Bullwhip Effect Prediction in a Single Echelon Supply Chain Using Regression Analysis

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***Abstract*—One of the main problems in supply chain systems is the bullwhip effect that can generate a huge cost for the companies in a chain. In this study, the factors and their impacts that can cause the bullwhip effect (order variance and net stock amplification) are investigated by using a simulation-based optimization approach. The proposed meta-prediction model is built using regression analysis, to predict the Total Stage Variance Ratio (TSVR) of the system. A single-echelon supply chain with uncertain customer demand operating under the periodic-review reorder cycle policy is studied. The parameters of the smoothing inventory replenishment and forecasting methods are required to search for their optimality in reducing the TSVR by OptQuest, an optimization tool in ARENA simulation software. Our results can assistdecision makers in the management of a supply chain, to realize, benchmark, and reduce the TSVR under an uncertain environment.**

***Index Terms*—Bullwhip Effect, Exponential Smoothing, Simulation-based Optimization, Meta-prediction Model, Regression Analysis**

I. Introduction

A supply chain is a combined system or networking for suppliers, manufactures, and retailers that is used until the products are in the hands of end customers. It aims to distribute the right product, at the right quantity and quality, at the right time to get the lowest cost [1]. A well-managed supply chain can play a large role in companies' logistics operations and the properties of the members in a chain. High attention must be paid in the logistics processes since better logistics processes could bring about better customer services [2]. However, the bullwhip effect can happen in a supply chain when orders, delivered to the manufacturers or suppliers, generate larger variance than the sales to the end customers. This order variance amplification is known as the bullwhip effect.

Inventory replenishment is a logistics process to transport the inventory from an upstream echelon to a downstream echelon. There are two types of inventory replenishment of interest: the reorder level policy and the reorder cycle policy. The difference is when and how many order quantities can satisfy the customer demand. The reorder level policy orders when the inventory level shrinks to the minimum reorder level point and the order quantity is set to be equal to the Economic Order Quantity (EOQ) (every time). In contrast, the reorder cycle policy defines a pre-determined "reorder cycle period". The difference between the on-hand stock at the review period and the maximum target stock level can be determined as the actual order quantity.

This study focuses on the replenishment by the Reorder Cycle Policy (ROC). With the ROC policy, the system is tracking the inventory position. The inventory position is reviewed periodically (daily, weekly, or monthly) and the order is fulfilled to the inventory position, up to the target stock level that determines order quantities [3]. When calculating the target stock level, the variation of the expected customer demand from the forecasting method is a key parameter, to control the variance in the supply chain system. Both the demand forecasting method and inventory replenishment policies are shown to contribute to the order variance and net stock variance problems.

Traditionally, the performance in a supply chain is evaluated by the order variance and the inventory variance. More researchers have studied the order variance ratio as the performance measure than the inventory variance ratio but our study combines both of them into one objective function called the "Total Stage Variance Ratio" (TSVR). Similarly, the studies of Wang and Shalaby [4] and Costantino et al. [5] also used the TSVRs to determine the overall performance of a supply chain. The order variance ratio increases the cost at the upstream echelon while the inventory variance ratio increases the holding and shortage costs. Hence, it is worthwhile to determine the TSVR, considering both factors as equally important at each echelon [6]. By minimizing the TSVR, the overall performance is improved in a supply chain.

In this study, the simulation-based optimization model is run to minimize the TSVR by OptQuest so that all smoothing parameters of the replenishment inventory policy and the forecasting method are searched for their optimal settings. Based on the results, the meta-prediction model can be used to determine the best level of the TSVR for a single-echelon chain under the ROC policy with the exponential smoothing forecasting technique under fluctuating lead time and end-customer demand. The major contribution of this study is to assist decision makers in predicting and realizing the amount of the bullwhip effect. They can then prepare and benchmark their supply chain system's performance to our optimal results, obtained from the meta-prediction model. The ordering quantity in each review period is searched for its optimality by adjusting two proportional controllers. Thus, a proper alleviation plan to reduce such effects can be made.

II. Literature Review

Only relevant research that is related to the bullwhip effect and inventory amplification problems are reviewed in this section

A. Bullwhip effect

The bullwhip effect has been measured by several models such as the statistical model [7], and [8], control theoretical model [3], [9], and [10], and simulation model [8], [11], and [12]. Chen et al. [7] studied the bullwhip effect of a two-stage supply chain using the statistical model. They considered only a retailer and a manufacturer. Their model applied two main factors (forecasting and lead time) to create the bullwhip effect. They concluded that the centralizing demand information can reduce the bullwhip effect but it cannot be eliminated.

B. Inventory Replenishment

Inventory replenishment policies are one of the major foundations of the bullwhip effect, in terms of variance amplification of stocking inventory in a supply chain. A majority of researchers in inventory replenishment have used the Reorder Cycle (ROC) policy [3]. The quantity to order in the ROC policy updates in every review period to fulfill inventories between the target stock level and inventory on hand. Disney and Lambrecht [6] explored variance amplification based on the ROC policy using different forecasting methods, including various operational conditions.

Dejonckheere et al. [9] also identified the smoothing replenishment of the reorder cycle policy by adding proportional controllers to the net stock term and the WIP term to satisfy the demand changes. This smoothing replenishment also decreases the bullwhip effect in the studies of [12], [13], and [14].

B. Demand forecasting methods

Demand forecasting is another factor causing the bullwhip effect [15] and [16]. Lee et al. [17] showed that both forecasting techniques (i.e., moving average and exponential smoothing method) always create demand variance amplification (bullwhip effect). An appropriate forecasting method can help reduce the bullwhip effect by minimizing the mean-square-error [15] and [18].

C. Simulation-based optimizations

Optimization is defined as the process of searching for the conditions that give the optimal value of a function, where the function indicates the efforts in that situation or environment. It is the act of gathering the best result under particular circumstances. There are two kinds of optimization algorithms to solve optimization problems: (1) the simplex algorithm that is usually used for the linear programming model, and (2) simulation based-optimization with heuristic algorithms, which is used to solve the problems in a reasonable time and where the problems are too complex (containing uncertainty or are too big to handle with the mathematical model as in the case of our studied model). Mazzuco et al. [19] applied simulation-based optimization with Simulated Annealing (SA) to the Vehicle Routing Problem (VRP) to find the optimal path that gives the minimum cost and delivery time. In their study, the OptQuest optimization tool was used to find the optimal parameter settings in a single-echelon supply chain model.

OptQuest is a powerful heuristic algorithm that is used in simulations. The OptQuest algorithm combines three metaheuristics, including scatter search, tabu search, and a neural network [20], and [21]. Bulut [22] used scatter search with OptQuest to solve the multi-scenario optimization problem on a large scale with the linear programming model.

III. Modeling Methodology

A. Supply chain model

The supply chain model in this study considers a single-echelon chain with the amount of end-customer demand following the normal distribution. A generalized periodic review with the Reorder Cycle (ROC) Policy inventory replenishment is used with two smoothing controllers under the exponential smoothing forecasting method. In practice, this is a case of a small supply chain where the retailers normally have higher bargaining power over the manufacturers due to the fact that they are closer to the end customers. As a result, they can control manufacturers' operations and be assured the availability of their supplies.

1) Single-echelon supply chain model

The retailer forecasts the expected demand and updates the target stock level in each period. Then, the retailer receives ordered products from the upstream echelon (i.e., manufacturer or supplier), and the actual demand (D_1) is monitored and satisfied. Next, the retailer monitors and updates its stock (inventory position) and finally places an order (O_t) to the upstream echelon at the end of each review period. The number of orders is determined, to fill back to the Replenishment ROC level (Target stock level). A single echelon supply chain model is considered with only one retailer and one manufacturer. It is assumed that the manufacturer can assure and distribute unlimited ordered quantities as addressed by the retailer. This single echelon model is shown in Fig. 1.

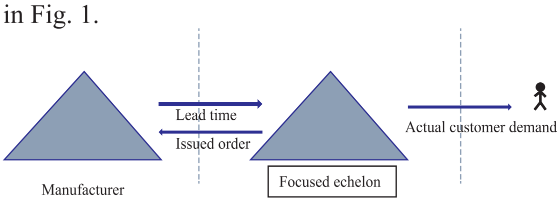

Fig. 1. Single-echelon supply chain model

2) Reorder Cycle policy (ROC)

The classical ROC policy can operate as follows. At the end of each Review period (R), an Order(O_t) is issued to the upstream echelon if the amount of the Inventory Position (IP_t) is less than the target stock level (S_t). The inventory position is reviewed at the end of every period, and an order is placed to raise the inventory position to the target stock level. The Inventory Position (IP_t) is equal to the stock-on-hand plus the inventory on order, minus the amount of the backlog (Net stock + inventory on order). The target stock level (S_t) is determined by (1).

$$S_t = (L_d + R + K)(\widehat{D}_t) \quad (1)$$

where
t = Time period
S_t = Target stock level
L_d = Lead time
R = Review period
K = Safety stock parameter
$\widehat{D}_t$ = Expected demand in period t

According to [9], the classical ROC policy with exponential smoothing or moving average always generates the bullwhip effect for any demand process. Therefore, as the process of demand is Independent and Identically Distributed (I.I.D), the best possible forecast process is the simple average of all previous demands. As a result, the order quantity can be written as (2).

$$O_t = Max\{(S_t - IP_t), 0\} \quad (2)$$

where
O_t = Order quantity in period t
IP_t = Inventory position in period t

From Equation (2), the inventory position is equal to the Net Stock (NS_t) plus the inventory on order (WIP_t). The net stock is equal to the difference between the Stock-On-Hand (SOH_t) and the backlog as shown in (3).

$$NS_t = SOH_t - Backlog_t \quad (3)$$

where
NS_t = Net stock in period t
SOH_t = Amount of stock on-hand in period t after clearing the backlog from period t (if any)
$Backlog_t$ = Amount of backlog in period t as SOH_t equal to 0

$$O_t = \widehat{D}_t(L_d + R) + K\widehat{D}_t - (NS_t + WIP_t) \quad (4)$$

$$O_t = R\widehat{D}_t + [L_d\widehat{D}_t - WIP_t] + [K\widehat{D}_t - NS_t] \quad (5)$$

In Equation (4), the order quatntity in each cycle is equal to the gap between the target stock level of that cycle minus the inventory position in that cycle. Equations (4) and (5) can be rearranged into three terms, which are the forecast term, the inventory discrepancy term, and the WIP discrepancy term. Therefore, the smoothing replenishment rule is applied to the order policies, in which the whole shortfall between the target stock level (S_t) and the available inventory may not be regained in each review period. As a result, only a fraction of the NS discrepancy and WIP discrepancy in each period is recovered. To implement smoothing replenishment patterns and adjust the amount of the gaps, an appropriate weight (T_n and T_w) is given to the gap term, as shown in (6)

$$O_t = R\widehat{D}_t + [L_d\widehat{D}_t - WIP_t]/T_w + [K\widehat{D}_t - NS_t]/T_n \quad (6)$$

where
WIP_t = Work in process in period t
T_w = Proportional controller for work in process discrepancy
T_n = Proportional controller for net stock

In Equation (6), two decision variables, T_w and T_n, are added as proportional controllers. This allows us to alter the dynamic behavior of the supply chain and decide the optimal ordering quantity in each period. These decision variables are used as simple amplifiers and are the most common controllers in control systems. By changing both of the proportional controllers, a set of ordering patterns, ranging from order variance amplification (bullwhip) to dampening (smoothing), are created.

B. Forecasting method

The forecasting method is introduced to calculate the expected demand for the next period at the end of each period. In this study, as the end-customer demand has no seasonality and trend (normally distributed), Exponential Smoothing (*ES*) is used to forecast the expected demand.

Exponential Smoothing method (ES)

As ES can only be used to make a one-period ahead forecast, Equation (7) shows the calculation of expected demand.

$$\widehat{D}_t = \alpha D_{t-1} + (1+\alpha)\widehat{D}_{t-1} \quad (7)$$

where

$\widehat{D}_t$ = Expected demand in period t

$\widehat{D}_t$ = Real demand in period t

α = Smoothing parameter

From Equation (7), α represents a parameter for ES that gives the weight between the recent demand observation (D_{t-1}) and historical forecasted demand ($\widehat{D}_{t-1}$).

C. Performance measure: Total Stage Variance Ratio (TSVR)

The efficiency of a supply chain can be measured by comparing the Total Stage Variance Ratio (TSVR) that can be calculated by the sum of the Order Variance Ratio (OVR) and Net Stock Amplification (NSA) [6], and [23]. This method assumes that the holding inventory cost is linearly close to the NSA and the production cost from inconsistent schedules is related to the OVR. It is also assumed that the costs of the OVR and NSA are equal so that the objective function minimizes the TSVR as shown in (8). Equations (9) and (10) represent the ratios of the order rate variance and net stock variance to the demand variance.

TSVR = OVR + NSA (8)

OVR = Order rate variance/Demand variance (9)

NSA = Net stock variance/Demand variance (10)

D. Simulation-based optimization with OptQuest

In this study, the ARENA simulation program is used to simulate the supply chain network. ARENA has an optimization tool called 'OptQuest'. The objective function minimizes the TSVR under various factors that might create the bullwhip effect and net stock amplification.

Simulation model

The initial net stock (period 0) is assumed to be equal to the Target Stock Level (S_0) to avoid any backlog during the initial state. In every period, the process starts by (1) picking up the required items from stock following the actual end-customer demand when the amount of stock is higher than the amount of demand. However, if the amount of stock is less than the amount of demand, all stock is picked up and any demand shortage is considered to be a backlog, (2) a demand ($\widehat{D}_t$) is forecasted based on the used forecasting method and the target stock level (St) is updated, (3) the order quantity (O_t) is then calculated. If the net stock is less than the target stock level, the order is issued to the upstream echelon. Flowcharts of these supply chain operations are presented in Fig. 2 and Fig. 3.

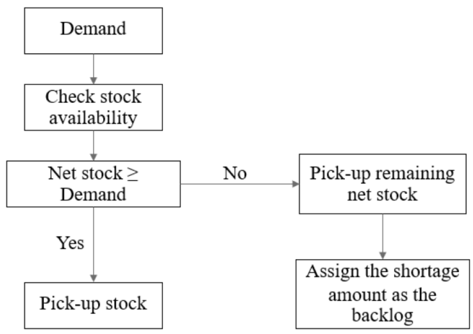

Fig. 2. Customer buying processes

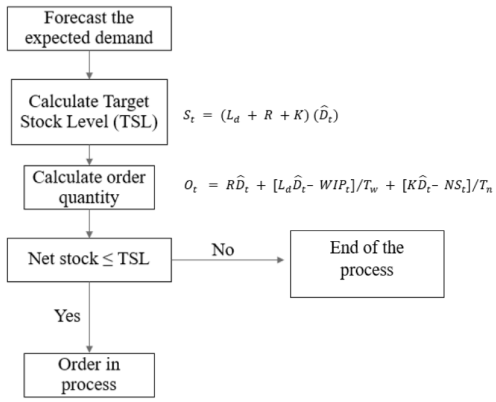

Fig. 3. Retailer ordering processes

E. Experimental condition

All experimental models are simulated and optimized with one decision variable, which is a smoothing decision variable of the forecasting methods. Then, two more decision variables from the order replenishment policy, which are T_n and T_w (proportional controllers), are added to the model to smooth the replenishment pattern and reduce the bullwhip effect. Operating parameters of the base case model are imposed with a Review period (R)= 1 period, Lead time (L_d)= 2 periods, and Safety stock (K) =1. The actual customer demand is assumed to follow the normal distribution with a mean of 50 units and a standard deviation of 5 units.

The simulation model is run under the terminating condition for 10 replications with a replication length of 5,000 periods and a warm-up period of 1,000 periods. Based on the supply chain model with exponential smoothing, various levels of controllable variable values (T_n, T_w and α) were used to find the steady-state conditions. The plot in Fig. 4 of these responses with three levels of the TSVR shows a warm-up period of 1,000 periods. With 10 replications, results can be obtained to guarantee the variation of the TSVR to be less than 3% of its mean.

IV. Analysis of the Results

Our experiment is divided into 3 studies. The first study finds the significance of our factors of interest. Then, the second study explains the effects of varying each significant factor in relation to the base case model (i.e., Review period (R)= 1 period, Safety stock (K)= 1, and Lead time (L_d)= 2 periods). Finally, the third study builds a meta-prediction model to predict the bullwhip effect (including order variance and stock amplification (TSVR)) of a single-echelon supply chain under lead time and customer demand uncertainties.

A. *First experiment: Full factorial design*

The experiment uses the full factorial design to incorporate the four factors of interest (i.e., lead-time duration, lead-time variation, customer demand variation, and safety stock) that might generate the bullwhip effect in the chain. The full factorial design uses 16 runs from 2^4 (each factor has two levels), with and without the two proportional controllers for the replenishment rule, as shown in Table I. These two levels of each factor cover the lower and upper limits and set the bounds of the experiment. Results of ANOVA are shown in Fig. 5 to Fig. 7 presents a Pareto chart of the TSVR with two proportional controllers.

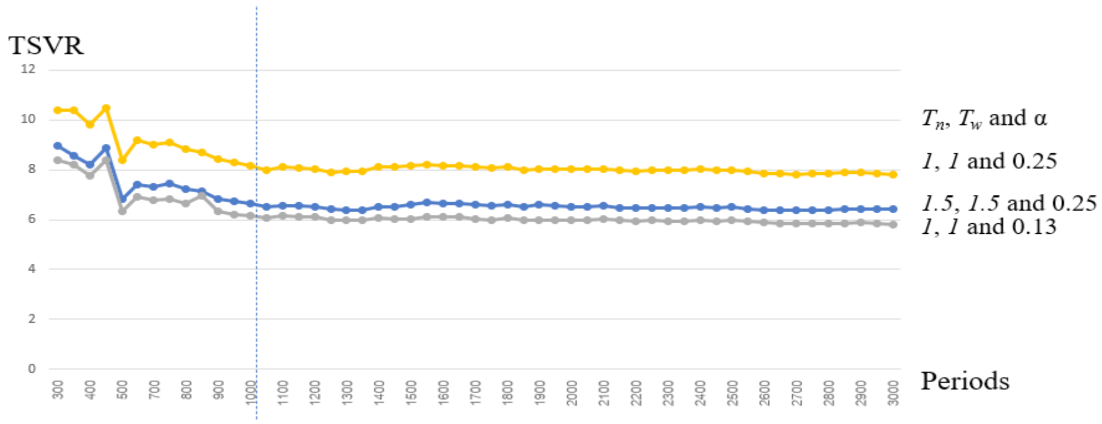

Fig. 4. Steady-state behavior of the TSVR

TABLE I
FULL FACTORIAL DESIGN OF FOUR FACTORS

Demand Variatio^{n}1	Lead time (period)	Lead-time Variation^2	Safety stock	TSVR^3 without proportional controllers	TSVR^3 with two proportional controllers
0.1	2	0	1	3.08	2.65
0.1	2	0.5	1	169.28	70.60
0.1	4	0	1	5.40	5.00
0.1	4	0.5	1	332.14	151.53
0.3	2	0	1	3.10	2.74
0.3	2	0.5	1	21.62	11.14
0.3	4	0	1	5.39	5.05
0.3	4	0.5	1	42.13	21.72
0.1	2	0	4	3.08	2.70
0.1	2	0.5	4	172.00	57.86
0.1	4	0	4	5.48	4.83
0.1	4	0.5	4	379.08	113.42
0.3	2	0	4	3.04	2.65
0.3	2	0.5	4	21.58	9.29
0.3	4	0	4	5.12	4.73
0.3	4	0.5	4	47.53	18.10

Remarks: 1. Demand variation = Standard deviation of demand/mean of demand
2. Lead-time variation = Standard deviation of lead time/mean of lead time
3. TSVR = Average TSVR from 10 replications

Analysis of Variance (without two proportional controllers)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	15	2,205,957	147,064	530.02	0.000
Demand V	1	0	0	0.00	0.999
Lead time	1	5	5	0.02	0.889
Lead time V	1	74	74	0.27	0.607
Safety stock	1	0	0	0.00	0.994
Demand V*Lead time	1	0	0	0.00	0.996
Demand V*Lead time V	1	32	32	0.12	0.73
Demand V*Safety stock	1	0	0	0.00	0.992
Lead time*Lead time V	1	25,612	25,612	92.31	0.000
Lead time*Safety stock	1	0	0	0.00	0.989
Lead time V*Safety stock	1	190	190	0.68	0.409
Demand V*Lead time*Lead time V	1	12,194	12,194	43.95	0.000
Demand V*Lead time*Safety stock	1	0	0	0.00	0.985
Demand V*Lead time V*Safety stock	1	71	71	0.26	0.613
Lead time*Lead time V*Safety stock	1	616	616	2.22	0.138
Demand V*Lead time*Lead time V*Safety stock	1	242	242	0.87	0.352
Error	144	39,956	277		
Total	159	2,245,912			

Model Summary

S	R-sq	R-sq (adj)	R-sq (pred)
16.6574	98.22%	98.04%	97.85%

Demand V = End-customer demand variation
Lead time V = Lead-time variation
Lead time = Lead-time duration variation
Safety stock = Safety stock level

Fig. 5. Analysis of variance (without two proportional controllers)

Analysis of Variance (with two proportional controllers)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	15	306,525	2,0435.0	7,835.22	0.000
Demand V	1	0	0.0	0.01	0.933
lead time	1	6	6.4	2.45	0.120
lead time V	1	104	104.3	39.99	0.000
safety stock	1	0	0.1	0.02	0.887
Demand V*lead time	1	0	0.0	0.00	0.974
Demand V*lead time V	1	59	59.0	22.62	0.000
Demand V*safety stock	1	0	0.0	0.00	0.948
lead time*lead time V	1	8,409	8,409.2	3,224.26	0.00
lead time*safety stock	1	0	0.1	0.02	0.886
lead time V*safety stock	1	69	69.3	26.58	0.000
Demand V*lead time*lead time V	1	4,043	4043.1	1,550.21	0.000
Demand V*lead time*safety stock	1	0	0.0	0.00	0.999
Demand V*lead time V*safety stock	1	39	39.4	15.11	0.000
lead time*lead time V*safety stock	1	682	682.0	261.49	0.000
Demand V*lead time*lead time V*safety stock	1	348	347.9	133.38	0.000
Error	144	376	2.6		
Total	159	306,901			

Model Summary

S	R-sq	R-sq (adj)	R-sq (pred)
1.61496	99.88%	99.86%	99.85%

Demand V = End-customer demand variation
Lead time V = Lead-time variation
Lead time = Lead-time duration variation
Safety stock = Safety stock level

Fig. 6. Analysis of variance (with two proportional controllers)

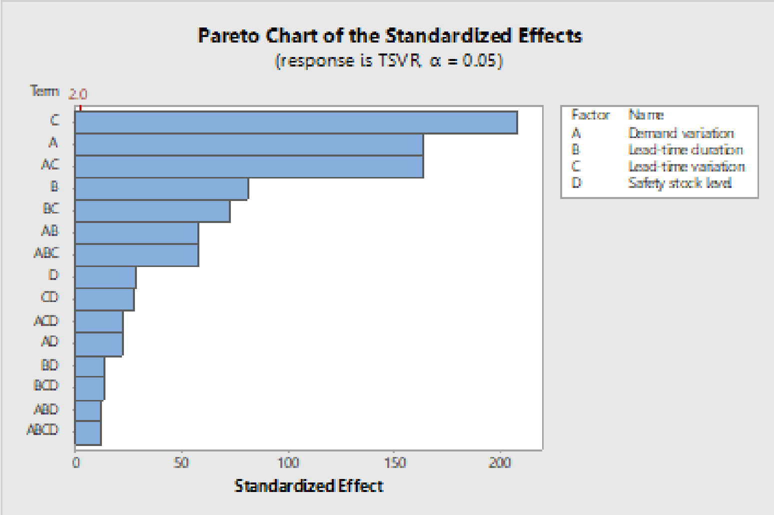

Fig. 7. Full factorial analysis under the 95% confidence level

According to Fig. 5 to 7, all main factors have a significant effect on the TSVR under the 95% confidence level, judging from the p-value. In addition, it is found that the lead-time variation has the most significant effect on the TSVR. Even though some main factors do not have a significant effect on the TSVR, their interactions have a significant effect. As a result, all factors of interest have a significant effect on the TSVR. Two proportional controllers for the replenishment rule are used to decide the best ordering quantity in each period. This significantly helps to reduce the effects of order variance and net stock amplification (see Table I for comparison). This allows us to alter the dynamic behavior of the supply chain and decide the optimal ordering quantity in each period.

B. Second experiment: Explanation of the effects of varying each significant factor

1) Base case model

The base case model is simulated under the ROC policy with the exponential smoothing forecasting method. There are three operating parameters in the base case model (i.e., Review period (R)= 1 period, Safety stock(K)= 1, and Lead time (L_d)=2 periods). Also, there are three smoothing decision variables to be optimized in the model; T_n, T_w and α. The results from the simulation-based optimization with OptQuest for the base case model are shown in Table II.

TABLE II
RESULTS OF THE BASE CASE MODEL

Reorder cycle policy					
Exponential smoothing with the end-customer demand = Norm (50,5) units					
T_n	*Tw*	*A*	*OVR*	*NSA*	*TSVR*
1.64	1.65	0	0.432	2.211	2.645

According to Table II, the optimal value of α obtained from OptQuest is 0, meaning that the demand forecast is similar to the long-term average of the customer demand. Furthermore, the demand forecast is found to be constant in every period. Shaban and Shalaby [1] also reported an α value of 0 in their experiment under the same customer demand pattern with the normal distribution. They concluded that the demand forecast should be constant in every review period regardless of the variation of end-customer demand, providing that there are no seasonality and trend effects in the demand pattern. The Total Stage Variance Ratio (TSVR) of the base case model is equal to 2.645, which shows a high level of the bullwhip effect. In addition, the net stock amplification appears to cause more variance amplification than the order variance. This is because the order variance has T_w and T_n as proportional controllers, to alter the dynamic behavior as stated earlier.

2) Lead-time duration variation

In this experiment, the lead-time duration (L_d) is varied from 1, 2, 3, to 4 periods while other parameters are fixed. This is similar to the base case model at the R = 1 period, and K = 1 under the reorder cycle policy with the exponential smoothing forecasting method.

TABLE III
LEAD-TIME DURATION VARIATION

Reorder cycle policy						
Exponential smoothing with the end-customer demand = Norm (50,5) units						
Lead times	T_n	T_w	*α*	*OVR*	*NSA*	*TSVR*
1	1.59	1.61	0	0.484	1.227	1.711
2	1.64	1.65	0	0.432	2.211	2.645
3	1.49	1.49	0	0.507	3.148	3.656
4	1.63	1.64	0	0.520	4.483	5.003

Tukey Pairwise Comparisons

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Grouping Information Using the Tukey Method and 95% Confidence

Factor   N     Mean  Grouping
SD 20   10  2.91378  A
SD 15   10  2.73422    B
SD 10   10  2.64578      C
SD 5    10  2.63676      C

Means that do not share a letter are significantly different.
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Fig. 8. Lead-time duration variation using the Tukey comparison test under the 95% confidence level

The results from the simulation-based optimization with OptQuest in each level of lead-time duration are shown in Table III. The lead time has an impact on the TSVR since there is a significant difference among the four different levels of the lead time under the 95% confidence level using the Tukey comparison test as shown in Fig. 8. When the lead-time duration is longer, the TSVR is also higher, mainly caused by the net stock amplification. While increasing the lead-time duration, a higher variance is mainly caused by the net stock term. After increasing the lead time, the net stock amplification becomes higher as a result of the end-customer demand fluctuation. The Order Variance Ratio (OVR) is stable throughout all levels of the lead time since the number of orders in each cycle is stable under the same pattern of end-customer demand due to the smoothing replenishment with two proportional controllers.

3) Lead-time variation

In this experiment, the lead-time duration (L_d) follows the normal distribution with the mean varying from 1 to 3 periods. The standard deviation at each mean level is varied into 2 levels (i.e., 50 and 100 percent of its mean) while other parameters are fixed at R = 1 period, and K = 1, similar to the base case model under the recycle order policy with the exponential smoothing forecasting method. Tables IV and V show the results from simulation-based optimization with OptQuest with lead-time variation.

The results from Tables IV and V show that the lead-time variation causes a huge TSVR in the supply chain system. The variance comes from the amplification of the net stock rather than the order variance due to the severe stock shortage and backlog. As the lead-time variation increases, the TSL (calculated from equation (1)) also varies and fluctuates in each period, causing a huge amplification in the net stock.

TABLE IV
LEAD-TIME VARIATION WITH STANDARD DEVIATION EQUAL TO 50% OF ITS MEAN

Reorder cycle policy						
Exponential smoothing with the end-customer demand = Norm (50,5) units						
Lead time (period)	T_n	*Tw*	*α*	***OVR***	***NSA***	***TSVR***
norm (1,0.5)	5.91	3.70	0.01	3.58	26.79	30.37
norm (2,1)	5.30	4.83	0.01	7.49	63.17	70.67
norm (3,1.5)	12.38	7.66	0.00	10.13	99.62	109.75

TABLE V
LEAD-TIME VARIATION WITH STANDARD DEVIATION EQUAL TO 100% OF ITS MEAN

Reorder cycle policy						
Exponential smoothing with the end-customer demand = Norm (50,5) units						
Lead time (period)	T_n	*Tw*	*α*	***OVR***	***NSA***	***TSVR***
norm (1,1)	9.01	4.26	0	9.01	55.41	64.42
norm (2,2)	7.83	7.38	0	16.70	116.71	133.41
norm (3,3)	748.1	10.72	0	21.99	175.92	198.01

4) End-customer demand variation

In this experiment, the end-customer demand follows the normal distribution with the mean fixed at 50 units but the standard deviation is varied with 4 levels (i.e., 10%, 20%, 30% and 40% of the mean). Other parameters are set similar to the base case model where the Review period (R) = 1 period, Safety stock (k) = 1, and Lead time (L_d) = 2 periods under the exponential smoothing forecasting method with the reorder cycle policy. The obtained optimal values of the TSVR from OptQuest of the four levels of standard deviation are shown in Table VI.

TABLE VI
END-CUSTOMER DEMAND VARIATION

Reorder cycle policy						
Exponential smoothing with the end-customer demand = Norm (50,5) units						
S.D. of end-customer demand	T_n	T_w	α	*OVR*	*NSA*	*TSVR*
10% of the mean	1.64	1.65	0	0.43	2.21	2.64
20% of the mean	1.40	1.40	0	0.55	2.10	2.65
30% of the mean	1.67	1.67	0	0.44	2.29	2.73
40% of the mean	1.44	1.41	0	0.55	2.36	2.91

Fig. 9. Tukey comparison test of four levels of the end-customer demand following the normal distribution with the mean equal to 50 units under the 95% confidence level

From Table VI and Fig. 9, it was found that increasing the variation of the end-customer demand can cause a certain bullwhip effect, in terms of the TSVR. However, the severity is worsened with a higher level of the demand variation from its standard deviation of 30% or higher (as indicated by the Tukey comparison test). Most of the effect comes from the net stock as the order variance is stable despite increasing the demand variation.

5) Safety stock level

The main parameters from the base case model are fixed except the safety-stock (K), which is varied from K=1 to 4. The results from the simulation-based optimization with OptQuest while varying the value of K are shown in Table VII. The Tukey comparison test is presented in Fig. 10, showing that varying only the level of the safety stock does not have a significant effect on the TSVR. This result is in the same direction as the result obtained from the analysis of variance in the first experiment, in which the safety stock level alone does not have a significant effect on the TSVR. However, its interaction with the lead-time variation has a significant effect on the TSVR.

TABLE VII
SAFETY STOCK VARIATION

Reorder cycle policy						
Exponential smoothing with the end-customer demand = Norm (50,5) units						
Safety stock (*K*)	T_n	*Tw*	α	*OVR*	*NSA*	*TSVR*
1	1.64	1.65	0	0.432	2.211	2.645
2	1.48	1.48	0	0.507	2.134	2.641
3	1.47	1.47	0	0.515	2.136	2.652
4	1.46	1.46	0	0.525	2.132	2.657

Tukey Pairwise Comparisons

```
Grouping Information Using the Tukey Method and 95% Confidence

Factor   N    Mean  Grouping
K 4     10  2.6569  A
K 3     10  2.6518  A
K 2     10  2.6416  A
K 1     10  2.6456  A

Means that do not share a letter are significantly different.
```

Fig. 10. Tukey comparison test of the safety stock level under the 95% confidence level

C. Third experiment: Meta-prediction model

A meta-prediction model was designed to predict the performance (TSVR) under a single-echelon supply chain with the ROC policy using the exponential smoothing forecasting method with and without the proportional controllers. The main purpose of this study is to assess the impact of the factors of interest on the severity of the bullwhip effect, in terms of the Total Stage Variance Ratio (TSVR). The independent variables include the lead-time duration, the standard deviation of lead time, the standard deviation of customer demand, and the level of safety stock. From the ANOVA results (Fig. 5 and 6), a multiple regression model can be built based on these 4 independent factors.

The behavior of these independent variables has a statistically significant effect on the TSVR, except for some interaction terms. However, some 3-way or 4-way interaction terms covering all main factors have a significant effect on the TSVR judged by a *p*-value of less than 0.05. Both R^2 (Adjusted) of the model with and without the proportional controllers indicate that both regression models can explain the TSVRs. This was also guaranteed by the lack-of-fit test, in which there is not enough evidence to state that the model has a "lack of fit" since the *p*-value is greater than 0.05, meaning that the prediction model is significant. Subsequently, the regression equation can be obtained.

Regression equation without two proportional controllers (replenishment policy):

TSVR = 0.8 - 0.1 Demand variation + 1.13 Lead-time duration
+ 37.4 Lead-time variation - 0.06 Safety stock level
+ 0.2 Demand variation*Lead-time duration
- 110 Demand variation*Lead-time variation
+ 0.4 Demand variation*Safety stock level

+ 220.0 Lead-time duration*Lead-time variation
+ 0.04 Lead-time duration*Safety stock level
- 20.7 Lead-time variation*Safety stock level
- 678.8 Demand variation*Lead-time duration*Lead-time variation
- 0.24 Demand variation*Lead-time duration*Safety stock level
+ 56.6 Demand variation*Lead-time variation*Safety stock level
+ 11.71 Lead-time duration*Lead-time variation*Safety stock level
- 32.8 Demand variation*Lead-time duration*Lead-time variation*Safety stock level

Regression equation with two proportional controllers (replenishment policy):

TSVR = 0.1 + 0.9 Demand variation
+ 1.23 Lead-time duration
- 44.4 Lead-time variation
+ 0.12 Safety stock level
- 0.1 Demand variation*Lead-time duration
+ 149 Demand variation*Leadtime variation
- 0.2 Demand variation*Safety stock level
+ 126.0 Lead-time duration*Lead-time variation
- 0.04 Lead-time duration*Safety stock level
+ 12.4 Lead-time variation*Safety stock level
- 390.8 Demand variation*Lead-time duration*Lead-time variation
+ 0.00 Demand variation*Lead-time duration*Safety stock level
- 41.8 Demand variation*Lead-time variation*Safety stock level
- 12.31 Lead-time duration*Lead-time variation*Safety stock level
+ 39.3 Demand variation*Lead-time duration*Lead-time variation*Safety stock level

Measure of accuracy by Mean Absolute Percentage Error (MAPE)

The MAPE is used to indicate the accuracy of the meta-prediction model as shown in (11).

$$\text{MAPE} = \frac{\sum \frac{|Actual - predicted|}{Actual}}{n} \quad (11)$$

The MAPE is expressed in terms of a percentage value. It is used to compare the error between the actual outcome and the outcome from the meta-prediction model. The lower the MAPE value, the better the accuracy of the prediction model. Lewis [24] proposed that if the value of the MAPE is from 10 to 20%, the model generates a good prediction. If the value of the MAPE is from 20 to 50%, the model is considered to be a reasonable predicting model. However, if it is more than 50%, the model cannot be used to predict any results.

Tables VIII and IX report the results in terms of the accuracy of the prediction model. The results are compared between the actual TSVR from the simulation model and the estimated TSVR from the meta-prediction model. We use similar input data within the boundary of the problem (Lead time = 1 to 4 periods, Lead-time variation from 0 to 50 percent of its mean, Demand variability from 0 to 40 percent of its mean, Safety stock (K) = 1 to 4). The results for similar input data within the boundary of the problem with proportional controllers show that the average MAPE is 1.84%. However, the results for different input data (but within the boundary of the problem) are slightly higher at 3.65%. Both MAPE values from these two tests are less than 5%, meaning that the meta-prediction model from the regression analysis is sufficiently accurate to predict the TSVR under a single-echelon supply chain operating with the ROC policy.

TABLE VIII
MAPE WITH SIMILAR INPUT DATA WITHIN THE BOUNDARY

MAPE with similar input data					
Demand Variation	**Lead time (period)**	**Lead-time variation**	**Safety stock**	**TSVR (predicted)**	**MAPE**
0.1	2	0	1	2.64	1.4
0.1	2	0.5	1	70.59	1.81
0.1	4	0	1	5.00	2.01
0.1	4	0.5	1	151.53	2.49
0.3	2	0	1	2.74	1.45
0.3	2	0.5	1	11.14	1.94
0.3	4	0	1	5.05	1.9
0.3	4	0.5	1	21.72	2.16
0.1	2	0	4	2.70	1.25

TABLE VIII
MAPE WITH SIMILAR INPUT DATA WITHIN THE BOUNDARY (CONT.)

MAPE with similar input data					
Demand Variation	**Lead time (period)**	**Lead-time variation**	**Safety stock**	**TSVR (predicted)**	**MAPE**
0.1	2	0.5	4	57.86	1.27
0.1	4	0	4	4.83	1.9
0.1	4	0.5	4	113.42	2.24
0.3	2	0	4	2.65	1.73
0.3	2	0.5	4	9.29	1.73
0.3	4	0	4	4.73	1.94
0.3	4	0.5	4	18.10	2.24
				AVERAGE	1.84

TABLE IX
MAPE WITH DIFFERENT INPUT DATA WITHIN THE BOUNDARY

MAPE with different input					
Demand Variation	**Lead time (period)**	**Lead-time variation**	**Safety stock**	**TSVR (Predicted)**	**MAPE**
0.2	2	0	1	2.69	1.57
0.15	2	0	1	2.67	2.64
0.1	3	0	1	3.82	4.57
0.1	2	0	2	2.66	0.6
0.1	2	0	3	2.68	3.36
0.1	3	0.5	1	111.07	3.65
0.25	2	0	1	2.71	1.97
0.1	2	0	3.5	2.69	3.99
0.15	2	0	2	2.67	0.95
				AVERAGE	2.25

For instance, to predict the TSVR with two proportional controllers when the Safety stock (K) = 1, Lead time (L_d) = 2 periods, Lead-time variability = 50 percent of its mean, and Demand variability = 10 percent of its mean:

$$
\begin{aligned}
TSVR = {} & 0.1+0.9*0.1+1.229*2-44.39*0.5+0.121*1 \\
& -0.11*0.1*2+149.3*0.1*0.5-0.25*0.1*1 \\
& +126.03*2*0.5-0.039*2*1 \\
& +12.41*0.5*1-390.82*0.1*2*0.5 \\
& -41.8*0.1*0.5*1 \\
& -12.311*2*0.5*1 \\
& +39.32*0.1*2*0.5*1
\end{aligned}
$$

As a result, TSVR = 70.59 as compared to TSVRs ranging from 68.405 to 74.711 from ten replications that were obtained from the simulation model running with the above-mentioned parameters. This prediction obtains a MAPE of 1.81%. Such a prediction model would help decision makers to be aware of the amount of the bullwhip effect in advance. This information would be of value to the decision makers for managing and benchmarking their supply chain operations, with or without the optimal ordering quantity. They can use the obtained information for deciding their operating conditions in their chains by realizing when each factor may need to be varied (and its effects), such as reducing the lead time or increasing the level of safety stock.

V. CONCLUSION

The bullwhip effect commonly occurs in a supply chain operating under uncertainties. This study examined four factors, which can generate the bullwhip in terms of order variance and net stock amplification: lead-time duration, lead-time variability, customer demand variability, and safety stock level. The performance of a supply chain is determined by the summation of the order variance and the net stock amplification (TSVR). The simulation-based optimization was applied in this study to find the optimal level of required parameters to minimize the bullwhip effect. A single-echelon supply chain model was simulated and optimized by ARENA software with the OptQuest optimization tool. Also, this study proposed the meta-prediction model based on regression analysis, to predict the total amplification.

This single-echelon supply chain operates with end-customer demand following the normal distribution under the Reorder Cycle (ROC) replenishment policy with the exponential smoothing forecasting technique. To compare the performances of each experiment, the Tukey comparison test is used at the 95 % confidence level. The results showed that all factors of interest, including the lead-time duration, lead-time variability, safety stock level, and end-customer demand variability, are significant, causing the bullwhip effect and net stock amplification. The lead-time variation has the highest significant effect on the severity of the TSVR. Two proportional controllers can alter the dynamic behavior of the supply chain system. They help to smooth the replenishment pattern by giving the optimal ordering quantity in each review period, and they significantly help to reduce the bullwhip effect and net stock amplification. In addition, the results obtained from the prediction model are accurate, giving a MAPE value of less than 3% for similar input data and less than 5% for different input data within the boundary of interest. Our findings would be of value to decision makers to realize, prepare, and benchmark the effects from uncontrollable uncertainties so that a proper alleviation plan can be made in advance.

Our study considered only one type of inventory ordering policy (i.e., the reorder cycle policy), which can be further explored with other types of inventory replenishment policies such as the reorder level policy, etc. In addition, our model was simulated only with a single-echelon supply chain. A further study can be extended to a multi-echelon supply chain with centralized or decentralized ordering policies (with or without information sharing). A combination of these policies can be studied for their roles in the bullwhip effect and net stock amplification. This could be a major research area that is worth exploring.

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