

An Analysis of the BWE-Associated Costs: The issue of Demand Forecasting Accuracy

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Abstract: The bullwhip effect (BWE) has a significant impact on increasing the total cost of a supply chain. Among the factors contributing to this effect, demand forecasting plays a vital role. This paper explores the role of demand forecasting accuracy on the amount of the BWE-related cost, taking an intervened demand process with stochastic perturbations into account. In this regard, a simulation study on a two-echelon supply chain is conducted to investigate the association between forecasting accuracy and the BWE-related costs. Subsequently, a new replenishment policy based on the classic order up to a target (OUT) policy is introduced to determine order values that mitigate the BWE-related costs in comparison to the classic OUT policy.

Keywords: Bullwhip Effect, Inventory Management, Simulation, Demand Forecasting, Experiment Design

1. INTRODUCTION

The bullwhip effect (BWE), also known as the Forrester effect, is defined as the variance amplification of orders from downstream members to up-stream parties in supply chains. Four factors causing this phenomenon are lead time and demand signal processing, order batching, rationing and shortage gaming, and price fluctuation (Lee, Padmanabhan & Whang 2015). Among the factors causing the BWE, the role of demand forecasting is challenging for researchers. Many studies have addressed the effect of demand forecasting on the BWE. However, some aspects still are not explored. This paper presents an experiment on the role of demand forecasting in reducing a defined cost consisted of the effect of the BWE on capacity-related plans. Different scenarios are run in a simulation model to investigate how various factors can affect BWE-related costs. In previous studies, the BWE has been quantified in the cases involving an autoregressive (AR) demand process (Chen et al. 2000), an autoregressive integrated moving average process (Chen et al. 2000; Gilbert 2005) and seasonal demand patterns (Bayraktar et al. 2008). However, exogenous perturbations have not been taken into account in the case of BWE analysis. (Sterman 1989) argued that demand spikes can act proportionally to shocks that happen at one side of the string and tend to get amplified as moving through the supply chain. Accordingly, this research addresses a situation in which partially forecastable spikes occur in some periods for a company that faces an autoregressive demand type with the order of one. Therefore, the demand process is affected by particular circumstances in which the mean changes for a certain amount of time. These events can be related to policy changes, strikes, promotions, and other similar events, namely interventions which due to vast data exchange among in IT based interoperability solutions

are porbable (Box, Jenkins & Reinsel 1994, Delaram and Valilai 2017).

The study explores the main factors affecting the role of spikes on BWE-related costs in different scenarios. In this regard, two distinct points of view about the upcoming perturbations are studied: the pessimistic and the optimistic approach in which the forecasters tend to underestimate and overestimate the future demand respectively in the periods of perturbation with specified forecasting accuracy.

Moreover, the role of different factors on the BWE cost using the response surface method (RSM) is analyzed to observe how various factors determine the way BWE cost varies. Furthermore, a modified ordering policy suitable for the studied setup is introduced. The new policy is able to reduce the BWE-associated costs substantially.

This paper is structured as follows. In section 2, a review of related research is presented to support the study. The third section offers a complete description of the problem addressed in this paper. In section 4, the simulation process is explained. Section 5 conducts a design of experiment process for the generated output of the simulation process. Section 6 deals with the simulation analysis on the modified policy, and finally the last section proposes concluding remarks and future extensions of the research.

2. LITERATURE REVIEW

The BWE has been studied in many aspects and ascribed multiple sources in academic literature. The first study to mention the BWE is widely known to be (Forrester 1961). Forrester noted that it is common for the orders to the manufacturer to have more variance comparing to the demands a retailer faces. Many studies have addressed the role of demand forecasting on the BWE. (Bayraktar et al. 2008)

concluded that longer lead-times and poor selection of forecasting parameters are the main causes of the higher amount of BWE in the E-SCM industry. (Chen et al. 2000) established that standard order up to a target (OUT) replenishment policy with exponential smoothing and a moving average forecasting method for AR demand processes will always result in the BWE. (Alwan, Liu & Yao 2003) argued that in the case of the AR demand process with the order of one, the MSE-optimal forecasting method is significantly beneficial when OUT replenishment policy is utilized. This method is able to eliminate the BWE when demand is negatively autocorrelated. (Zhang 2004) compared the BWE resulted by three different forecasting methods on AR demand with the order of one and concluded that increasing accuracy of the forecasting method can reduce the BWE in some cases. (Chiang, Lin & Suresh 2016) aimed to revalidate the claim that higher forecasting accuracy can reduce the BWE by examining the relationship between forecast accuracy and the BWE. Their finding indicated that there is no significant association between the accuracy and the BWE. (Chaharsooghi, Faramarzi & Heydari 2008) also found that more accurate forecasting methods do not necessarily reduce the BWE.

Based on the abovementioned studies, it is not fully explained that under which circumstances accuracy can be of high positive impact on supply chain costs. Therefore, in this paper, an experiment is conducted to identify circumstances under which forecast accuracy mitigates the BWE-associated costs. The investigation is performed based on the optimistic and pessimistic forecasting view of future demand perturbations.

There is a paucity of studies on the financial influences of the BWE. (Metters 1997) Concluded that although financial results of BWE is depended on each business characteristics, eliminating this effect can lead to a 10 to 30% increase in the profitability. The potential causes of the BWE cost-incurring nature can be the rational actions of decision-makers as to optimize the profit (Naish 1994) or the tendency to avoid stockouts (Kahn 1987). (Zhang 2004) posited that the impact of the BWE on the inventory costs is of a complex relationship depending on demand parameters. (Disney & Lambrecht 2005) argued that one possible source of cost for the BWE can be investing in extra capacity, which is subsequently remained idle. In addition, periods with high demand quantities, cause firms to face expenses such as over-time working costs. On the other side, due to the high variability of demand, firms incur under-utilization costs in periods with low demand.

3. PROBLEM STATEMENT

In order to decrease the BWE, a company may plan to pile up the inventory to meet the demands when specific spikes are anticipated. In this case, the firm can face high holding costs. Two prevailing factors in businesses amplify the impact of BWE: (1) The capacitated manufacturers, (2) The excess loss of missing customer deadlines, pointed out as ramifications (Metters 1997). Accordingly, this paper has addressed the capacity-related costs directly as an additional source of supply chain cost in a capacitated manufacturing case. Nevertheless, the manufacturer can outsource the retailer's

orders when there is a shortage of capacity, and the production can be performed while idle capacity remains. Anyhow, the two mentioned scenarios will lead to outsourcing and opportunity costs, respectively. As a result, a capacitated manufacturing system is assumed here. This system is able to increase its capacity by paying for its costs.

3.1 Setup Characteristics

The analysis is performed on a simple, two-stage supply chain, which is mainly consisted of one manufacturer and one retailer. The retailer has a separate department responsible for demand forecasting generating forecasts with particular levels of accuracy. The demand process includes some perturbation causing costs associated with the BWE. The BWE costs are not completely clear as an integrated formula. Therefore, based on the literature studies (Disney & Lambrecht 2005), a proposed method for cost calculating is used in the experiment. The method in use is the inventory process simulation. The paper aims to analyze the different scenarios in cost generation.

3.2 Optimistic and Pessimistic Approach

In order to fully explore the order variations represented by BWE-related costs, the experiment is decomposed into two distinct points of view regarding the upcoming perturbations: the *pessimistic* and the *optimistic* approach in which the forecasters tend to underestimate and overestimate the future demand in the periods of perturbation, respectively. The pessimistic view is mainly observed in perishable goods supply chains in which companies are likely to incur inventory obsolescence costs in addition to regular inventory holding costs (Hsu 2003), which makes them more conservative in ordering inventory items. On the contrary, the optimistic approach emerges in other supply chains where maintaining customer satisfaction is of high importance. Therein, it is highly recommended to provide a high order fill rate, which is possible by keeping considerable inventory to reduce the unfilled demand (Lam & Ip 2011). Furthermore, supply chains producing emergency goods such as tents, and blankets aim to keep an available inventory to reduce the possible damages in emergency conditions (Özdamar & Ertem 2015).

3.3 Accuracy indicator

The accuracy indicator, which is consisted of the integer numbers between 0 and 20, is indicating the extent of which perturbation amount is predicted. The indicator is consistent with the Mean Absolute Percentage Error (MAPE). This is equivalent to the MAPE of perturbation forecasting, ranging from 0 to 1. Based on the optimism and pessimism of the forecaster's approach, the forecasted demand level will be either above or under the real perturbation level. Foreexample, the value of 10 and 20 of the accuracy indicator means that the MAPE of forecasting the perturbation equals to 0.5 and 1 respectively. The formula of MAPE is given by

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|z_t - \hat{z}_t|}{z_t} \quad (1)$$

Where \hat{z}_t is the forecasted value of demand while Z_t is the actual value of demand (Chiang, Lin & Suresh 2016).

3.4 BWE-associated costs

The BWE cost is associated with variation of capacity usage according to (Disney & Lambrecht 2005). It is assumed for the supplier to have a specific amount of capacity in every period. In practice, the supplier needs to adjust its capacity to be able to fulfill the retailer's orders (Bayraktar et al. 2008). Due to uncertain characteristics of demand and the effects of perturbations, to manage the order efficiently, it is necessary to outsource the overcapacity orders, which causes the BWE costs. Furthermore, when the demand is lower than the capacity, the company incurs idle cost because of under-utilized capacity (Disney & Lambrecht 2005).

Equation (2) calculates BWE cost for each period.

$$BWE \text{ cost} = \begin{cases} (O_i - Cap) * C1 & \text{if } O_i \geq Cap \\ (Cap - O_i) * C2 & \text{if } O_i < Cap \end{cases} \quad (2)$$

Where, $C1$, is the cost of outsourcing a production job requiring one unit of capacity and $C2$ is the unit of under-utilized capacity, Cap is the capacity of the firm.

3.5 Inventory Policies

Order up to a target (OUT) policy: The inventory replenishment policy utilized in this paper is "the order up to a target" policy. The formula for this policy is adopted from (Gilbert 2005). Under this policy, the order at period t can be calculated according to the equation below.

$$O_t = SS - I_t + \hat{D}_t(1) + \hat{D}_t(2) + \dots + \hat{D}_t(L) - O_{t-1} - O_{t-2} - \dots - O_{t-L+1} \quad (3)$$

Where SS is the safety stock, introduced as target inventory in (Gilbert 2005), I_t is the inventory level in period t , $\hat{D}_t(l)$ is the forecasted demand for the period l obtained in the current period (t). O_t is the orders placed in period t and L is the lead time of the orders arriving from the supplier.

Modified OUT (MOUT) policy: As discussed in previous sections, the OUT policy can generate the BWE. As a result, in this part, a new replenishment policy is introduced to alleviate BWE-related costs. This policy uses the determined order of OUT (O_{out}) to solve an optimization problem that helps the retailer decide on the desired number of items to order. According to the MOUT, the retailer, which is in charge of ordering, minimizes the following objective functions to determine the number of items ordered in each step.

$$\begin{aligned} \min Z = & P_{optimist} (c|Cap - O_{np}| + \\ & P_{10}c|Cap - a_1(O_{out} - Cap) - O_{np}| + \\ & P_{20}c|Cap - a_2(O_{out} - Cap) - O_{np}|) + \\ & P_{pessimist} (c|Cap - O_{np}| + \\ & P_{10}c|Cap - b_1(O_{out} - Cap) - O_{np}| + \\ & P_{20}c|Cap - b_2(O_{out} - Cap) - O_{np}|) \end{aligned} \quad (2)$$

s. t

$$O_{np} \geq 0$$

Where: (5)

$$\begin{aligned} P_{optimist} + P_{pessimist} &= 1 \\ a_1 &= b_1 = 1 \end{aligned}$$

And:

$$\begin{cases} a_2 = 0.5, b_2 = 1.5 & O_{out} < Cap \\ a_2 = 1.5, b_2 = 0.5 & O_{out} > Cap \end{cases} \quad (6)$$

In which c is the unit cost that occurs due to the BWE, which is assumed to be equal here in case of outsourcing the production or idle capacity remained. O_{np} is the decision variable of the MOUT, P_i ($i = 10, 20$) is the probability of the forecasting department to have a forecasting accuracy consistent with the paper's definition of accuracy index. Here, the probability is assumed to be equally 0.5 for accuracy indicators of 10 and 20, which means that each department has the confidence of 50% or more in the forecasting department accuracy. $P_{optimist}$ and $P_{pessimist}$ are the probability of the forecasting department to have an optimistic or pessimistic approach, respectively. This probability is obtained by the retailer, using historical data. However, in this study, it is assumed that the retailer does not have any information and assumes both probabilities to be equal to 0.5. O_{out} represents the quantity of the items to be ordered determined by the OUT policy in each step. a_1 and b_1 are equal to one for the case where the forecast is completely accurate with the probability of P_{20} . a_2 is the coefficient to compensate for the optimist overestimating the perturbations in case of positive perturbation and underestimating perturbations in case of negative perturbation. b_2 is the coefficient to compensate for the pessimist overestimating the perturbations in case of negative perturbation and underestimating perturbations in case of positive perturbation.

This policy takes the OUT determined order at every period and performs optimization on a problem minimizing an objective function. The objective function terms are the actual cost of the BWE that is incurred right away and the potential costs that can be incurred later due to the forecasting errors. According to the fact that the overall mean of the process is equal to Cap , and that OUT policy is trying to place order as to leave an amount equal to SS which is equal to Cap in the inventory, it is assumed that in the case of complete information, the number of items that are going to be ordered at L -period ahead is equal to Cap . Therefore, the amount of remained or excessive orders, are creating the amount of deviation from Cap and are going to contribute to BWE occurrence. As a result, these expected deviations are multiplied by c to calculate potential BWE-related costs in the future.

4. THE SUPPLY CHAIN SIMULATION MODEL

The simulated system is a two-echelon supply chain consisting of one manufacturer and one retailer. The supplier provides a single product, and the retailer is in charge of customers' order fulfillment. Additionally, there is a forecasting department which is in charge of market research and is responsible for predicting the perturbations before they happen. After that, the retailer obtains the forecasted demands and decides on the number of items it orders to the supplier. The whole system is

observed as a whole, in a way that the cost incurred to each party affects the entire firm.

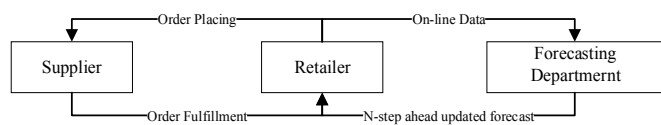


Fig. 1. Simulated supply chain model

At the beginning of each period, the retailer faces a specific quantity of orders. It also receives the orders which it has placed L periods ago from the supplier. The retailer fulfills the current customer demands, and the back-orders remained from periods before. Any unfulfilled demand will be regarded as a back-order. As shown in Fig. 1, after satisfying the actual demand, the retailer sends the information to the forecasting department in which the forecast is performed and shared with the retailer. The retailer makes orders every period to the supplier.

The first step of the simulation generates the demand process with specific parameters. The second step conducts the demand fulfilment process. The next step produces demand forecasts as inputs of the subsequent stage of ordering. Finally, the last step deals with setting the cost parameters and calculating the inventory and BWE-associated costs.

4.1 Customer demand

Customer demands are affected by particular circumstances in which the mean changes for a certain amount of time. It is assumed that the forecasting department is capable of determining the actual timing and direction of the interventions caused by exogenous factors. It is also presumed that forecasts related to the amplitude of perturbations need to be delivered to the retailer L periods before the perturbation occurs. This is due to the fact that significant variations in capacity utilization need to be planned beforehand. Based on the industry features or managers' behavioral characteristics, the intervention forecasting is assumed to be either *optimistic* or *pessimistic* concerning the change in average demands.

4.2 Generation of demand and demand forecasts

It is assumed for the retailer to have an overall stationary demand process. However, specific non-stationary properties are exhibited due to exogenous factors. Consequently, an autoregressive demand process with a particular order is generated as the demand process.

Intervened AR(p) demand generation: The simulated demand vector $Z_t \geq 0$ is represented by an intervened AR(p) process in which p represents the number of autoregressive terms and interventions that are characterized as perturbations that happen from time to time. The mean-centered AR demand pattern which is an intervened version of the process mention in (Disney 2006) is described below:

$$Z_0 = \mu + w_0 + \varepsilon_t \quad (7)$$

$$Z_t = \mu + \omega_t + \phi_1(Z_{t-1} - \mu - \omega_{t-1}) + \phi_2(Z_{t-2} - \mu - \omega_{t-2}) + \dots + \quad (8)$$

$$\phi_p(Z_{t-p} - \mu - \omega_{t-p}) + \varepsilon_t$$

Where Z_t is demand at the period t , μ is the process average, ϕ_i is the autoregressive coefficient, ω_t is the intervention term at time t and ε_t is the white noise term. The main vector is forecasted using an autoregressive integrated moving average forecasting method. It is assumed for the forecasters to know the exact starting time, length, and direction in which each perturbation is going to occur as they update their market research. An L-step-ahead demand forecast vector is generated in which a random number of perturbations are happening with random means and lengths. The information sharing and capacity sides of the business do not allow the department to change the perturbation forecast at the time when disruption is happening.

For the simulation process, the length of the generated demand is set 400 in which the first 150 periods belong to the warm-up session. The generated demand follows the AR process with the order of one with a mean of 200. Moreover the AR coefficient is -0.7 and the maximum perturbation scale is half of the mean demand. The lead time of supplier order fulfilment is considered to be six and the lead time of the retailer is assumed to be zero. The initial inventory equals 200, and the value of the target inventory is 200. The unit costs of holding and backorder are supposed to be of equal values and equal to 2. The unit values of BWE-associated costs are set to be equal to 1.

5. DESIGN OF EXPERIMENT

Experimentation was carried out for the three factors affecting the BWE-associated costs. By investigating the literature (Chaharsooghi, Faramarzi & Heydari 2008), the design of the experiment designed to include 12 combination of levels that each was repeated 10 times leading to 120 simulation runs. The simulation was used to implement a Response Surface Methodology (RMS).

The design level of the experiment ID demonstrated in Table 1, where X_1 denotes the accuracy index, X_2 denotes the number of positive perturbations, and X_3 represents the unit cost of the BWE. Furthermore Y_1 and Y_2 are the responses of the experiment that represent BWE cost for optimist and pessimist setup, respectively. The variables namely X_1, X_2 and X_3 are the uncontrollable factors that are being controlled in the simulation for the purpose of the experiment. The factors X_2 and X_3 are analyzed using two factors coded as -1 and 1. According to the literature, the effect of accuracy indicators on BWE-related costs remains controversial. Therefore, to search for possible quadratic effects of accuracy on the costs, three levels are taken into account for the accuracy factor with levels coded as -1, 0, and 1. This can help in finding response curvatures.

Table 1. Design Levels

Notation	Levels		
X_1	0 (-1)	10 (0)	20 (1)
X_2	0 (-1)	20 (1)	
X_3	1 (-1)	5 (1)	

The experimental results were fitted to the second-order regression:

$$Y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + \beta_{23}x_2x_3 + \beta_{113}x_1^2x_3 + \beta_{112}x_1^2x_2 + \beta_{11}x_1^2 \quad (9)$$

Where Y represents the predicted response (the BWE-associated costs), β_0 represents the intercept; $\beta_1, \beta_2, \beta_3$ signify linear coefficients, β_{11} denotes the squared coefficient and $\beta_{12}, \beta_{13}, \beta_{23}, \beta_{112},$ and β_{113} are notation interaction coefficients.

5.1 Statistical analysis

After applying the regression procedure, the predicted model can be described by (10) and (11). It can be noticed that (10) does not have the terms X_1 and X_1X_2 and (11) lacks the terms X_1 and $X_1^2X_2$ since the mentioned terms are of insignificant effect ($|t\text{-statistic}| < 2$).

$$Y_1 = -3187.85 + 385.214X_2 + 8959.978 X_3 + 121.0714X_2X_3 - 278.92X_1X_3 + 7.232X_1^2X_3 - 1.96X_1^2X_2 + 17.751 X_1^2 \quad (10)$$

$$Y_2 = 3395.496 - 425.923X_2 + 12590.832 X_3 - 181.741 X_1X_2 - 385.341 X_1X_3 + 11.289 X_1^2X_3 - 22.664X_1^2 \quad (11)$$

An Analysis of Variance (ANOVA) is utilized to test the adequacy and significance of the quadratic model. The results for Y_1 and Y_2 are shown in Table 2 and Table 3, respectively. The Y_1 and Y_2 regression models are highly significant (P-value < 0.01).

Table 2. Analysis of variance of the optimist

Factors	Sum of Squares	df	F	PR(>F)
X_2	2.13E+09	1	110.5423	2.12E-18
X_3	3.54E+10	1	1833.476	2.88E-71
X_2X_3	7.04E+08	1	36.44957	2.08E-08
X_1X_3	6.22E+08	1	32.24304	1.09E-07
$X_1^2X_3$	1.55E+08	1	8.007897	0.005521
$X_1^2X_2$	1.33E+09	1	69.02284	2.53E-13
X_1^2	9607835	1	0.49773	0.481964

Table 3. Analysis of variance of the pessimist

Factors	Sum of Squares	df	F	PR(>F)
X_2	3E+09	1	128.432	2.69E-20
X_3	3.72E+10	1	1594.448	4.47E-68
X_1X_3	1.59E+09	1	67.98161	3.51E-13
X_2X_3	1.13E+09	1	48.41723	2.46E-10
X_1X_2	1.82E+09	1	78.07983	1.59E-14
$X_1^2X_3$	3.62E+08	1	15.51569	0.000143
X_1^2	1.94E+08	1	8.333996	0.00467

Determination coefficient (R^2) of the predicted model of Y_1 and Y_2 is 0.951 and 0.947, which is indicating that the model is reliable in explaining the variations. The experiment is showing a noticeable linear effect for all of the significant regression variables except for X_1^2 for the optimist.

5.2 Analysis of the response surface

Response surface was plotted between variables X_1 and X_2 , while keeping the X_3 variable at one coded level.

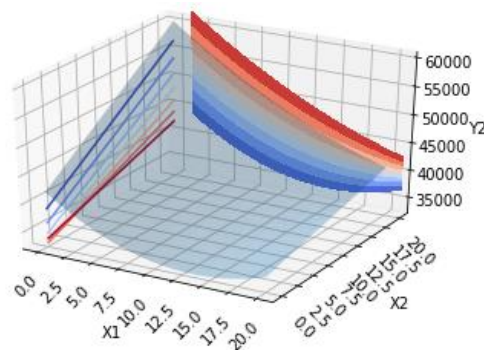


Fig. 2. The effect of the number of positive perturbation on the BWE cost for the optimistic approach under OUT policy

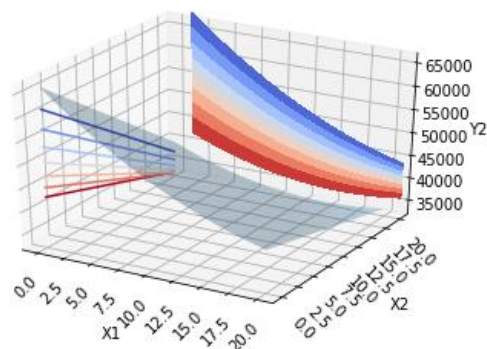


Fig. 3. The impact of the number of positive perturbation on the BWE cost for the pessimistic approach under OUT policy

Fig. 2 presents the response surface for the optimistic view of the unit idle cost of 5. The figure demonstrates the effect of changing the number of positive perturbations from zero to 20 on the BWE cost. As the number of positive perturbation increases, the values of BWE-related cost tends to alter from having a quadratic shape to a descending linear form. Furthermore, the figure reveals that the more negative demand perturbation leads to more reduction in the BWE cost. Similarly, as can be noticed from Fig. 3, for the pessimistic approach, when all perturbations are negative the BWE-related cost follows a diminishing linear line. Furthermore, the more positive perturbation leads to a more reduction of the BWE-related cost

The above analysis shows that accuracy demonstrates a quadratic form in some situations. This is mainly happening when the deviation caused by the perturbation is mainly underestimated. According to this study setting, this is related to the times when a pessimist forecaster is facing mostly positive perturbation, or an optimist is facing mostly negative perturbations.

5.3 Further analysis of the accuracy indicator

To further explore the order's behavior under OUT policy, providing a comparison of order values before and during perturbations is necessary. In this way, Fig. 4 presents the dispersion of order values for the pessimistic approach when all the perturbations have negative values (which has a curved shape BWE-cost) before and during perturbations for a random experiment. It can be noticed that as the accuracy increases, the dispersion of order values before the perturbations increases and the dispersion during perturbation decreases. In other words, orders with the lowest variance occur when the accuracy index is 10. This is because in this point the orders before and during perturbation are of almost similar values. Furthermore, it can be understood from the box plots that two main factors contributing to high BWE costs are either caused in order placing period in which a real cost is incurred (happening in the box plot of the most accurate forecasts) or after shortage or excessive inventory in the middle of a perturbation resulting from lack of precision in forecasting.

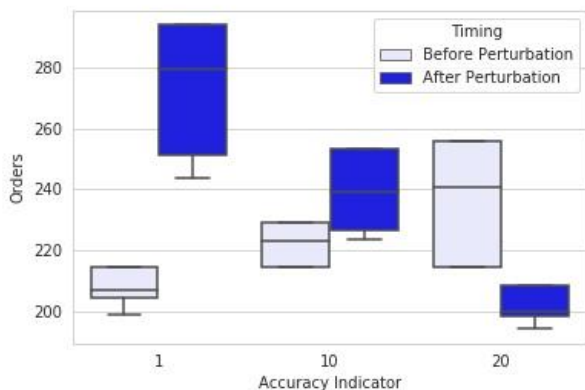


Fig. 4. Box plots of order values before perturbations and during perturbations.

6. SIMULATION ON THE MODIFIED POLICY

According to section 5.2, the BWE is, to a reasonable extent, related to two main occurrences in the inventory. Firstly, the L -period ahead forecast, which contributes to the determination of orders made by OUT policy and secondly, the significant order variation happening due to forecasting error made at previous periods that forces the order policy to order in huge amount or small quantity. As a result, the MOUT is presented to minimize the sum of the two aforementioned sources.

To test the effectiveness of the MOUT which was presented in section 3.5, a simulation is run with eight experiments with random perturbations. The mean cost of this experiment is then compared to the same settings happening with the classic OUT policy. The replicability is assured by using the same seeds in simulation runs. It is worth mentioning that before solving the optimization problem for the new policy a linearization on the problem is done. The problem is solved using package pulp in python 3.6.

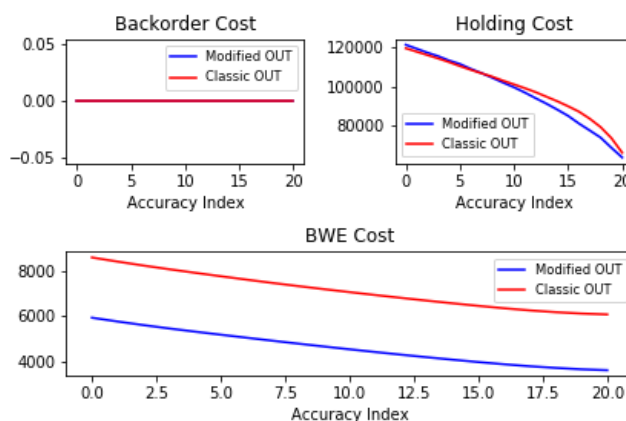


Fig. 5. Comparing classic OUT with the modified OUT in optimistic setup

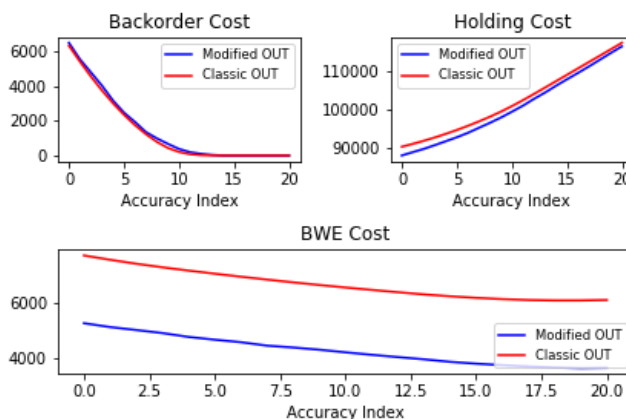


Fig. 6. Comparing classic OUT with the modified OUT in pessimistic setup

Fig. 5 and Fig. 6 provides a clear comparison of OUT and MOUT policy about the cost of the BWE, inventory holding, and backorder cost for the optimistic and pessimistic setup. It is observed that the MOUT has successfully decreased the BWE-related costs in both approaches. Furthermore, the new policy does not have an increasing effect on the holding and backorder costs in both views.

7. CONCLUSIONS

This research has shown that higher forecast accuracies do not necessarily reduce the BWE-related cost. Moreover, the forecast accuracies' effect on the BWE-related cost depends on the characteristics of the ones that make forecasts whether the forecaster has an optimistic or pessimistic view of the future demand. The paper proposes the supply chain planners to use modified policy introduced in this paper to avoid costs associated with the BWE when dealing with demand perturbations. Future research can deal with methods of analyzing the behavior of retailers toward forecasting future demand perturbations whether it is optimistic or pessimistic. In this way, reinforcement learning approaches are also highly recommended for determining the way the retailer behaves.

These methods can be deployed to learn on the probabilities of different scenarios of the reaction of the retailer towards forecasting perturbations. Moreover, in the future works, the capacity can be regarded as another variable by which the BWE behavior can be analyzed better.

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