A Study on Various Forecasting Methods and Their Effects on the Bullwhip Effect and Inventory in the Simulated Supply Chain

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This study conducted a simulation of a four-echelon linear supply chain measuring the bullwhip effect and inventory-related markers of each echelon within the system. The research model is examined using both fixed demand with a sudden change in its pattern and 20 various stochastic demands. Simple exponential, Holt's exponential smoothing, and Brown's double exponential smoothing methods are employed to predict the demand, and the smoothing replenishment ordering system is utilized in placing orders. Results revealed that the supply chain performs the best when using the simple exponential method. Simple exponential method's superiority is notable in all the markers observed.

Keywords: simulation, linear supply chain, forecasting, smoothened replenishment order, bullwhip effect

INTRODUCTION

Effective supply chain management (SCM) is the backbone of every business (Ritzman et al., 2004). Regardless of the business' size, anything out of ordinary can negatively affect, not only one unit within the chain, but the whole chain instead (Ivanov et al., 2017). Therefore, it is an academic imperative to provide an in-depth analysis on the processes happening within the supply chain (SC), find ways to further improve them, and lastly, find ways to avoid and or decrease the impacts of any unwanted situations in the SC (Ivanov et al., 2017).

In SC, there are many different markers that are used to track the effectiveness of the SC. One of the thoroughly researched markers is the so-called bullwhip effect (BWE) (Cachon et al., 2007; Bray, & Mandelson, 2012). BWE may arise even from the smallest fluctuations in a customer order. Such changes may lead to a progressive increase of an order variation as the order information passes upstream the SC. In operations management, this phenomenon is described negatively as it is responsible for inefficiencies in the SC. To successfully manage and reduce the BWE in a SC, a significant amount of effort is required (Geunes et al., 2002; Hall, & Saygin, 2012).

In addition to observing the BWE, this study also observes what is happening with the local inventories of each echelon to further show how given echelons behave under different circumstances. However, BWE is still deemed to be the most important marker of each echelon's performance.

This study conducts a simulation of a 4-echelon linear SC as it seems to be the most researched type of the SC. Study utilizes 3 different forecasting methods (FMs), since they have shown to outperform other frequently used ones in separate studies, but have never been used within the same simulation to show which method is superior among them. As such, research may provide some valuable insights into the tested FMs and how they influence the SC network.

LITERATURE REVIEW

Ordering System and SC Structure

One of the key decisions when creating a SC simulation is to determine the scope of the simulated SC and its structure. While some simulations only simulate single echelon SC (e.g. Xie, & Zhou, 2012), many simulate n-echelon systems. Wright, & Yuan (2008), Hussain, & Saber (2012), and Jeong, & Hong (2017) all simulated four-echelon SC. While all these simulations have different research objectives, they have many aspects in common. One of them being, they are all of the linear structure. Up to date, there seems to be a lack of studies dealing with the convergent SC, but there are some studies on the divergent structure SC. Domingueza et al. (2013) conducted a comparative analysis of both the linear and the divergent structure SC networks in order to find the differences of the BWE on the SC. The main result obtained from the study is that the divergent SC networks are more prone to unexpected changes in the demand, causing the BWE to be more severe as opposed to its effect on the linear SC network.

While there are many different ordering systems used (e.g. order-up-to policy, the periodic review), each has its own shortcomings. Hence, a new ordering system called smoothing replenishment order (SRO) has been introduced and utilized by several simulations (e.g. Cannella, & Ciancimino, 2010; Jeong, & Hong, 2017). This ordering system model was developed by Disney et al. (2006) by combining both the net stock variability and order variability into a single model. The model itself contains two controllers (variables) that can be used to further smooth out the order or do the opposite.

Approaches to Measuring the BWE

While BWE can be measured using several different methods as pointed out by Towill et al. (2007), each method is more suitable for different scenarios. For instance, in case of stochastic input demand, variance ratio or standard deviation ratio should be used, in case of fixed demand with a sudden change in the demand, the peak value of the demand should be measured. Furthermore, the same study also divided different methods into three different categories – “variance lens”, “shock lens”, and “filter lens” perspective. As for measuring the bullwhip in a stochastic demand scenario, some authors like Fransoo, & Wouters (2000), Wangphanich et al. (2010) measure BWE by firstly diving both demand and sales variance by their respective means, then dividing them to obtain the final measure.

On the other hand, some authors employ slightly different method, where they merely divide order variance by demand variance, omitting their respective means in the equation (Boute, & Lambrecht, 2009; Bottani, & Montanari, 2010; Hussain, & Drake, 2011; Xie, & Zhou, 2012; Ma et al., 2014). The second variation is more common due to being more simple and due to the fact, two means are assumed to be equal, hence canceling each other as stated by Hussain, & Drake (2011).

As for the “shock lens” perspective, many studies utilized said approach of measuring the peak in their research (Hussain, & Saber, 2012; Li, 2012; Badar et al., 2013). Jeong, & Hong (2017) also conducted a simulation using the “shock lens” perspective on a 4-echelon SC testing how the system works under different customer demand (CD) ISR, measuring the BWE in its peak. Said study also concluded, like other previously done studies (e.g. Lee et al., 1997a; Agarwal et al., 2009; Hussain, & Saber, 2012), the higher the ISR, the lesser the BWE is. The topic of ISR and its effect on the SC was previously researched by Ouyang (2007), who found out, while higher ISR indeed can significantly decrease the BWE, but it still cannot completely negate its unwanted effects on the chain. Cannella, & Ciancimino (2010), Hussain, & Saber (2012), Li (2012), and Costantino et al., (2014) all concluded the higher the ISR the lower the effects of the BWE on the whole chain. Additionally, Hussain, & Saber (2012) also implied in their study that ISR will have a cost associated with its implementation and that the ISR as a remedy for the BWE will be more useful when the batch size is smaller. Li (2012) concluded that in case of inadequate information flows, the BWE can be lessened through appropriate adjustment in the ordering strategy. Moreover, the study also proved, information sharing is indispensable in improving the performance of the SC. Lastly, Costantino et al., (2014) determined that the main cause of the BWE is, apart from the lack of the information sharing within the whole chain, also poor forecasting, and high safety stock.

Therefore, in the case of the "shock lens" perspective, BWE is going to be measured as a peak value of the SRO after the demand change is introduced in the system (eq. 1). On the other hand, for the "variance lens" perspective, variance ratio of SRO_i and $Demand_i$ is used to measure the BWE (eq. 2).

$$BWE = max\{O_i\} \tag{1}$$

or

$$BWE = \frac{\sigma^2_{SRO_i}}{\sigma^2_{Demand_i}} = \frac{\frac{\sum_{i=1}^{n}(O_i - \bar{O})^2}{n-1}}{\frac{\sum_{i=1}^{n}(D_i - \bar{D})^2}{n-1}} \tag{2}$$

O_i = order towards an upstream echelon
$\bar{O}$ = average order size towards an upstream echelon
D_i = demand coming from a downstream echelon
$\bar{D}$ = average demand size coming from a downstream echelon
n = number of cases

Importance of Proper Forecasting Method Selection

Liu, & Wang (2007) proved in their study, the right selection of a FM is of the utmost importance when it comes to decreasing the BWE in the SC. Methods proposed to be used in the study are moving average and exponential weighted moving average. Duc et al. (2008) quantified the impact of the BWE on a simple two-stage SC (consisting of one supplier and one retailer). The study employed autoregressive moving average model ARMA(1,1) to investigate the effects of the autoregressive coefficient, the moving average parameter, and the lead time on the BWE. Based on the conclusions, the existence of the BWE heavily depends on the values of the autoregressive and moving average coefficients of the used ARMA(1,1) model. The study concluded, the BWE occurs only when the autoregressive coefficient of the demand process is larger than the moving average parameter.

Wright, & Yuan (2008) tested Holt's exponential smoothing method and Brown's double exponential smoothing method instead of a simple exponential (SE) smoothing method that is widely used, to mitigate the BWE in the SC. Their results prove that the choice of these two methods significantly helps reduce the effects of the BWE across the whole SC when compared to the moving average FM. Alizadeh (2012) investigated the effects of selecting appropriate forecasting parameters on the four-echelon SC network. CD FM used in this study was the exponential smoothing method. Based on the results, increasing weighing factor in the smoothing formula results in increasing ordering variances for all the echelons of the network. That means, the higher the weighing factor, the more intense the BWE is going to be. Additionally, it was suggested, when making CD forecasts, not only to use the most recent data but also older ones. In this way, the BWE can be reduced as possible extremes will not be that reflected in the forecasts. Sadeghi (2015) used two-product, two-echelon SC to quantify the BWE. The main focus of the research was to compare the moving average and exponential smoothing methods. Based on the results, the exponential smoothing method proved to be superior when compared with the moving average method. The same result was also concluded by other researchers. Furthermore, the study also analyzed the effects of the lead time on the BWE. Results prove, the lover the lead time the less will the SC be affected.

Following Are Three Different Forecasting Methods Employed in This Research

The rationale behind choosing the SE method is that many studies (e.g. Alizadeh, 2012; Sadeghi, 2015) deemed this FM as considerably better than other ones. As for the Holt's and Brown's method, research published by Wright, & Yuan (2008) has shown, these two methods perform significantly better than moving average FM. However, these FMs have not been compared in a single study yet.

Simple Exponential Smoothing Method

SE method is used because it is the most widely used method providing decent results. See eq. 3.

$$f_{t+1} = \alpha y_t + (1-\alpha) f_{t-1} \tag{3}$$

α = smoothing factor (0 ≤ α ≤ 1)

y = actual values of the forecasted series

Holt's Exponential Smoothing Method

In order to compute Holt's exponential smoothing method, two components of the final equation have to be known first, that is level and trend value. Moreover, the values of the two coefficients have to be set. Their values are usually set using software to determine the best values so the produced forecast most accurately fits the real data (Hyndman, & Athanasopoulos, 2018). See eq. 4,5, 6.

$$a_t = \alpha y_t + (1-\alpha) * (a_{t-1} + b_{t-1}) \tag{4}$$

$$b_t = \beta * (a_t - a_{t-1}) + (1-\beta) * b_{t-1} \tag{5}$$

$$f_{t+m} = a_t + m b_t \tag{6}$$

a_t = level value of the forecast
α = level smoothing factor (0 ≤ α ≤ 1)
y_t = actual values of the forecasted series
b_t = trend value of the forecast
β = trend smoothing factor (0 ≤ β ≤ 1)
m = number of periods

Note that should the value of β be set to 0, Holt's method would become a SE method.

Furthermore, in order to compute the initial forecast, initial values have to be computed in a different way as a_t and b_t have not been defined yet, hence (See eq. 7. 8):

$$a_1 = y_1 \tag{7}$$

$$b_1 = 0 \tag{8}$$

Brown's Double Exponential Smoothing Method

Initially, two equations calculating simple and double exponential smoothing have to be calculated. Similarly to the Holt's method, they both utilize some data from previous periods and actual values of the series. Both of them are being adjusted by their respective smoothing factor (Hamilton, 1994). See eq. 9 – 13.

$$A_t = \alpha y_t + (1-\alpha) * A_{t-1} \tag{9}$$

$$A"_t = \alpha A_t + (1-\alpha) * A"_{t-1} \tag{10}$$

$$a_t = 2A_t - A''_t \tag{11}$$

$$b_t = \left(\frac{\alpha}{1-\alpha}\right) * (A_t - A''_t) \tag{12}$$

$$f_{t+m} = a_t + mb_t \tag{13}$$

A_t = simple exponential smoothing value
α = smoothing factor ($0 \leq \alpha \leq 1$)
y_t = actual values of the forecasted series
A''_t = double exponential smoothing value
a_t = level value of the forecast
b_t = trend value of the forecast
m = number of periods

Same as in the Holt's exponential smoothing method, it is necessary to set some initial values to calculate the first forecast. Foremost, values for A_1 and A''_1 are set as follows (See eq. 14):

$$A_1 = A''_1 = y_1 \tag{14}$$

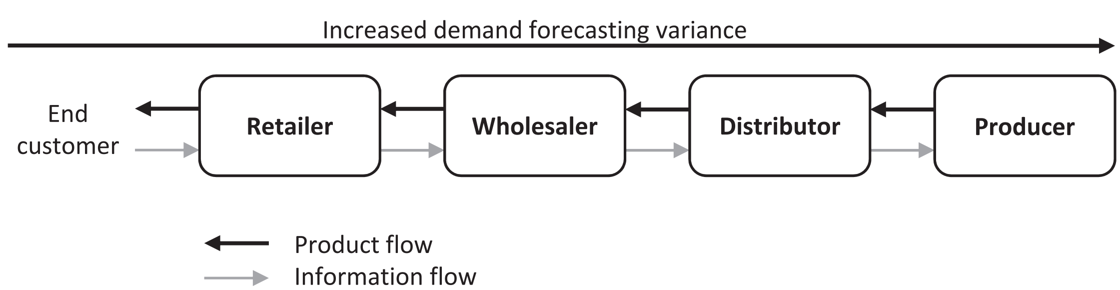
Regardless of the FM used, initial forecast f_1 equals to 0, as some variables in each forecast's equation have not been defined yet.

SUPPLY CHAIN SIMULATION

Software used for the research is called "iThink" created by isee systems. The whole model of the SC is created using stocks, flows, converters, and connectors. A simplified model is shown in Figure 1, and a complete model is presented later in the paper. Echelons within the simulation are defined as follows:

Retailer: i = 4
Wholesaler: i = 3
Distributor: i = 2
Producer: i = 1

FIGURE 1
SIMULATED 4-ECHELON LINEAR STRUCTURE



Each Echelon and Its Components Are Defined by the Following Variables

$D_i(t)$: Demand towards the echelon. Initial demand towards the retailer is manually inputted in the system, simulating desired/real world demand. Subsequent demands toward other upstream echelons are based on forecasts and other computations. (eq. 15, 16)

$$D_i(t) \; for \; i = 4 \tag{15}$$

$$D_i(t) = O_{i+1}(t) \; for \; i = 1, 2, 3 \tag{16}$$

$\hat{D}_i(t)$: Forecast of the demand using one of the three aforementioned FMs. (eq. 17)

$$\widehat{D}_i(t) = f_i(t) \tag{17}$$

$O_i(t)$: Smoothened replenishment order is based on echelon's own forecast and smoothed difference between target inventory and current inventory position and target WIP and current WIP. (eq. 18, 19)

$$O_i(t) = \widehat{D}_i(t) + \varphi\big(TI_i(t) - I_i(t)\big) + \chi\big(TW_i(t) - W_i(t)\big) \tag{18}$$

$$O_i(t) \geq 0 \tag{19}$$

$TI_i(t)$: Target inventory, or in the other words – safety stock, is calculated as s simple multiplication of the safety stock factor with the demand forecast. (eq. 20)

$$TI_i(t) = Tc_i\widehat{D}_i(t) \tag{20}$$

$I_i(t)$: Inventory position or net stock equals the local inventory minus any backlogged orders. (eq. 21)

$$I_i(t) = LI_i(t) - B_i(t) \tag{21}$$

$TW_i(t)$: Target work in progress is physical lead time multiplied by the demand forecast. (eq. 22)

$$TW_i(t) = Tp_i\widehat{D}_i(t) \tag{22}$$

$W_i(t)$: Work in progress (WIP) is an accumulation of orders that have been placed, but not delivered yet. For echelons other than producer, WIP equals inventory currently being transported and the backlog of the immediate upstream echelon. (eq. 23, 24)

$$W_i(t) = T_i(t) \; for \; i = 1 \tag{23}$$

$$W_i(t) = T_i(t) + B_{i-1}(t-1) \; for \; i = 2, 3, 4 \tag{24}$$

$L_i(t)$: Shipment leaving towards downstream echelon, or in other words, total sales for the current time period. The size of the shipment is determined in a way that prevents its value from being negative, and also prevents negative local inventory. (eq. 25)

$$L_i(t) = \min\{LI_i(t), D_i(t) + B_i(t-1)\} \tag{25}$$

$B_i(t)$: Backlog is the accumulation of all the orders placed from a downstream echelon or final customer that have not been fulfilled yet. (eq. 26)

$$B_i(t) = B_i(t-1) + D_i(t) - L_i(t) \tag{26}$$

$B_{i-1}(t-1)$: Backlog of the immediate upstream echelon. This equation is used by all downstream echelons to calculate the necessary information on its own, without directly taking the information from the upstream echelon. Equation not calculated for i = 1. (eq. 27)

$$B_{i-1}(t) = \sum_{t=1}^{n} O_i(t-1) - \sum_{t=1}^{n} S_i(t-1) \tag{27}$$

$LI_i(t)$: Local inventory equals to the quantity present in the previous time period increased by arriving shipment and decreased by realized sales. (eq. 28)

$$LI_i(t) = LI_i(t-1) + A_i(t) - L_i(t) \tag{28}$$

$A_i(t)$: Shipment arriving from an upstream echelon that is immediately available for further processing. Shipments arriving from $T_i(t)$ to $A_i(t)$ have a delay equal to the lead time Tp_i. (eq. 29)

$$A_i(t) = T_i(t - Tp_i) \tag{29}$$

$T_i(t)$: Inventory currently transported is a sum of all presently transported batches plus any dispatched shipment minus any shipment, that already arrived and is available for use. Part of this function ($T_i(t)$) is presented as conveyor type stock in the simulation with its own delay time in accordance with the lead time. (eq. 30)

$$T_i(t) = T_i(t-1) + S_i(t) - A_i(t) \tag{30}$$

$S_i(t)$: Dispatched shipment to be delivered to an upstream echelon after the lead time period. This equation for echelon i = 1 guarantees infinite stock capacity, as any order will be 100% fulfilled. However, the simulation itself uses a slightly different method, where the ordered quantity is withdrawn from a warehouse. This is only done to keep a track of the amount that has been withdrawn by the system, but the discussed equation still applies. (eq. 31, 32)

$$S_i(t) = O_i(t) \; for \; i = 1 \tag{31}$$

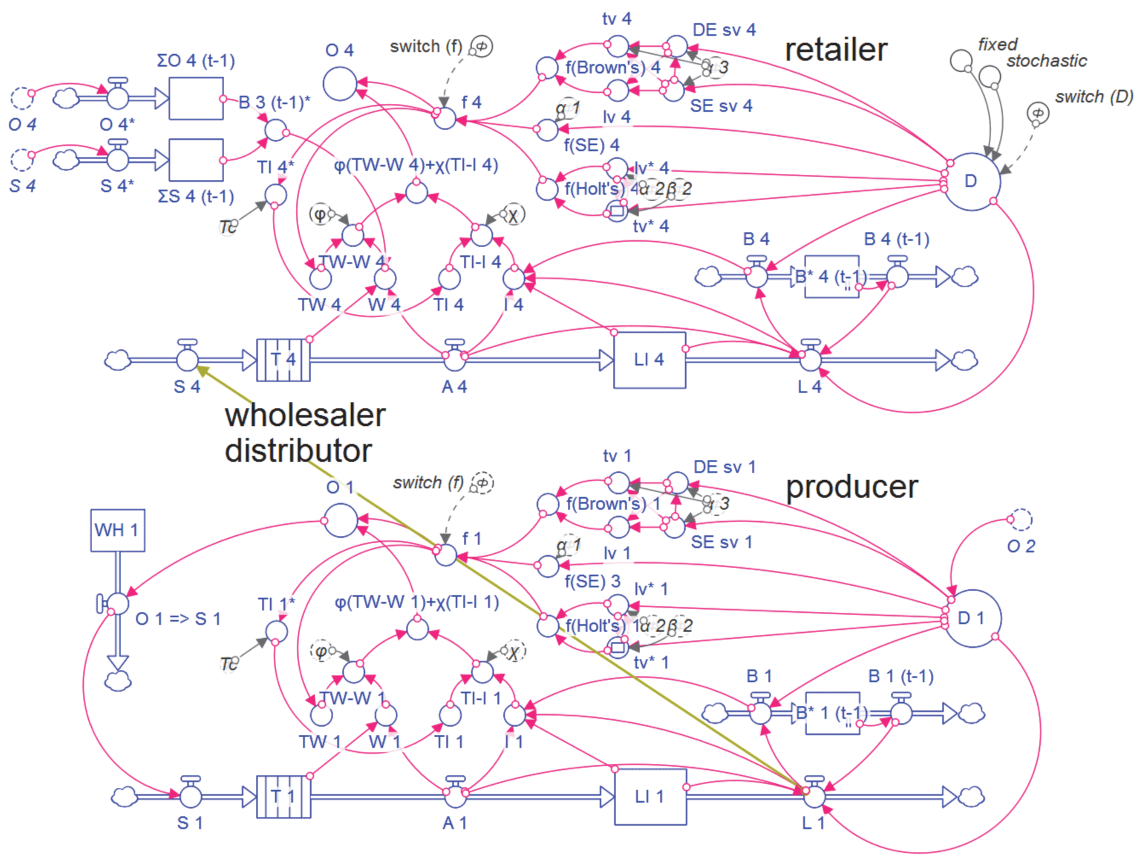
$$S_i(t) = L_{i-1}(t) \tag{32}$$

Tp_i: Physical lead time
Tc_i: Safety stock factor
Ty_i: Smoothing parameter/controller for inventory (marked as φ)
Tw_i: Smoothing parameter/controller for work in progress (marked as χ)

Furthermore, parameters of the forecasts are also treated as important variables but are already mentioned earlier in the paper.

Following Is the Figure Presenting the Simulation Model

FIGURE 2
SIMULATION MODEL



For easier comprehension, only retailer and producer echelons are shown in the Figure 2. Both the wholesaler and distributor echelons are omitted as they are, in their structure, completely identical to the retailer echelon.

EXPERIMENT DESIGN

Following experiment assumptions are a list of rules which all the echelons in the simulation abide, regardless of the experiment conducted. Furthermore, the study is divided into two different experiments (experiment A, B). Both experiments are described with additional simulation rules and most important equations are introduced.

Assumptions

- CD ISR is regarded as 0 % for wholesaler, distributor, and producer. Therefore, each echelon conducts its own forecast in order to determine the SRO that is to be passed to an immediate upstream echelon in the SC.
- Physical lead time Tp_i = 2 and safety stock factor Tc_i = 3. Both smoothing controllers for inventory and work in progress (Ty_i, Tw_i) equal to 0.25. These values are set according to the reviewed researches and values suggested.
- All echelons use identical FM, its parameters, physical lead time, safety stock factor, and smoothing parameter for both inventory and WIP, as set for the retailer.

Experiment A

- Utilizes "shock lens" perspective. That means, the $D_{i=4}(t)$ is fixed to a certain value. Then, after the whole SC stabilizes (orders, local inventories, etc.), a shock in a form of increased demand is introduced into the system. Initial demand of 4 units per round is increased by 100 % to 8 units per round at t = 151, that is after 150 initial rounds. The simulation ends at t = 250. Initial 100 rounds are used to let the SC reach its equilibrium. Therefore, the whole duration of the simulation is 250 rounds, with the first 100 rounds being "warp-up" rounds.
- Parameters used in the forecasts are fixed as follows: for SE method, α = 0.33; for Holt's method, α = 0.3 and β = 0.2; for Brown's method, α = 0.3. The parameter for the SE method is chosen in accordance with the reviewed researches, other parameters are chosen based on the relevant literature.
- Average inventory size is measured as (See eq. 33):

$$\frac{\sum_{t=101}^{250} LI_i(t)}{150} \tag{33}$$

- Resulting BWE is then measured as the fluctuations in each echelon's SRO happen (their maximum).

Experiment B

- "Variance lens" perspective is employed. Therefore, demand $D_{i=4}(t)$ is not, unlike in the previous experiment, fixed with only one change introduced. Each simulation is to last a total of 200 rounds, where initial 100 rounds are meant to be "warm-up" rounds just like in experiment A. Following 100 rounds are used to collect the data.
- To determine the best parameters for all three FMs, each forecast is first to run on the historical data to minimize RMSE. Simulation is then resumed with updated parameters. (eq. 34)

$$RMSE_f = \sqrt{\frac{\sum_{i=1}^{n}(f_i - D_i)^2}{n}} \tag{34}$$

- A total of 20 different simulations are to be run, each using a totally different real-world demand dataset (each simulation is run 3 times, every time with different FM).
- Average local inventory over the period of the 100 observed rounds is calculated to determine whether or not there are any fluctuations under different FMs and to observe any relationship between other observed markers.
- As another measure of the efficacy of the FMs, numbers of total stock-outs are measured during the tested period (stock-out is a situation when $B_i(t) > 0$; the total number of stock-outs for echelon i is, therefore, defined as (See eq. 35):

$$\sum_{t=101}^{200} \frac{B_i(t)}{B_i(t)} \; for \; B_i(t) > 0). \tag{35}$$

- Lastly, BWE is measured using the variance ratios of SRO and Demand.

RESULTS AND ANALYSIS

Experiment A

Graphs showing separate results of the BWE under each FM are not presented here. Instead, consolidated results in form of a table are shown in Table 1. Results, both graphical and numerical, from using the SE method produced by the simulation are identical to the study conducted by Jeong, & Hong (2017) under the scenario with 0% CD ISR in the whole SC for all the echelons.

Looking at Table 1, it is very clear that as the demand moves upstream, it is getting significantly amplified, producing a substantial BWE and distorting the SC as a result. Identical trend can be seen in Table 2 where the average inventory size increases in the upstream echelons.

TABLE 1
MAXIMUM ORDERS AT EACH ECHELON

forecast	retailer	wholesaler	distributor	producer
SE	11	15.86	24.11	37.3
Holt's	12.57	21.73	39.54	76.04
Brown's	13.09	24.25	47.78	96.98

TABLE 2
AVERAGE INVENTORY SIZE AT EACH ECHELON

forecast	retailer	wholesaler	distributor	producer
SE	17.76	18.24	18.64	21.72
Holt's	18.10	18.29	23.45	51.40
Brown's	18.31	18.45	20.94	46.67

Note that "ideal" inventory size (safety stock) before the shock lens would be 3*4 units and 3*8 units after, as given by the safety stock parameter of 3. Under such ideal conditions, average inventory size would be 20 (see eq. 36). High average inventory sizes, especially in producer echelons under both Holt's and Brown's forecasts are caused by the demand amplification in the SC – that is by the BWE.

$$\frac{3*(50*4+100*8)}{150} = 20 \tag{36}$$

As presented in Table 1 and Table 2, the SE method clearly outperforms both Holt's and Brown's method under the "shock lens" perspective. Not only the peak order values are significantly higher under Holt's and Brown's method as one moves upstream, but also the time required for the SC to reach the point of equilibrium is considerably longer as most upstream echelons have greatly elevated inventories. During the stabilization period, also more fluctuations in order quantities are present. Lastly, average inventory size is highly elevated in the most upstream echelons compared to the SC method, which would result in significant expenses related to stock maintenance.

However, given the nature of this experiment, these results cannot be conclusive in terms of deciding whether these two FMs are really underperforming when it comes to minimizing the BWE. For such claims, more rigorous testing under stochastic demand is necessary.

Experiment B

In this experiment, forecasting parameters are set based on the calculation done at the retailer (minimizing RMSE) over the period of the initial 100 rounds. These parameters are then used for the remaining 100 rounds by all echelons.

Tables A1, A2, A3 (tables shown in appendices) represent the consolidated results of all the 20 simulated stochastic demands. Data are sorted by the dataset tested and the FM used. Next, each FM under the given dataset has its own corresponding value of the average local inventory (Table A1), the total number of the stock-outs (Table A2), and measured BWE (Table A3) per its respective echelon. Both the average local inventory and BWE are rounded to two decimal places.

In order to analyze the average local inventory levels, some steps have to be taken first. Since each demand curve is of a different scale, simply averaging the data would provide flawed results. Therefore, for each dataset, the average local inventory size is compared to its counterpart under different FM. Results are then averaged to determine the average difference between FMs used.

Results presented in Table 3 can be interpreted as follows: since the final result is computed as eq. 37, negative numbers signify, average inventory of echelon a is lower than the average inventory of echelon b. Positive numbers indicate the opposite.

$$\frac{\sum_{t=1}^{20}\frac{\overline{LI}_a(t)-\overline{LI}_b(t)}{\overline{LI}_a(t)}}{20} \tag{37}$$

TABLE 3
AVERAGE LOCAL INVENTORY COMPARISON

forecasts compared	average local inventory comparison [%]			
	retailer	wholesaler	distributor	producer
SE - Holt's	-0.024	-0.299	-0.574	-3.891
SE – Brown’s	0.016	0.021	-0.683	-11.269
Holt's-Brown's	0.042	0.319	-0.102	-7.156

Results suggest, average inventory size is the lowest under the SE method, however, the difference in all, but producer echelon, is miniscule (less than ±1 %). In the producer echelon, the SE method outperforms both the Holt’s (by 3.9 %) and Brown’s (by 11.27 %). Additionally, Holt’s method performs better as opposed to Brown’s method in lowering the average local inventory.

To further analyze the effects of different FMs on local inventories and their changes as one moves upstream, data from Table A1 has to be transformed to find an average difference between each echelon (under given forecast) related to a certain base value. The base value for each FM was determined to be 1 (100 %) for the retailer. Therefore, the value of average local inventory for the retailer, in all three cases, equals to 1 (100 %). All other values are then derived from this base value as a deviation in percent from the retailer. The measure is calculated as follows (See eq. 38):

$$\frac{\sum_{t=1}^{20}\frac{\overline{LI}_a(t)}{\overline{LI}_{i=4}(t)}}{20} \tag{38}$$

Table 4 represents each echelon’s average inventory over the course of all 20 simulations per forecast used.

TABLE 4
AVERAGE LOCAL INVENTORY PER ECHELON

forecast	average local inventory size [%]			
	retailer	wholesaler	distributor	producer
SE	100	100.127	100.551	104.229
Holt's	100	100.403	101.132	108.578
Brown's	100	100.121	101.273	116.692

If Brown's method were chosen to be the base for all other computations (Brown's method produced the lowest average inventory in the retailer echelon), other numbers would vary minimally, as the average local inventory of SE and Brown's method only differs by 0.016 %.

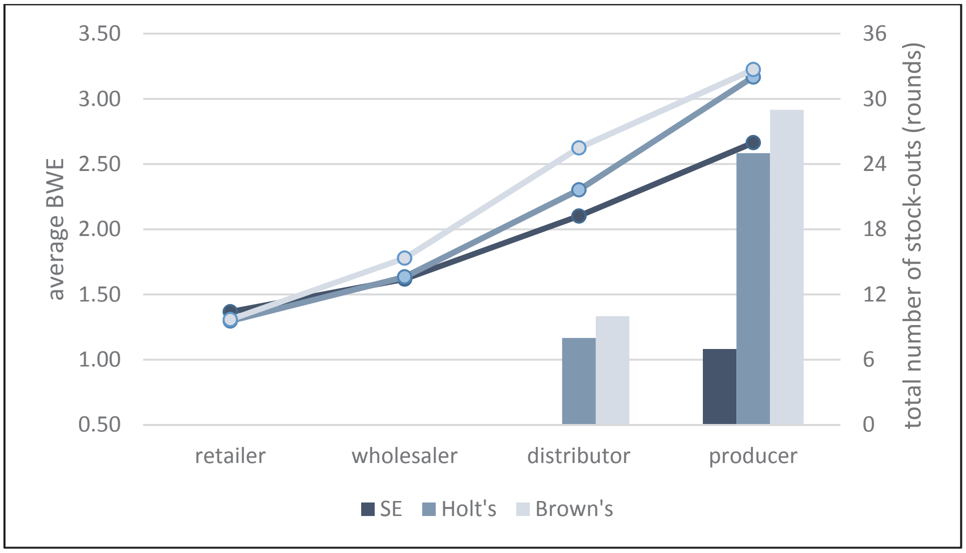
Results confirm each of the three FMs chosen performs nearly identically in the retailer, wholesaler, and distributor echelon. However, the differences in how well can they perform are very prominent in the producer echelon. Once again, the SE method strongly outperforms the other two methods.

Following Table 5 and Figure 3 represent consolidated results from all the simulations done providing a clear-cut picture of the echelons' performance regarding the average BWE and the total number of stock-outs.

TABLE 5
AVERAGE BWE AND THE TOTAL NUMBER OF STOCK-OUTS COMPARISON

	forecast	retailer	wholesaler	distributor	producer
average BWE	SE	1.37	1.62	2.10	2.66
	Holt's	1.30	1.63	2.30	3.17
	Brown's	1.31	1.78	2.62	3.22
total number of stock-outs	SE	0	0	0	7
	Holt's	0	0	8	25
	Brown's	0	0	10	29

FIGURE 3
AVERAGE BWE AND THE TOTAL NUMBER OF STOCK-OUTS COMPARISON



Analyzing stock-outs, none happened for either retailer or wholesaler echelon regardless of the FM used. However, due to the greatly amplified demand in the upstream echelons and inability of those echelons to cope with occasional spikes in the demand, some stock-outs occurred. The vast majority of all the stock-outs occurred under Holt's and Brown's method, with only 7 total stock-out rounds occurring under the SE method in all 20 simulations. These results also signify the SE method is performing better than the other two FMs. Additionally, the longest stock-outs were 7 consecutive rounds, the shortest ones were 1 round long. Each stock-out lasted an average of 2.82 rounds with a total of 28 unique stock-outs registered. Under SE FM, stockouts lasted an average of 1.75 rounds, 2.82 rounds under Holt's method and 3.15 rounds under Brown's method.

In most cases where a strong negative demand amplification occurred in the upstream echelons, SRO reached 0 for few rounds as given echelon's inventory levels were sufficient and demand was considerably low. However, since negative demand amplification is often followed by a positive demand amplification (rebound), reaction to such usually quickly occurring change may not be adequate enough due to the lead times and insufficient inventory levels. As a result, stock-outs may occur. Stock-outs are then followed by an excessive reaction in the form of high SRO, resulting in high inventory levels. Hene, both elevated local inventories and stock-outs can be attributed to the demand amplification – BWE. Simulation results clearly show, while the BWE under Holt's and Brown's method is slightly lesser in the most downstream echelon compared to the SE method, it then surpasses it and causes upstream echelons to suffer from various effects of high BWE (i.e. elevated local inventory and stock-outs).

In Table A3 there are several occurrences of a reverse BWE. Reverse BWE happens when $BWE_i < BWE_{i+1}$. This phenomenon occurs due to the forecast (and subsequently demand) being more accurate in the upstream echelons as opposed to their downstream counterparts. Should there be an echelon with non-zero CD ISR, reverse BWE would occur much more frequently as echelons that have CD ISR > 0 % can have superior forecasting capability over the next directly adjacent downstream echelon, just as shown by Jeong, & Hong (2017).

Additionally, there are also a few cases, where the BWE measure is smaller than 1. Such situations reflect the smoothing scenario. Smoothing scenarios occur when the fluctuations in the demand (divisor) are greater than those in the SRO (dividend). Since the study assumes 0% CD ISR, smoothing scenarios occur rather rarely (only in 7 cases out of 60). However, due to the way the BWE is calculated, smoothing scenarios occur much more often under non-zero CD ISR. For example, should the producer echelon utilize 100% CD ISR, its σ^2_{SRO} would in many cases be lower than σ^2_{Demand}, resulting in BWE < 1.

Possible Remedies

As all the observed negative fluctuations can be attributed to the BWE and its influence on the SC, one should strive to minimize the BWE and, as a result, improve the total performance of the SC (Lee et al., 1997b). Nevertheless, the amount of possible remedies is rather limited, as some variables (e.g. lead time) cannot be easily adjusted, or their adjustments are rather costly.

In this simulation, there are certain possibilities to further improve separate markers by changing the variables (not considering the lead time). However, by improving one, other ones may worsen significantly. Slight adjustments of the smoothing parameters for inventory (φ) and WIP (χ) may provide better results of all the observed markers, but each dataset requires different adjustments, and suggested values of 0.25 still offer the most optimal results on average. Lowering safety stock factor results in significantly lower average inventory levels and lower BWE, but at the same time results in vast numbers of stock-outs, paralyzing the whole SC. On the other hand, increasing the safety stock factor leads to immense overstocking in the upstream echelons caused by strongly amplified BWE. Therefore, trying to improve the functionality of the SC by adjusting these variables cannot be deemed as a proper remedy. In the environment similar to the one set by the simulation, the most viable remedy would be the choice of the best-performing FM. In such case, simple exponential would clearly be the proper choice.

CONCLUSION

The study investigates the effects of three different FMs, namely simple exponential method, Holt's exponential smoothing method and Brown's double exponential smoothing method in a linear SC of one retailer, one wholesaler, one distributor, and one producer. SC was tested both using the "shock lens" and "variance lens" perspective with various methods used to analyze the data afterward.

Employing the "shock lens" perspective, results as to which FM is superior were unequivocal. SE method outperformed the other two FMs. Especially, since the BWE is further amplified as one moves upstream, the peak differences (used as a BWE measure) were more than double in the most upstream echelon (producer). Furthermore, Holt's and Brown's FMs caused severe fluctuations in the demand rate as opposed to the SE method, resulting in the SC requiring more time to reach equilibrium. In addition to the BWE measure being lowest for the SE method, average inventory size was also lowest for the SE method with the difference being particularly obvious in the producer echelon.

Under the "variance lens" perspective, 20 different real-world demand curves were tested. Average local inventory comparison and analysis suggest, there are some noticeable differences in the producer echelons among the tested FMs. SE method proves to be superior to other methods, with Holt's method outperforming Brown's. This implies that regardless of the FM, average inventory levels remain nearly identical (in a long-term scenario) in all but the producer echelon. As for the number of total stock-outs, numbers are significantly lower when using the SE method with stock-outs occurring only in the highest echelon. In comparison, both under Holt's and Brown's methods, stock-outs begin to occur in the distributor echelon and their numbers noticeably increase in the highest echelon. Looking at the BWE, the average BWE for the retailer was the lowest using Holt's method. In all other echelons, the SE method was the FM providing the lowest BWE measures. Clearly outperforming other FMs as in the local average inventory and stock-outs.

These results imply that under the SRO system, SE FM provides better results when it comes to minimizing the size of the average local inventory, minimizing the number of stock-outs, or minimizing the BWE, with the differences being more noticeable as one moves upstream. Furthermore, should the CD ISR system be introduced in the SC, all the followed markers could be further lowered, including the costs related to maintaining the local inventory. Conversely, it is important to remember the high costs related to the implementation of the CD sharing system as mentioned by Hussain, & Saber (2012).

Since the study examined linear SC, future studies could examine how FMs used in this study behave under more complex structures, like convergent or divergent, or further compare SE method to other, more complex FMs. Another aspect worth examining would be employing different ordering systems, as there are many different ones that are being used.

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APPENDICES

TABLE A1
AVERAGE LOCAL INVENTORY – EXPERIMENT RESULTS

	forecast	average local inventory			
		retailer	wholesaler	distributor	producer
1	SE	254.21	251.30	246.83	240.83
	Holt's	251.66	245.34	233.48	249.59
	Brown's	253.69	248.71	241.32	230.34
2	SE	146.09	144.12	141.10	139.57
	Holt's	144.83	143.16	139.47	139.90
	Brown's	144.95	142.42	137.74	168.12
3	SE	73.37	72.19	71.71	80.34
	Holt's	72.27	72.36	71.88	81.42
	Brown's	72.80	71.45	75.16	150.65
4	SE	442.16	436.53	432.57	529.29
	Holt's	436.96	430.21	446.53	738.56
	Brown's	436.78	429.73	454.72	794.85
5	SE	79.17	76.67	74.03	71.39
	Holt's	77.84	76.39	72.66	69.44
	Brown's	74.82	71.37	67.63	71.49
6	SE	3,113.49	3,111.06	3,105.74	3,101.41
	Holt's	3,113.74	3,104.58	3,090.86	3,074.46
	Brown's	3,112.95	3,103.81	3,089.97	3,072.92
7	SE	2,420.66	2,483.00	2,543.30	2,599.22
	Holt's	2,468.14	2,531.82	2,595.73	2,657.57
	Brown's	2,468.14	2,531.80	2,595.69	2,657.67
8	SE	908.62	929.65	949.09	966.10
	Holt's	929.01	952.92	972.09	987.83
	Brown's	929.83	951.69	963.68	1,016.19
9	SE	139.86	144.38	149.37	159.25
	Holt's	142.11	146.79	151.58	162.00
	Brown's	142.52	147.34	149.57	197.96
10	SE	3,909.63	3,783.05	3,950.51	4,575.03
	Holt's	3,840.70	3,728.24	4,106.53	4,627.77
	Brown's	3,840.78	3,737.73	4,116.13	4,743.57
11	SE	1,331.39	1,374.52	1,406.74	1,447.53
	Holt's	1,361.95	1,398.95	1,423.08	1,463.21
	Brown's	1,361.18	1,397.98	1,420.58	1,466.30
12	SE	930.02	962.22	995.85	1,029.80
	Holt's	949.78	983.67	1,019.86	1,058.60
	Brown's	951.42	986.17	1,025.32	1,072.19
13	SE	232.76	235.58	236.61	239.68
	Holt's	230.76	238.40	238.62	243.08
	Brown's	233.60	238.08	240.43	251.80

	forecast	average local inventory			
		retailer	wholesaler	distributor	producer
14	SE	282.72	293.05	301.43	325.19
	Holt's	289.24	305.46	322.04	356.33
	Brown's	291.50	308.17	326.93	362.51
15	SE	305.24	283.25	261.93	257.31
	Holt's	280.34	257.58	236.02	265.19
	Brown's	280.39	257.85	235.04	257.87
16	SE	10,012.49	10,373.33	10,781.69	11,248.26
	Holt's	10,297.78	10,720.06	11,218.81	11,796.67
	Brown's	10,285.17	10,700.22	11,190.44	11,773.98
17	SE	182.12	184.87	188.14	191.94
	Holt's	189.10	193.03	197.28	203.66
	Brown's	187.60	191.86	196.75	201.76
18	SE	313.68	311.29	308.41	309.95
	Holt's	311.89	309.03	305.54	320.35
	Brown's	311.82	308.92	305.08	325.60
19	SE	638.26	621.10	602.41	582.96
	Holt's	629.98	611.55	591.86	571.40
	Brown's	629.53	611.31	591.68	583.87
20	SE	246.13	246.72	247.71	248.85
	Holt's	246.43	247.26	246.21	246.38
	Brown's	246.37	247.41	248.46	248.29

TABLE A2
STOCK-OUTS – EXPERIMENTS RESULTS

	forecast	Stock-outs			
		retailer	retailer	retailer	retailer
1	SE	0	0	0	0
	Holt's	0	0	0	5
	Brown's	0	0	0	0
2	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	3
3	SE	0	0	0	2
	Holt's	0	0	0	3
	Brown's	0	0	0	1
4	SE	0	0	0	2
	Holt's	0	0	1	1
	Brown's	0	0	1	1
5	SE	0	0	0	0
	Holt's	0	0	0	2
	Brown's	0	0	4	7
6	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0

	forecast	Stock-outs			
		retailer	retailer	retailer	retailer
7	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
8	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	3
9	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	2
10	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
11	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
12	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
13	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
14	SE	0	0	0	1
	Holt's	0	0	0	4
	Brown's	0	0	0	4
15	SE	0	0	0	2
	Holt's	0	0	7	8
	Brown's	0	0	5	8
16	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
17	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
18	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
19	SE	0	0	0	0
	Holt's	0	0	0	0
	Brown's	0	0	0	0
20	SE	0	0	0	0
	Holt's	0	0	0	2
	Brown's	0	0	0	0

TABLE 3
BWE – EXPERIMENT RESULTS

	forecast	BWE			
		retailer	retailer	retailer	retailer
1	SE	1.42	1.43	1.57	1.92
	Holt's	1.34	1.33	1.81	4.01
	Brown's	1.37	1.33	1.34	1.58
2	SE	1.41	2.35	3.64	4.29
	Holt's	1.42	2.42	3.81	4.44
	Brown's	1.40	3.00	5.58	4.96
3	SE	1.78	2.72	3.72	3.84
	Holt's	1.79	2.75	3.73	3.82
	Brown's	2.00	4.14	5.44	4.24
4	SE	1.59	2.03	2.80	2.56
	Holt's	1.67	2.50	3.54	2.48
	Brown's	1.68	2.61	3.65	2.55
5	SE	1.06	1.06	1.16	1.52
	Holt's	1.05	1.06	1.19	1.64
	Brown's	1.03	1.08	1.43	2.16
6	SE	3.63	4.28	4.70	4.95
	Holt's	2.51	4.06	5.64	6.25
	Brown's	2.48	4.32	6.13	6.70
7	SE	1.06	1.14	1.43	2.28
	Holt's	1.03	1.07	1.24	1.91
	Brown's	1.03	1.07	1.24	1.89
8	SE	1.34	1.50	1.95	2.82
	Holt's	1.35	1.50	1.93	2.82
	Brown's	1.35	1.59	2.54	4.44
9	SE	1.20	1.41	2.26	3.54
	Holt's	1.20	1.40	2.23	3.58
	Brown's	1.20	1.64	3.74	4.45
10	SE	1.34	1.38	1.40	1.41
	Holt's	1.32	1.41	1.44	1.64
	Brown's	1.32	1.42	1.48	1.79
11	SE	0.82	1.34	2.92	4.45
	Holt's	0.79	1.26	3.06	5.00
	Brown's	0.78	1.29	3.26	5.31
12	SE	1.09	1.11	1.28	2.00
	Holt's	1.09	1.10	1.26	2.07
	Brown's	1.08	1.10	1.42	3.00
13	SE	1.35	1.67	2.21	2.82
	Holt's	1.32	1.68	2.21	2.76
	Brown's	1.31	1.76	2.38	2.91
14	SE	1.17	1.17	1.30	1.79
	Holt's	1.15	1.11	1.17	1.60
	Brown's	1.13	1.09	1.13	1.53

	forecast	BWE			
		retailer	retailer	retailer	retailer
15	SE	1.00	1.04	1.20	1.49
	Holt's	0.97	0.99	1.13	1.35
	Brown's	0.97	0.99	1.12	1.33
16	SE	1.12	1.15	1.30	1.78
	Holt's	1.11	1.15	1.40	2.41
	Brown's	1.11	1.14	1.34	2.03
17	SE	1.14	1.14	1.16	1.23
	Holt's	1.08	1.08	1.33	3.31
	Brown's	1.12	1.12	1.14	1.28
18	SE	1.34	1.80	2.66	3.21
	Holt's	1.33	2.02	3.37	3.53
	Brown's	1.32	2.08	3.62	3.69
19	SE	1.09	1.14	1.50	2.86
	Holt's	1.09	1.17	1.72	3.61
	Brown's	1.09	1.22	2.13	4.76
20	SE	1.39	1.52	1.85	2.53
	Holt's	1.33	1.63	2.83	5.14
	Brown's	1.35	1.58	2.37	3.87