A Single-Level Forecasting Inventory Simulation Model Integrating Downstream Forecast Information

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Abstract

In the field of operations and production management, inventory systems is the most studied aspect due to its high contributions to most companies' expenses. In that respect, effective stock control is essential to the improvement of many businesses. Problems arise, however, when conducting inventory management due to the many uncertainties faced. In this paper, the researchers address issues concerning the said uncertainties in inventory management through forecasting and supply chain integration in an inventory simulation model via Microsoft Excel and Visual Basic applications. The proposed model incorporates information coming from downstream tiers of the supply chain in computing the forecasts. The model was tested using a set of heuristic data using the incurred costs as performance measure. The findings show that the proposed model, in comparison with basic and classical forecasting and inventory management models, performs significantly better under the different conditions tackled in the study. The findings also suggest that the proposed model could be the basis of more complex inventory management models.

Keywords
Single-level forecast, Inventory management, Downstream forecast information, and Simulation model.

1. Introduction

Inventory management plays a vital role in many organizations since inventories usually contribute the largest expenses incurred by businesses. The theory on inventory systems is also the most thoroughly researched field in production and operations management (Nenes et al, 2010). There are many types of inventory management systems, with a single-pro, duct, multi-period being the most basic. It is still tedious, however, to be able to conduct this optimally since there are a great number of variables involved. These variables include stochastic demand (Waller, 2014), (Dekker et al, 2005), (Petropoulos et al, 2013), varying lead times and cycle service levels (Porras, 2008), forecast accuracy (Porras et al, 2008), (Ali et al, 2012), (Boylan and Syntetos, 2006), (Syntetos et al, 2015), (Boylan et al, 2008), (Silver et al, 1998), supply chain management (Bob, 2016), (Bob, 2017), (Costantino et al, 2014), (Chien et al, 2011), (Chien et al, 2010) and cost parameters. All of which greatly affect overstocking and shortages exhibited by upstream manufacturers. This study proposes an inventory management model which takes into consideration basic applications of the above mentioned variables in a single-item multi-period inventory problem.

Accurate demand forecasting is an essential aspect that should be considered in supply chain management (Willemain et al, 2004). Downstream forecast information can be defined as the customer's forecast regarding the size of their demand requirements for future periods given to their suppliers or to upstream players in the supply chain. Incorporation of this information could lead to more accurate forecast computation by upstream manufacturers. In this study, the researchers considered two types of forecasting tools such as the Simple Exponential Smoothing (SES) and TSB (Teunter et al, 2011). The former is still one of the most used basic forecasting tools in empirical practices, while the latter is a modified version specifically designed to handle appearance of intermittent and random demand with some periods wherein absolutely no demand occurs (Syntetos and Boylan, 2005).

This research combines both forecasting and inventory management in a single model. The mentioned forecasting tools are modified such that they include downstream forecast information in their forecast computations and used in the reorder point (ROP) computation of the inventory management system. The proposed model uses a simple Monte Carlo inventory simulation with allowed backordering and control limits consideration. This study aims to show the significant effects of including downstream forecast information in the accuracy of forecasts made and how this increased accuracy leads to less costs incurred by inventory systems.

2. Methodology

2.1 Forecasting Model Formulation

Exponential smoothing is still widely used as a forecasting method in many businesses and empirical studies. It is also one of the most used statistical tools in forecasting intermittent demand (Willemain et al, 2004). In that respect, this study uses Simple Exponential Smoothing as the basis for its model. The classic Simple Exponential Smoothing equation is shown below:

$$F_t = F_{t-1} + \alpha \times (D_{t-1} - F_{t-1})$$

where, F_t is the forecast made for period t, α is the smoothing constant, and D_{t-1} is the actual demand in period t -1.

Evidence show, however, that when demand suddenly drops or in the occurrence of intermittent demand, SES does not work well. (Romeijnders et al, 2012). In order to cope with this, this study considered using another forecasting approach. As mentioned in the previous section, the TSB method is the latest modification of the SES specifically designed for handling demand intermittency with concerns on demand obsolescence. Unlike its predecessor, SBA (Syntetos Boylan Approximation), it calculates and updates the probability of demand occurrence rather than demand interval during every cycle or period. Although, comparisons of the performance of the TSB method with that of the SBA are not discussed in this study and should be researched extensively in further studies.

The equations for the TSB method are shown below:

$$If\ D_{t-1} = 0, \begin{cases} P_t = (1-\gamma) \times P_{t-1} \\ Z_t = Z_{t-1} \\ F_t = P_t \times Z_t \end{cases}$$

$$If\ D_{t-1} \geq 1, \begin{cases} P_t = \gamma \times (1) + (1-\gamma) \times P_{t-1} \\ Z_t = \alpha \times D_{t-1} + (1-\alpha) Z_{t-1} \\ F_t = P_t \times Z_t \end{cases}$$

where F_t is the forecast made for period t, P_t is the estimate for the demand occurrence probability for period t, Z_t is the estimate for the demand size for period t, $\alpha\ and\ \gamma$ are the smoothing constants, and D_{t-1} is the actual demand at the previous period.

The problem with Simple Exponential Smoothing and the TSB method, however, is that it only uses historical demand or past data in computation of its forecasts. This study proposes a simple form of supply chain integration in its model, which would improve the accuracy of the discussed forecasting methods. As discussed above, a problem commonly faced by the supply chain industry is the bullwhip effect and the most common solution found in scholarly articles tackling the bullwhip effect is better information communication between the downstream and upstream players in the supply chain. In accordance to this, the researchers thought of including downstream forecast information in the forecast computation. They believe that this would account for the "better communication" stated in the literary articles. Though elimination of the bullwhip effect is not the course of action prioritized in this paper, approaches in minimizing it also present as solutions towards better inventory control. In doing so, the proposed computation of the forecasted values does not only use historical demand. The "actual demand" term used in both the SES and TSB method is computed as the average of the latest downstream forecast information available and the historical demand provided, with just the historical demand used if there are no downstream forecast information available. The researchers believe that the addition of this estimation would result in more accurate forecasts, assuming that downstream forecast information are much closer to the actual demand values.

The modified Simple Exponential Smoothing and TSB equations are presented below:

$$F_t = F_{t-1} + \alpha \times (X_t - F_{t-1})$$

and

$$If\ D_{t-1} = 0, \begin{cases} P_t = (1-\gamma) \times P_{t-1} \\ Z_t = Z_{t-1} \\ F_t = P_t \times Z_t \end{cases}$$

$$If\ D_{t-1} \geq 1, \begin{cases} P_t = \gamma \times (1) + (1-\gamma) \times P_{t-1} \\ Z_t = \alpha \times X_t + (1-\alpha) Z_{t-1} \\ F_t = P_t \times Z_t \end{cases}$$

respectively, wherein,

If $U_{(t,s_{max})}$ has a value, then

$$X_t = \frac{D_{t-1} + U_{(t,s_{max})}}{2};\ s \leq t$$

If $U_{(t,s_{max})}$ has no values, then

$$X_t = D_{t-1}$$

where $U_{(t,s_{max})}$ is the latest available downstream forecast information for period t made at time s.

2.2 Model Description

For simplicity, only the equations used all throughout the paper are marked with (n), where n is the corresponding equation number. The indices and the parameters of the researchers' proposed model are defined as follows:

Table 1 summarizes all the parameters used in the proposed model.

Table 1. Notations of parameters

Parameters	Description
α_i	$alpha\ used\ for\ method\ i$
β	$beta\ used\ for\ MSE\ (Mean\ Squared\ Error)$
γ	$gamma\ used\ for\ TSB\ Computation$
μ	$mean\ demand\ of\ historical\ data$

σ	$standard\ deviation\ of\ historical\ data$
ϕ	$cumulative\ distribution\ of\ demand\ per\ period$
$F_{(t,i)}$	$forecast\ for\ period\ t\ using\ method\ i$
$U_{(t,s)}$	$downstream\ forecast\ for\ period\ t\ made\ at\ time\ s$
P_t	$demand\ occurence\ indicator\ for\ period\ t$
Z_t	$estimate\ of\ demand\ size\ in\ period\ t$
D_t	$actual\ demand\ at\ period\ t$
X_t	$average\ of\ historical\ demand\ and\ downstream\ forecast\ for\ period\ t$
$R_{(t,i)}$	$reorder\ point\ for\ period\ t\ using\ method\ i$
$CL_{(t,i)}$	$centerline\ for\ period\ t\ using\ method\ i$
$UCL_{(t,i)}$	$upper\ control\ limit\ for\ period\ t\ using\ method\ i$
$LCL_{(t,i)}$	$lower\ control\ limit\ \ for\ period\ t\ using\ method\ i$
Q_j	$order\ quantity$
H	$holding\ cost$
C	$shortage\ cost$
S	$ordering\ cost$
LT	$lead\ time$

wherein the indices are:

$$i = 1\ or\ 2\ where\ \begin{cases} 1\ is\ SES \\ 2\ is\ TSB \end{cases}$$

$$t = 1, 2, \dots 52\ is\ the\ index\ of\ the\ periods$$

$$s = 1, 2, \dots 52\ is\ the\ index\ of\ the\ time$$

$$j = 1, 2, or\ 3\ where\ \begin{cases} 1\ using\ total\ demand \\ 2\ using\ mean\ demand \\ 3\ using\ LTD \end{cases}$$

For the proposed inventory management model, the researchers constructed a simulation model via Microsoft Excel and Visual basic that would simulate the optimal inventory management for a company given the following assumptions:

(1) There is historical demand for at least the same number of periods that will be simulated
(2) The inventory capacity is unlimited
(3) Smoothing constants are computed via Excel solver (minimizing average MSE)
(4) The lead time used in simulation is fixed
(5) The ordering quantity for every simulation is fixed
(6) Backlogging is considered
(7) Holding, shortage and ordering costs are provided
(8) Orders arrive on time and are never disrupted

For the inventory management model, the study uses a dynamic continuous review inventory system. This allows for the system to update the reorder every period while maintaining a low inventory level due to the lack of protection period. The inventory system choice influenced by the fact that one of the researchers' goals is to propose an inventory management system that minimizes inventory on hand, and the lack of protection period in the reorder point computation of said inventory system helps them achieve this goal.

In order to integrate the formulated model on an inventory management system, the study uses a reorder point formula which incorporates forecasts in its computation. The reorder point formula is similar to that of the classic approach except for the computation of the safety stock. Instead of using the standard deviation, the formula uses the error of the forecasts since it serves as the variation of the forecast from the actual demand. It is also multiplied by the inverse cumulative function since that accounts for the probability that the forecasted value used is incorrect.

The formula for the ROP is presented below:

$$R = LT \times F_t + \phi^{-1} \times (CSL) \times \sqrt{MSE_t \times LT}$$

where, R is the reorder point level, LT is the lead time, F_t is the forecast for period t, ϕ^{-1} is the inverse cumulative function of the demand per period, CSL is the target Cycle Service Level (in z-score), and MSE is the Mean Squared Error of the Forecast for period t

Using the above equation, the researchers proceeded on to integration of the two formulated models (SES and TSB) in an inventory management system.

For Simple Exponential Smoothing, the following equations were formulated:

$$R_{(t,1)} = LT \times F_{(t,1)} + \phi^{-1} \times (CSL) \times \sqrt{MSE_{(t,1)} \times LT} \qquad (1)$$

$$F_{(t,1)} = F_{(t-1,1)} + \alpha_1 \times \left(X_t - F_{(t-1,1)}\right) \qquad (2)$$

For the TSB method, the following equations were formulated:

$$R_{(t,2)} = LT \times F_{(t,2)} + \phi^{-1} \times (CSL) \times \sqrt{MSE_{(t,2)} \times LT}(3) \qquad (3)$$

$$If\ D_{t-1} = 0, \begin{cases} P_t = (1-\ \gamma) \times P_{t-1} \\ Z_t = Z_{t-1} \\ F_{(t,2)} = P_t \times Z_t \end{cases} \qquad (4)$$

$$If\ D_{t-1} \geq 1, \begin{cases} P_t = \gamma \times (1) + (1-\ \gamma) \times P_{t-1} \\ Z_t = \alpha_2 \times X_t + (1-\alpha_2) Z_{t-1} \\ F_{(t,2)} = P_t \times Z_t \end{cases} \qquad (5)$$

The variance for forecast error for both forecasting methods is computed using smoothed Mean Squared Error (Syntetoset al, 2010) wherein:

$$MSE_{(t,i)} = \beta \times (X_t - F_{t-1,i})^2 + (1-\beta) \times MSE_{t-1,i} \quad (6)$$

β is set to be equal to 0.25 since according to Syntetos et al (2010) it produces robust results.

For a regular Monte Carlo inventory simulation, the ordering logic is based solely on whether the current inventory position is lower that the set reorder point. If it is lower, then the simulation will automatically place an order, if not then no orders will be placed. The proposed model incorporates control limits in the simulation's ordering logic. Instead of only comparing the inventory position with the reorder point, the model would also compare it with both the upper and lower control limits computed. The current inventory position would have to be lower than both the reorder point and the upper control limit or just lower than the lower control limit before the system triggers an ordering. This will ensure that the inventory position 99.73% of the inventory position would be within the upper and lower control limits minimizing both inventory-on-hand and stock-outs incurred.

All control limits are computed using the following formulas:

$$CL_t = Min\left(R_{t,i}, F_{t,i}\right) \times LT + \sigma \times (CSL) \times \sqrt{LT} \qquad (7)$$

$$UCL_t = CL + 3 \times \sigma \tag{8}$$

$$LCL_t = Max(0, CL - 3 \times \sigma) \tag{9}$$

where σ is the standard deviation of forecast values up to period t.

The proposed inventory model consists of two parts, forecasting and the Monte Carlo simulation.

The forecasting part of the model consists of the following steps:

1. Read the inputted historical demand data.
2. Compute for the mean and standard deviation of said data. And choose which EOQ formula to be used, using the Equations (10), (11) or (12).
3. If downstream forecast information is available use the average of the historical demand data and the latest downstream forecast as the actual demand (X_t) for the computation of the forecasting method, if not only use the historical demand (D_{t-1}).
4. If there is demand for the previous period in the demand history use Eqs. (2) for SES or (4) for TSB, if not use Eqs. (2) for SES or (5) for TSB in the computation of the forecasts.
5. Compute for the smoothed Mean Squared Error for every forecast using Eq. (6);
6. Compute for the average MSE for all forecast periods.
7. Excel solver used in order to compute for the appropriate smoothing constants for the forecasting method $(\alpha_1, \alpha_2, \gamma)$ which would minimize the average MSE;
8. Compute for the normal distribution of the forecast for period t, which will then be used to compute for the standard normal cumulative distribution leading to the computation of the inverse cumulative distribution;
9. The reorder point for period t will then be computed using Eqs. (1) for SES or (3) for TSB;
10. Compute control limits are calculated using Eqs. (7), (8), and (9) using either ROP or Eq. (13), whichever is higher. The control limits are included in the ordering logic of the Monte Carlo inventory simulation.

The Monte Carlo simulation part of the model consists of the following steps:

1. Determine which is the larger value – the lead time demand or the sum of the first demand values, where the number of periods to be summed up is the lead time. The higher value will be used as the beginning inventory of the first period of the simulation.
2. Determine if there are order arrivals for the current period, if there are then it will be added to the current inventory level, if none then the simulation will proceed to the next step.
3. Subtract this period's demand as well as last period's backorders from the inventory level.
4. If all the demand is satisfied (inventory level > demand + backorders) then the inventory level left would be used as the ending inventory, if not then the number of unsatisfied demand would be considered as current period's backorders.
5. Check if there are orders placed last period, if there are then the quantity of the order would be added to the inventory position, if not then it will proceed to the next step.

6. Check whether the current inventory position is lower than the reorder point and upper control limit, or the lower control limit for current period. If it is then an order will be placed, if it is not then no orders are placed.

7. If an order is placed this period then the "lead time" column of the spreadsheet would be updated based on the lead time used for the simulation, if there is no order placed then the simulation will simply move to the next period.

8. Press "arrival" button to generate arrival dates and move on to the next period, if it is the last period, the simulation ends.

9. Update the beginning inventory based on the previous period's ending inventory.

10. Return to step 2 wherein the model will check if there are orders that are set to arrive in the current period.

The simulation will continue until the process reaches the last period set.

In order to show that the proposed model can be applied in most inventory situations, 10 random demand scenarios with very different distributions are generated. Though the study aims to propose a generalized inventory management model for any industry, it was conducted with a specific product in mind. The demand scenarios were generated in a way that it would mimic the demand patterns exhibited by semiconductor products. Because of the product's shortening life cycle, it experiences high demand fluctuation which the researchers also try to mimic with their randomly generated dataset. The demand for semiconductor product follows no seasonality nor trend since advancements in technology provide a constant need for the product. Each scenario consisted of having different demand variances between each period, half of which had intermittent demand. The demand variances for each scenario ranges from as little as 5,000,000 – 6,000,000 to as much as 0 – 10,000,000. Using said demand scenarios, the researchers simulated inventory management systems using the proposed Monte Carlo simulation model presented above with ROP computed using three different approaches: the two proposed models using SES and TSB, and the classic reorder point method. The different variables discussed in the earlier parts of the paper were changed with each simulation run, incorporating more and more changing variables as the simulation testing progresses. The results for the different approaches were compared based on the total costs each one incurred for a simulation of 15 periods. The number of times each approach presented the lowest cost for each of the 10 scenarios were considered as the performance measure. The holding (H), shortage (C) and ordering (S) costs are all assumed with the total cost used as the performance measure for each simulation. The formula for the classic approach is presented below:

$$R = LT \times \mu + SS, where\ SS = (CSL) \times \sigma \times \sqrt{LT}. (13)$$

The costs are computed using the following formulas:

Holding Cost (H) = $\sum_{t=1}^{15} E_t \times h$
Shortage Cost (C) = $\sum_{t=1}^{15} BO_t \times c$
Ordering Cost (O) = $\sum_{t=1}^{15} OP_t \times o$
where, E_t is the ending inventory for period t, BO_t is Backorders for period t, OP_t is orders placed on period t, h is holding cost per unit, c is shortage cost per unit, o is ordering cost per unit

The first part of the testing phase consisted of 180 simulation runs. 10 runs (each containing all 3 approaches) for each lead time (2, 4 and 8) followed by 30 runs (10 for each lead time) for each of the two cycle service level (90% and 99%) and 30 for each of the 3 ordering quantities. The demand for each period t for the Monte Carlo inventory simulation is the same as the historical demand for each period t used in the forecasting part of the model. The equations used in computation of the three ordering quantities are described below:

$$Q_1 = \sqrt{\frac{2 \times D \times S}{H}} \qquad (10)$$

$$Q_2 = \sqrt{\frac{2 \times \mu \times S}{H}} \qquad (11)$$

$$Q_3 = \sqrt{\frac{2\times f(LT)\times S}{H}} \quad (12)$$

where, $f(LT) = \mu \times LT$ or LTD

Another 180 simulations were run wherein the ordering during the first period would be mandatory. This is because the safety stock used in the beginning inventory is only either good for the first few periods, with the number of periods based on the lead time, or equal to the lead time multiplied by the mean demand, whichever is the higher value. This means that after a period equal to the lead time has passed, the beginning inventory would most likely be depleted. This condition would determine a simple optimal inventory policy for the model.

The last part of the testing phase included 1,080 simulation runs. The first 360 simulation runs consisted of using a different set of demand for the Monte Carlo inventory simulation. Instead of using the historical demand dataset, a new set of demand was generated and used as "actual demand" while still using the historical demand data set in computation of the forecasts. The next 360 runs also used the new set of demand as the "actual demand" for the Monte Carlo inventory simulation with the availability of downstream forecast information in the computation of forecasts. Both the new demand dataset as well as the downstream forecast information are generated randomly with the same demand variance with its paired historical demand scenario. The last 360 simulation runs considered the new "actual demand" and the availability of downstream forecast information under a set of different cost constraints. Instead of using the old set of costs wherein Holding cost is ($10/unit) 5% of shortage cost ($500/unit) per unit and Ordering cost is $100,000,000, the researchers used the following: C = $200/unit; H = $50/unit (20% of shortage cost); S = $100,000,000/order.

Determination of the cost parameters was based on Syntetos et al (2010), which stated that current businesses often use cost parameters in which the ratio between holding cost to shortage cost is 10%. Since the researchers wanted to test the model under extreme scenarios, they decided to use ratios of 5% and 25% for the above mentioned cost parameters. This decision would show that the proposed model performs adequately under any scenario. The same concept was used for the target Cycle Service Level used by Syntetos et al (2010) using CSL's ranging from 87% - 99%. To depict high and low service levels, the researchers used only 90% and 99% as their test parameters for the proposed model. Several articles (Krever et al, 2003), (Rego and Mesquita, 2015), (Syntetos et al, 2010) showed that most target Cycle Service Levels fall within these ranges (90 – 99).

For both the testing simulations as well as the model proposed, the researchers used Microsoft Excel with the addition of several Visual Basic components for ease of use. The Excel consists of four different spreadsheets, "Testing (15 periods)", "Future Forecast", "Results", and "Inventory (52 periods). The first three spreadsheets' purpose are mainly for proofing since the researchers wanted to show that their proposed model "TSB" produces better results as compared to using Simple Exponential Smoothing and the Classic Re-order point method. The fourth spreadsheet "Inventory (52 periods)" is the part that the user should use. It consists of the same parts as the "Testing" spreadsheet but it only uses the proposed "TSB" method and it consists of 52 periods.

3. Results and Discussions

The first simulations runs showed that although the proposed TSB method produces the most number of least cost runs under most of the conditions, it underperforms when a low CSL and Q_2 are used. Although incorporation of the first period ordering policy did lower the overall total costs incurred by all 180 runs, the proposed methods were still outperformed (resulting in the most number of least cost runs) by the classic approach under a low CSL and use of Q_2. Use of a new set of demand for the Monte Carlo inventory simulation, however, resulted in significantly lower overall costs incurred by the proposed methods as well as both methods outperforming the classic approach for every 30 simulation runs under all conditions, with the SES method outperforming the TSB under a low CSL and Q. With the last 720 simulation runs, it was shown that the availability of the downstream forecast information leads to the TSB method outperforming the other two methods for every 30 simulation runs under all conditions. It only incurred a higher overall total cost under the different cost parameters with the use of Q_2, with the least overall total cost in all other conditions. The results of the performance measure of all 1,440 simulation runs are summarized in Table 2. Figure 1 shows a sample graph of one scenario simulation's inventory position under the control limits.

Table 2. Performance results for 1,440 simulation runs. Best results hachured

Only Historical Demand (360 runs)			
	SES	TSB	Normal
Frequency of Occurrence with lowest cost	139 (38.61%)	180 (50.00%)	89 (24.72%)
Frequency of Occurrence with middle cost	76 (21.11%)	31 (8.61%)	30 (8.33%)
Frequency of Occurrence with highest cost	145 (40.28%)	149 (41.39%)	241 (66.94%)
With New Actual Demand (360 runs)			
	SES	TSB	Normal
Frequency of Occurrence with lowest cost	215 (59.72%)	263 (73.06%)	31 (8.61%)
Frequency of Occurrence with middle cost	64 (17.78%)	27 (7.50%)	11 (3.06%)
Frequency of Occurrence with highest cost	81 (22.5%)	70 (19.44%)	318 (88.33%)
With New Actual Demand and Downstream Forecast Information (360 runs)			
	SES	TSB	Normal
Frequency of Occurrence with lowest cost	170 (47.22%)	290 (80.56%)	28 (7.78%)
Frequency of Occurrence with middle cost	118 (32.78%)	12 (3.33%)	4 (1.11%)
Frequency of Occurrence with highest cost	72 (20.00%)	58 (16.11%)	328 (91.11%)
With New Actual Demand, Downstream Forecast Information, New Costs (360 runs)			
	SES	TSB	Normal
Frequency of Occurrence with lowest cost	154 (42.78%)	268 (74.44%)	26 (7.22%)
Frequency of Occurrence with middle cost	142 (39.44%)	8 (2.22%)	8 (2.22%)
Frequency of Occurrence with highest cos	64 (17.78%)	84 (23.33%)	326 (90.56%)

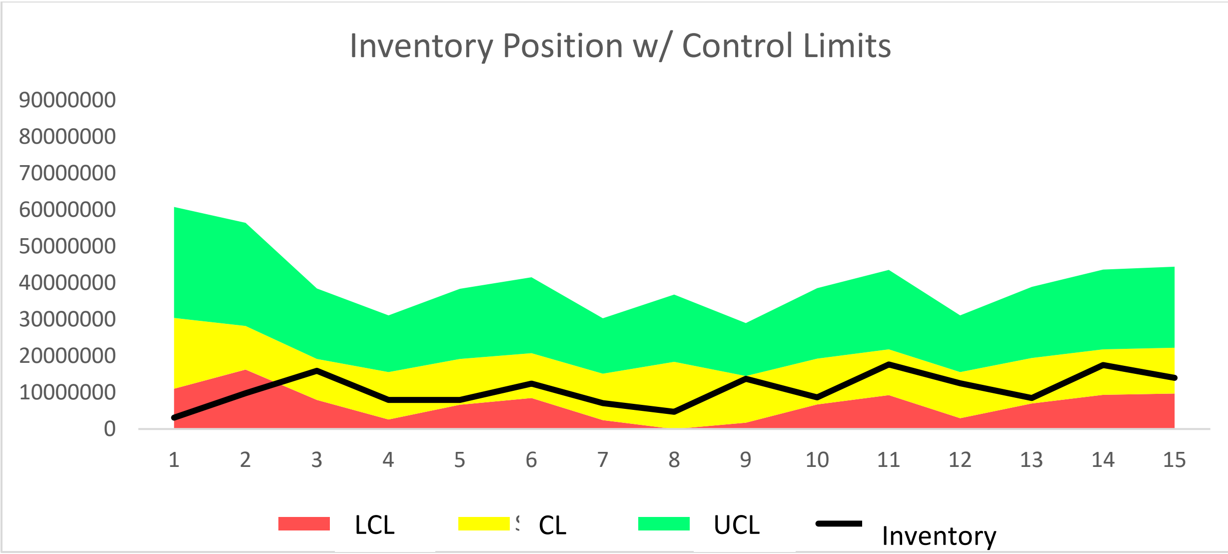

Figure 1. Sample Graph of Inventory Position under Control Limits

4. Conclusion

The study uses and modifies two similar forecasting tools, Simple Exponential Smoothing and the TSB method. For the modifications done, instead of just using the previous demand occurrence in the forecast computation, the average between the latest available downstream forecast and the actual demand last period are used, using only last period's demand if no information from downstream tiers are available.

Implication of the proposed forecasting method was done through an equation found in related literature. The ROP equation formulated by Syntetos and Babai (2007) uses forecasts for each period in calculating the ROP for the same period. By using this equation, the researchers were able to incorporate the two forecasting techniques in an inventory management system. The methods were then tested against the classical ROP computation approach in 1,440 Monte Carlo inventory simulation runs using a heuristic set of data. The results show that the proposed methods outperforms the classical approach under all conditions. For the first set of 360 runs without the availability of downstream forecast information, the TSB method generated the least cost on 180 runs (50% of the time), with SES having 139 runs (38.11%) and classic approach with 89 (24.72%). For the third set of 360 simulation runs, with the availability of downstream forecast information, the TSB method generated the least cost on 290 runs (80.56%), SES with 170 (47.22%) and classic approach with 28 (7.78%).

Several enhancements can be done to further improve the model's application on real-life scenarios. Since the model proposed in this study was only tested under a heuristic set of data, the researchers recommend doing case study using said model. Although the 10 randomly generated demand patterns could closely represent an empirical set of data, using the proposed model on a real life business situation would help prove its effectiveness. Particularly in a case involving the semiconductor industry. Since the simulations and results in the paper involved very high numbers, it was only able to prove that the model works robustly under a product which experiences the same range and variation. The study was also limited by the assumption that the demand pattern follows a Normal Distribution in computation of the ROP using forecasts. Assuming a more widely used probability distribution in the computation of the ROP could lead to a more controlled inventory simulation. Another step towards improving the proposed model is through modification for a multi-product inventory problem since the model proposed can only be using for a single-product inventory model. The model proposed is a very basic approach towards solving current inventory problems but it can be a baseline in coming up with a model to face more complex scenarios.

References

Ali, M. M., Boylan, J., & Syntetos, A. A. (2012). Forecast errors and inventory performance under forecast information sharing. *International Journal of Forecasting*, *28*(4), 830-841. https://doi.org/10.1016/j.ijforecast.2010.08.003

Babai, M.Z., Syntetos, A.A., (2007). An empirical comparison of parametric and nonparametric forecasting methods for intermittent demand items. In: Proceedings of the OR 49, Edinburgh, 4–6 September, 2007.

Bob, Liu (2016), Supply Chain Management: Solutions to High Cost,High Inventory and Asset Heavy Problems. China: China Machine Press

Bob, Liu (2017), Supply chain management as a profession. China: China Machine Press

Boylan, J., & Syntetos, A. (2006). Accuracy and Accuracy Implication Metrics for Intermittent Demand (Vol. 4).

Boylan, J., A. Syntetos, A., A. H. Kobbacy, K., & N. Prabhakar Murthy, D. (2008). Forecasting for Inventory Management of Service Parts.

Chien, Chen-Fu, Hsu C., and Chang K. (2011), "Overall Wafer Effectiveness (OWE): A Novel Industry Standard for Semiconductor Ecosystem as a Whole," Computers and Industrial Engineering. (NSC 99-2221-E-007 -047 -MY3)(SCI) doi:10.1016/j.cie.2011.11.024 (2011 Impact Factor: 1.589)

Chien, Chen-Fu, Chen Y., and Peng J. (2010), "Manufacturing Intelligence for Semiconductor Demand Forecast based on Technology Diffusion and Product Life Cycle," International Journal of Production Economics, 128(2), 496-509.(NSC 96-2628-E-007-035-MY3) (SCI) (2011 Impact Factor: 1.76)

Costantino, F., Di Gravio, G., Shaban, A., & Tronci, M. (2014). The impact of information sharing and inventory control coordination on supply chain performances. Computers & Industrial Engineering, 76, 292-306. doi:https://doi.org/10.1016/j.cie.2014.08.006

Daniel Waller (2014) MRes Research (Intermittent Demand Forecasting) doi:http://www.lancaster.ac.uk/pg/waller/pdfs/Intermittent_Demand_Forecasting.pdf

Dekker, R., Krever, M., Wunderink, S., & Schorr, B. (2005). Inventory control based on advanced probability theory, an application (Vol. 162).

Dekker, R., & Porras, E. (2006). An efficient optimal solution method for the joint replenishment problem with minimum order quantities (Vol. 174).

Nenes, G., Panagiotidou, S., & Tagaras, G. (2010). Inventory management of multiple items with irregular demand: A case study (Vol. 205).

Petropoulos, F., Nikolopoulos, K., P. Spithourakis, G., & Assimakopoulos, V. (2013). Empirical heuristics for improving intermittent demand forecasting (Vol. 113).

Porras, E. and Dekker, R. (2008) An Inventory Control System for Spare Parts at a Refinery: An Empirical Comparison of Different Re-Order Point Methods. European Journal of Operational Research, 184, 101-132.

Rego, José & Mesquita, Marco. (2015). Demand forecasting and inventory control: A simulation study on automotive spare parts. *International Journal of Production Economics*. 161. 10.1016/j.ijpe.2014.11.009.

Romeijnders, W., Teunter, R., & van Jaarsveld, W. (2012). A two-step method for forecasting spare parts demand using information on component repairs. *European Journal of Operational Research*, *220*(2), 386-393. DOI: 10.1016/j.ejor.2012.01.019

Silver, E., Pyke, D., & Peterson, R. (1998). Inventory Management and Production Scheduling (Vol. 19).

Syntetos, A.A. & Babai, M.Z. & Davies, J. & Stephenson, D., 2010. Forecasting and stock control: A study in a wholesaling context, *International Journal of Production Economics,* Elsevier, vol. 127(1), pages 103-111, September.

Syntetos, A., Babai, M. Z., & Gardner, E. (2015). Forecasting intermittent inventory demands: Simple parametric methods vs. bootstrapping (Vol. 68).

Syntetos, A. A., & Boylan, J. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting*, 21(2), 303-314. DOI: 10.1016/j.ijforecast.2004.10.001

Teunter, R., A. Syntetos, A., & Babai, M. Z. (2011). Intermittent demand: Linking forecasting to inventory obsolescence (Vol. 214).

Willemain, T. R., Smart, C. N., & Schwarz, H. F. (2004). A new approach to forecasting intermittent demand for service parts inventories. International Journal of Forecasting, 20(3), 375-387

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