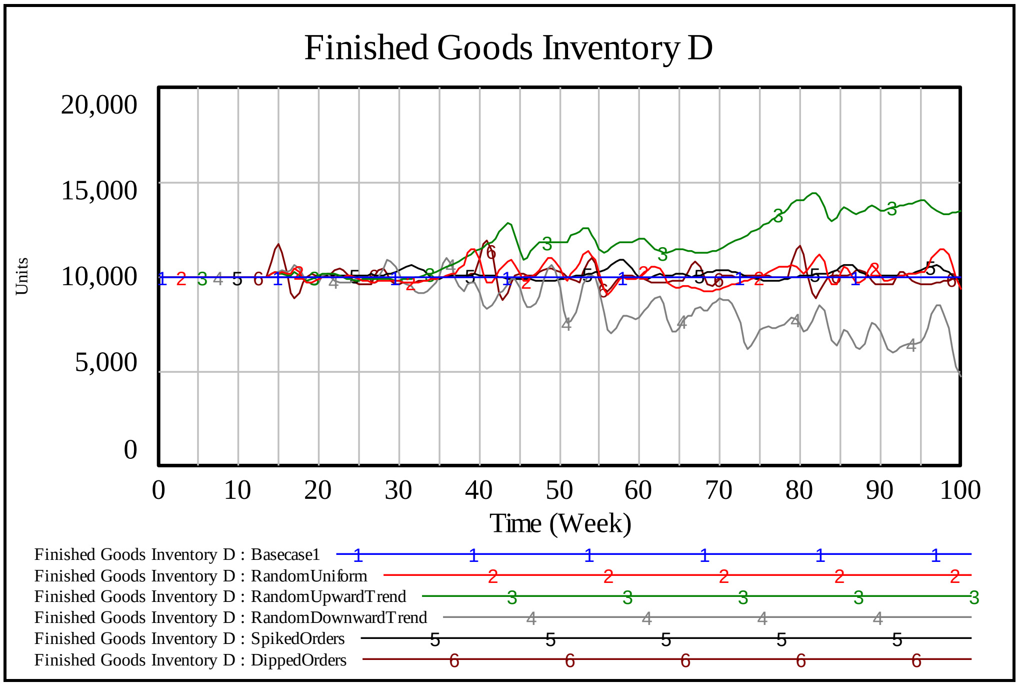

Figure 8: Finished Goods Inventory of Distributor under various scenarios

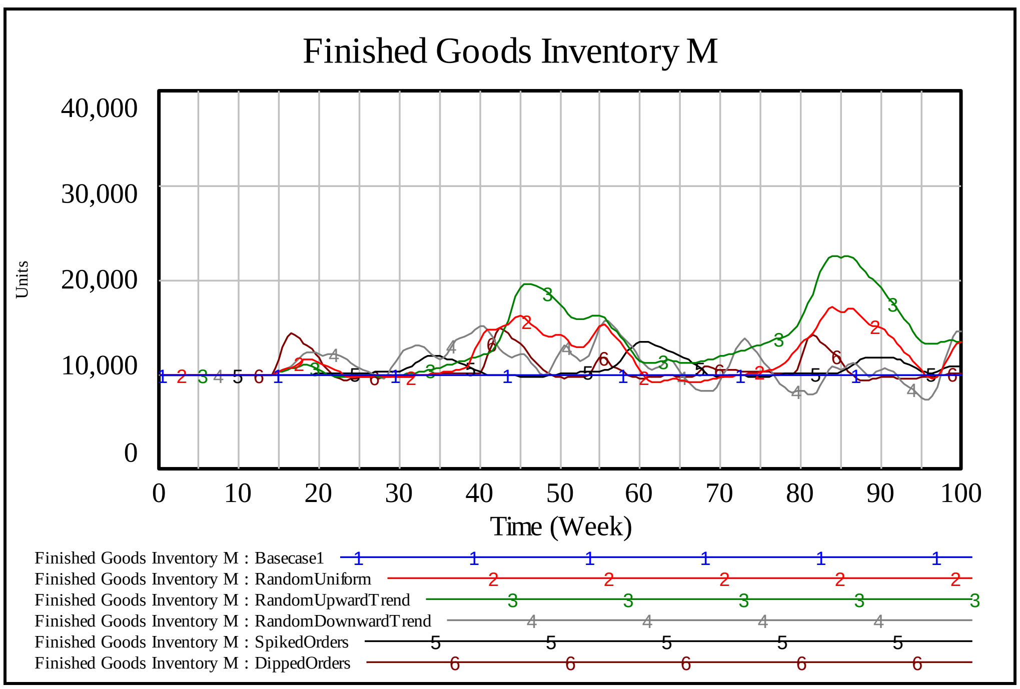

Figure 9: Finished Goods Inventory of Manufacturer under various scenarios

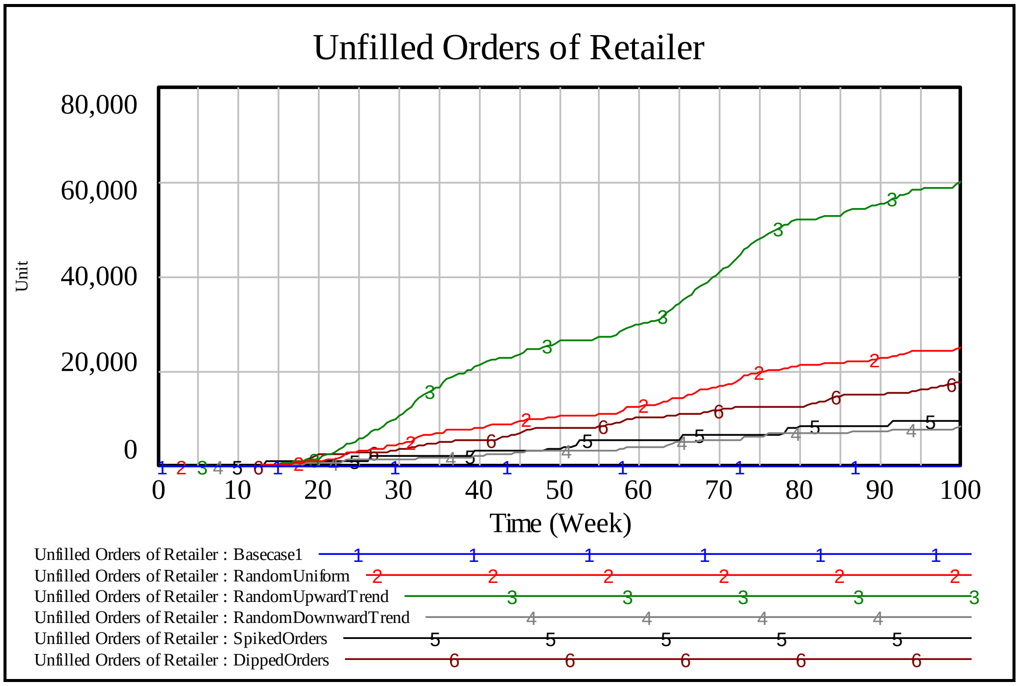

Figure 10: Unfilled orders of Retailer under various scenarios.

All SC partners experience unfilled orders. Even though it's important to eliminate unfilled orders for all, eliminating unfilled orders at the Retailer are much more critical for the overall success of the SC. In order to understand what might fix this issue of unfilled orders, we experiment with optimizing the objective function of minimizing unfilled orders while keeping inventory costs low- run with subscript Opt (see Table 3). As stated in Table 3, we assign relative weights of 0.39, 0.19, 0.19 and 0.19 to unfilled orders of Retailer, Distributor, Manufacturer and Supplier and a weight of 0.01 each for the inventory costs of all four SC partners. This objective function minimization effort is attempted by invoking the built-in optimization feature of Vensim. While not all unfilled orders are eliminated, this effort definitely yields an acceptable level of performance as may be seen from Figure 11 showing unfilled orders of Retailer under this Optimization effort. Further, as described above, when policy1 is formulated, it yields acceptable results as well as seen in Figure 12.

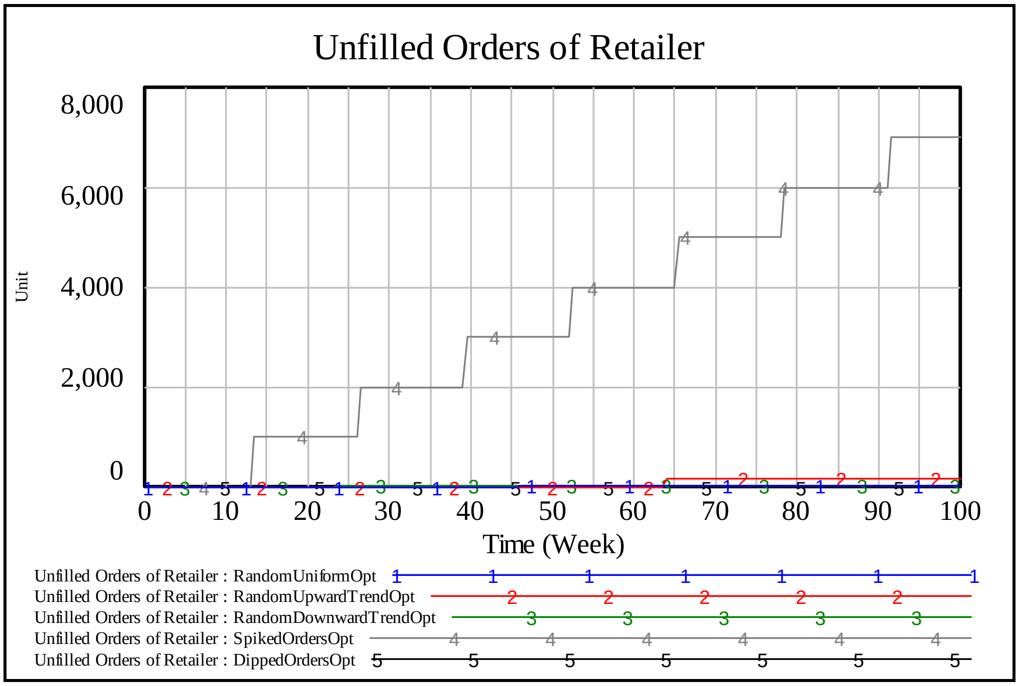

Figure 11: Substantial Elimination of Unfilled Orders of Retailer Under Optimization runs

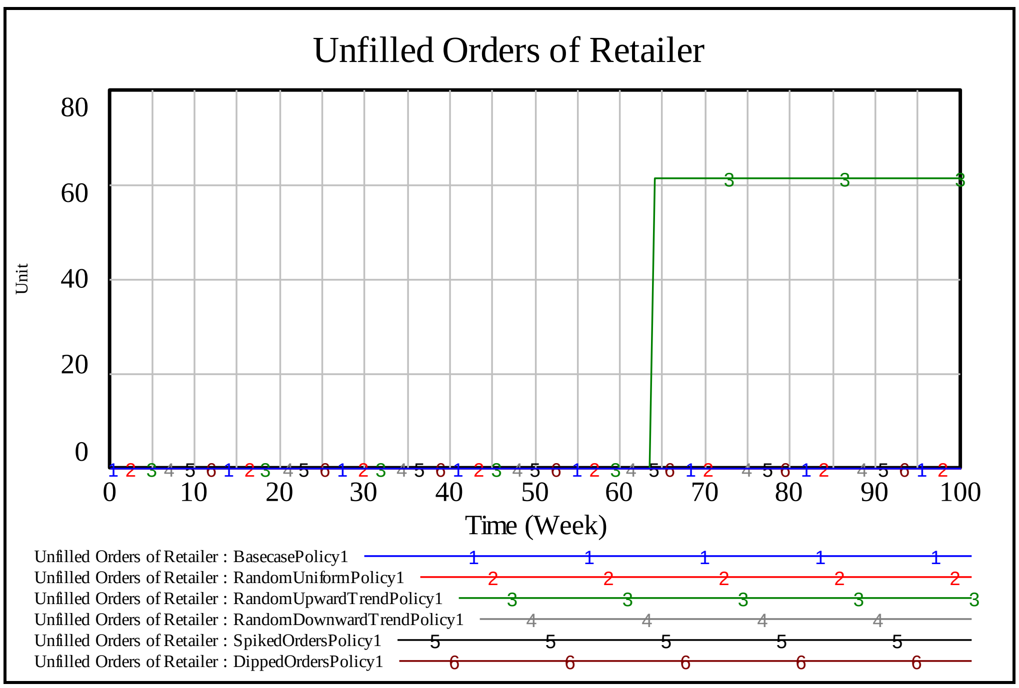

Figure 12: Substantial Elimination of Unfilled Orders of Retailer Under Policy1 settings

This policy1 result goes to prove that, *"if the handpicked parametric values of Policy 1 were the initial parameters then the supply chain partners need not have been affected adversely under all five alternate customer order scenarios simulated."* But then how were the supply chain partners going to zero in on the policy1 parametric listings with a collaborative planning forecasting and replenishment (CPFR) initiative? However, the Policy1 parametric setting is not desirable from the inventory turns point of view as may be seen from the inventory turns of Supplier and Manufacturer depicted in Figures 13 and 14 respectively.

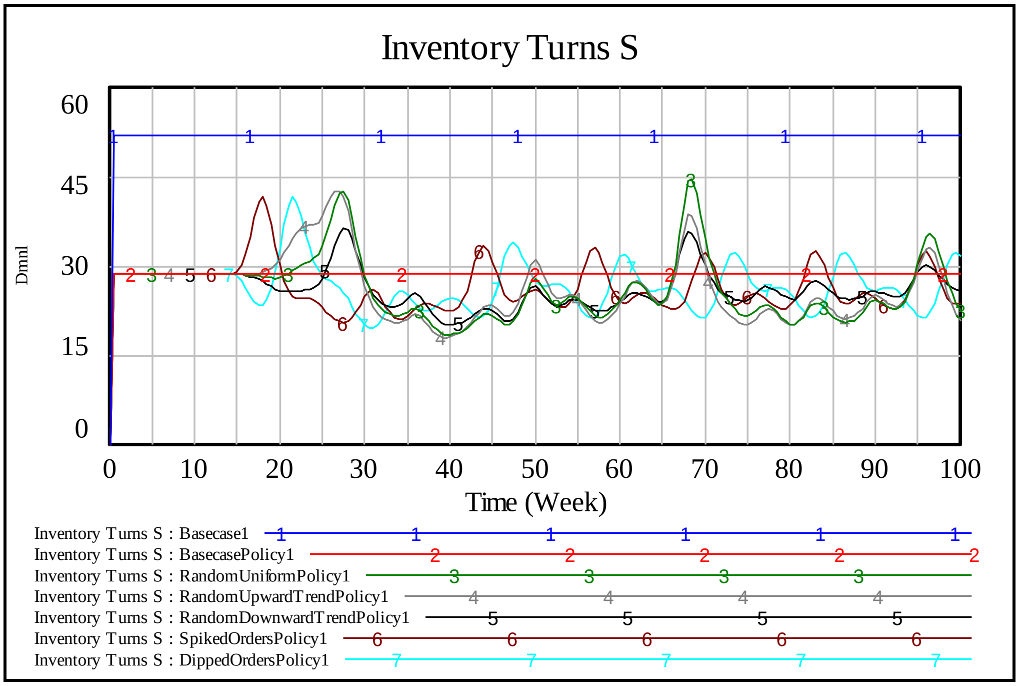

Figure 13: Inventory Turns of Supplier under Policy1

From a business perspective, the dropping of inventory turns from around 52 to 30 and below is not a profitable result. The same is true for the inventory turns of manufacturer as well, as may be seen from Figure 14.

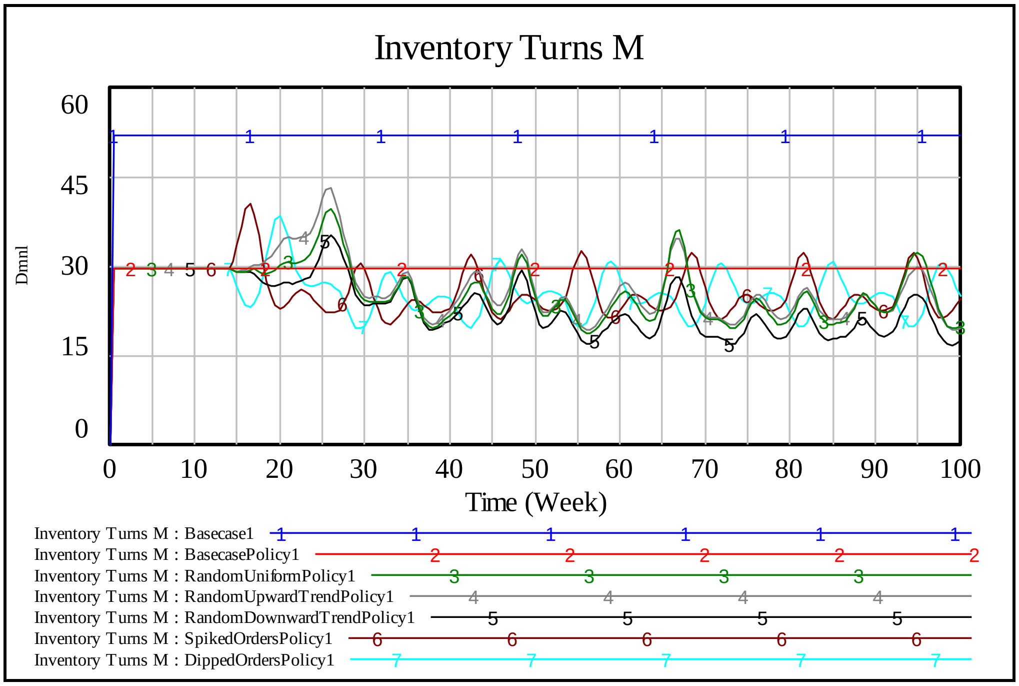

Figure 14: Inventory Turns of Manufacturer under Policy1

The overall objective of SC operation is implicitly to keep the inventory levels low and thereby the inventory carrying costs low and inventory turns high, besides ensuring avoidance of any unfilled orders at the retailer. So we now turn to defining a more improved objective function as discussed in OptB in Table 3. As may be noted, inventory turns are captured for each of the SC partners.

Inventory Turns: Since the quantity sold and finished goods inventory are both valued at "cost price" we may be able to use the quantity rather than $ value to compute inventory turns. Inventory turns is annualized by converting end-of- the-week data using the following general formula.

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

On an experimental basis, we include both positive coefficient terms and negative coefficient terms in a single objective function for OptB scenario. We want to maximize inventory turns and minimize the unfilled orders and inventory costs. However, inventory costs are based on the cumulative costs for the entire 100 weeks so they end up being an order or two higher in magnitude than the unfilled orders and inventory costs. So we assign relatively small weights for the inventory cost terms and higher weights for other terms as described in table 3. Predictably, the inventory turns for SC partners improve from around 30 to around 40 as may be seen from Figure 15 and 16 of Supplier and Manufacturer.

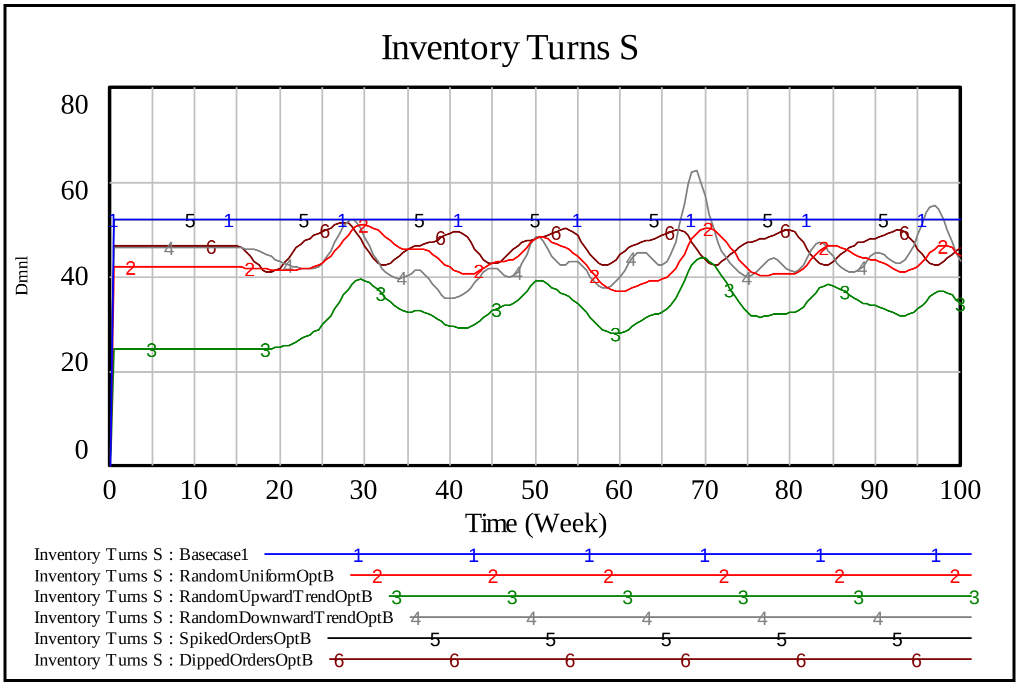

Figure 15: Inventory Turns of Supplier under Policy1

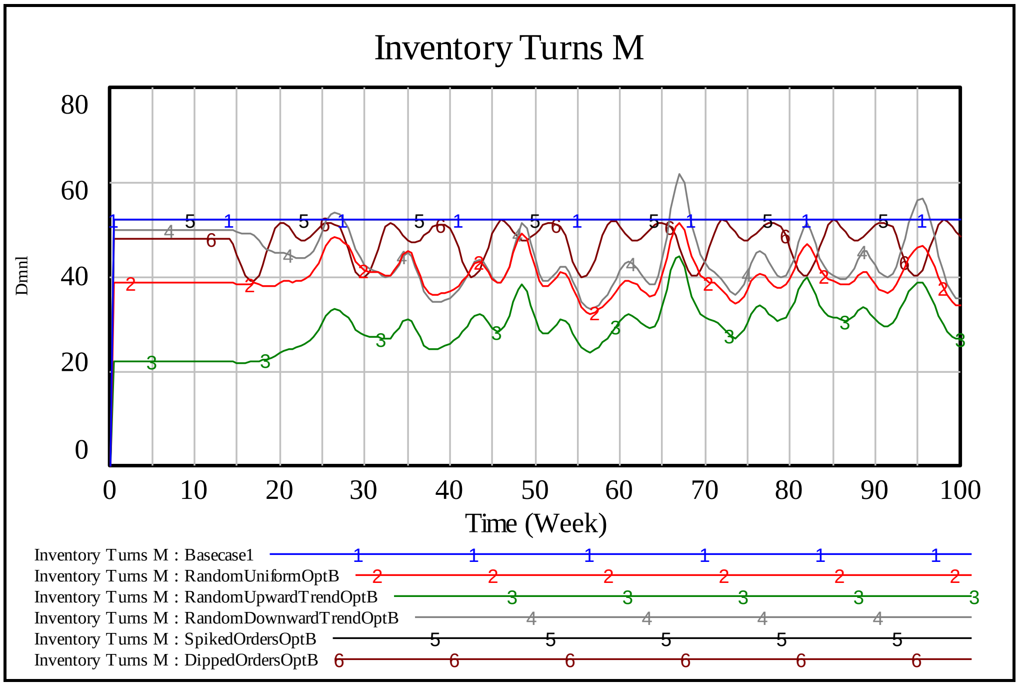

Figure 16: Inventory Turns of Manufacturer under Policy1

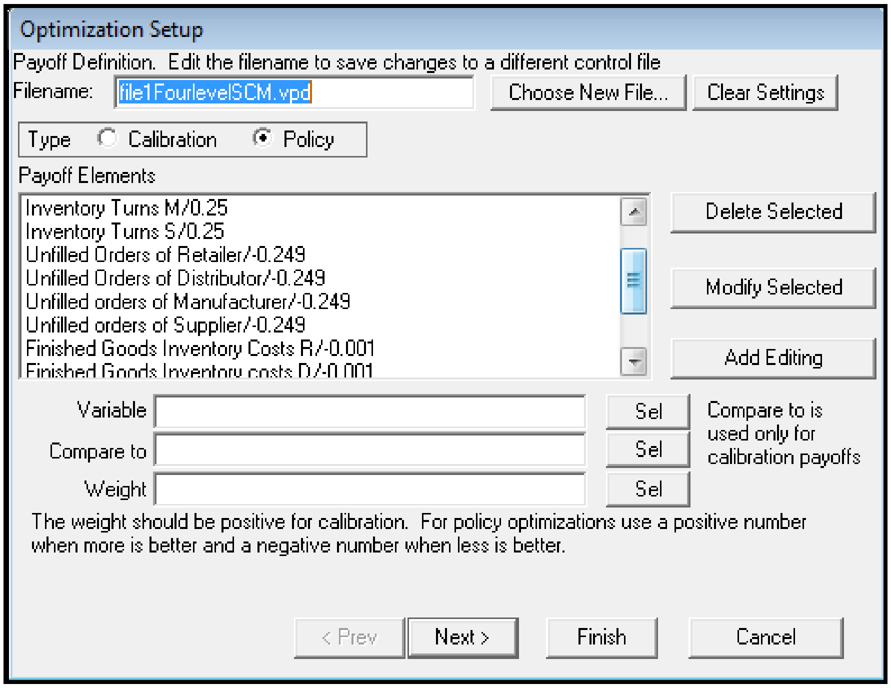

Figure 17: Selecting the payoff elements for optimization scenario OptB

Figure 17 and Figure 18 depict the process of selecting the objective function and searching for the optimal parametric values in the desired range (as considered feasible or desirable from management's perspective) in Vensim environment. In particular these two figures, Figures 17 and 18 capture the process of optimization run OptB where the objective function is a combination of, "maximizing inventory turns, minimizing the unfilled orders and minimizing the inventory costs at all supply chain partners with differential weights," while searching for desired Safety Stock levels and smoothing factor alpha for each.

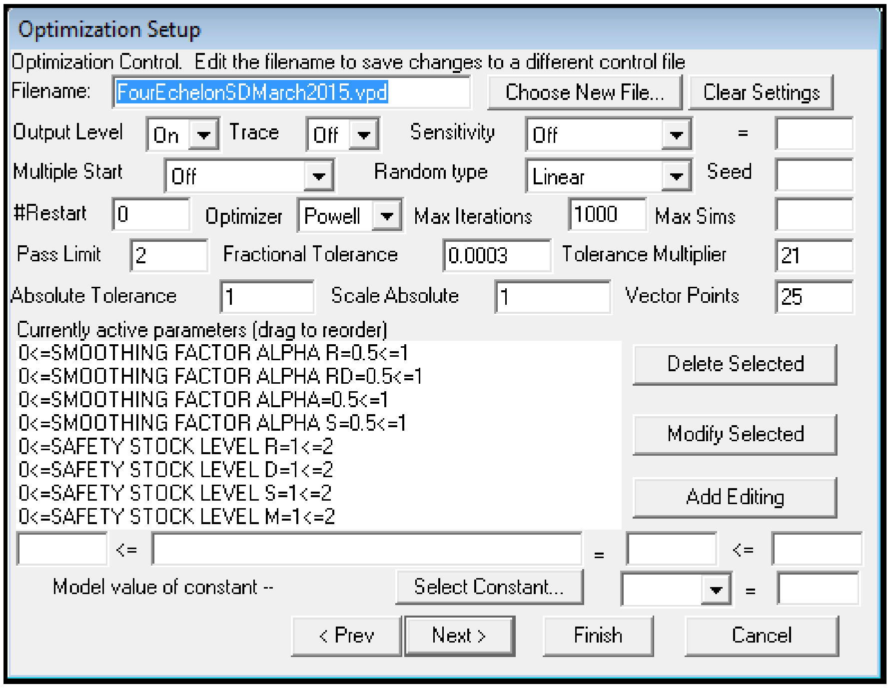

Figure 18: Defining the search range for parameters for optimization OPT2

Both Opt and OptB prescribe quite low levels of Safety Stocks for all supply chain partners while accomplishing the objective of eliminating unfilled orders. However, these runs do allow a certain level of unfilled orders which need not be a serious concern in that elimination of such unfilled orders may result in more than proportionate carrying costs. Results from all runs in terms of safety stock levels, smoothing factor values and unfilled orders are summarized in table 4.

	BaseCase and alternate orders			Optimization			Policy1				OptimizationB	
Parameters	**Safety stocks (weeks)**	**smoothing factor Alpha (S1)**	**unfilled orders**	**Safety stocks (weeks)**	**smoothing factor Alpha (S1)**	**unfilled orders**	**Safety stocks (weeks)**	**smoothing factor Alpha (S1)**	**unfilled orders**	**Safety stocks (weeks)**	**smoothing factor Alpha (S1)**	**unfilled orders**
Basecase - S	0	0.5	0									
Basecase - M	0	0.125	0									
Basecase - D	1	0.25	0									
Basecase - R	1	0.25	0									
Random Uniform - S	0	0.5	15380	0.26	0	1	0.81	0.5	0	0.24	0	0
Random Uniform - M	0	0.125	34687	0.29	0.014	10	0.76	0.5	0	0.341	0	0
Random Uniform - D	1	0.25	29452	1.23	0	257	1.44	0.5	0	1.272	0	0
Random Uniform - R	1	0.25	24885	1.16	0	21	1.3	0.051	0	1.165	0.004	0
Random Upward Trend - S	0	0.5	34185	0.81	0.044	4	0.81	0.5	526	1.111	0.025	0
Random Upward Trend - M	0	0.125	92044	0.76	0.054	1	0.76	0.5	0	1.371	0.018	0
Random Upward Trend - D	1	0.25	72203	1.44	0.03	252	1.44	0.5	0	1.427	0.094	0
Random Upward Trend - R	1	0.25	60104	1.3	0.043	149	1.3	0.051	62	1.197	0.189	99
Random Downward Trend - S	0	0.5	1142	0.08	1	99	0.81	0.5	0	0.128	1	0
Random Downward Trend - M	0	0.125	0	0.01	0.084	1	0.76	0.5	0	0.043	0.202	0
Random Downward Trend - D	1	0.25	11358	1.07	0.038	1	1.44	0.5	240	1.05	0.006	0
Random Downward Trend - R	1	0.25	8159	1.07	0.051	1	1.3	0.051	0	1.054	0.001	0
Spiked Orders - S	0	0.5	7665	0	0.5	0	0.81	0.5	0	0	0.5	0
Spiked Orders - M	0	0.125	14745	0	0.5	0	0.76	0.5	0	0	0.5	0
Spiked Orders - D	1	0.25	12890	1	0.5	0	1.44	0.5	0	1	0.5	0
Spiked Orders - R	1	0.25	9428	1	0	7000	1.3	0.051	0	1	0	7000
Dipped Orders - S	0	0.5	9583	0.12	0.142	0	0.81	0.5	0	0.117	0.133	0
Dipped Orders - M	0	0.125	18555	0.08	0.066	1	0.76	0.5	0	0.084	0.66	0
Dipped Orders - D	1	0.25	22399	1.15	0	0	1.44	0.5	0	1.152	0.004	0
Dipped Orders - R	1	0.25	17560	1.04	0	0	1.3	0.051	0	1.043	0	0

Table 4: Summarized results of all runs in respect of safety stock prescription and unfilled orders

Policy Formulation: As explained in Table 3 describing the scenario runs in this study, upon reviewing the results from Opt runs for various customer order scenarios it's possible to hand pick the threshold level of Safety Stock levels for all supply chain partners, viz., Retailer, Distributor, Manufacturer, and Supplier that would ensure elimination of unfilled orders and yet keep the inventory levels as low as possible for all supply chain partners. This will be possible, without having to make any other changes in the other parametric values. In other words, by simply changing the Safety Stock levels, and forecasting policy without having to alter any other policy decision the supply chain partners can meet the twin objectives of elimination of unfilled order to end users as well as keep the inventory cost low.

Discussion and Insights from the Results: We have several useful insights from these results. As may be observed from Table 4, when the objective function is set to minimize the unfilled orders and inventory costs, inventory turns suffers. And when, inventory turns are included in the objective function, then inventory levels are curtailed, allowing some negligible level of unfilled orders under both Opt and OptB optimization runs. Another significant insight from Table 4 data is that retailer experienced unfilled orders whenever the customer orders experience, upward trend or spiked order trend. Safety stock is inevitable if unfilled orders are to be eliminated.

The intent here is to suggest the need for an analytical assessment of alternate objective functions and the relative parametric settings to understand that defining a comprehensive and composite objective function is important as well as the search for parameters within the management's control. As a matter fact, the results in this study may not come as a surprise for a system dynamist who knows very well that, complex systems exhibit counter intuitive behavior on many an occasion.

4.0 CONTRIBUTIONS AND LIMITATIONS

Some contributions of this study are:

a) This study highlights the need for the supply chain partners to understand the effect of defining the objective functions.

b) The study demonstrates that inventory policies can help accomplish the desired objective function values.

c) The study also demonstrated that safety stocks can't be overlooked in supply chains involving significant lead times between supply partners.

d) Further, the study reaffirms the usefulness of information visibility and flexible workweek in stabilizing the production schedules,

e) The study emphasizes that defining a comprehensive and composite objective function is the clue to obtain useful parametric setting that would help tackle difficult scenarios.

4.1 Limitations of the model: Although the model captures the typical supply chain behavior observed in the real world, there is no denying that the model is quite simplified compared to the complex real world. The following explicit assumptions helped simplify the model. a) uniform shipping cost per unit, b) uniform ordering costs, c) decimal values allowed in the workforce numbers, d) Manufacturer is assumed to be supplying to dealer servicing a retailer and e) sufficient surplus capacities at supplier end are assumed available.

4.2 Future studies: Further studies will focus on obtaining more useful insights into other possible scenarios involving different patterns of customer orders, like cyclic or seasonal trends. Simplification assumptions made in developing the model can be relaxed one-by-one to develop more complex SD models capturing more complex business scenarios.

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