Dynamic Safety Stock Considerations

A simulation based comparative analysis

by:

Albert Hunduza

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ROP	Reorder Point
MRP	Material Requirement Planning
FOI	Fixed Order Inventory
EOQ	Economic Order Quantity
KPI	Key Performance Indicator
GDP	Gross Domestic Product
CSL	Cycle Service Level

1 Introduction

1.1 Problem Description

In order to maintain competitive advantage, manufacturing companies aim to reduce inventory levels and shorten lead times as much as possible[1]. Frequent disruptions of the production schedule caused by erratic sales, unreliable delivery from suppliers or force majeure can result in reduced productivity[2]. The Supply Chain must therefore interpret and understand customer requirements to accurately order raw materials at the right quantity and quality[3]. Inventory typically refers to the components which are assembled or integrated together in order to deliver the final product[4]. A stock out event occurs when there is higher demand than inventory[5]. To avoid stock outs, manufacturing firms carry safety stock in the form of extra raw material and packaging[6]. Safety stock is used to assure timely production and delivery of products in production environments with dynamic demand and lead times[7]. Essentially, it is utilized to buffer the firm against unforeseen variations in demand and compensate for forecast inaccuracies. This helps to keep customer service and satisfaction levels high. Calculating safety stock accurately is therefore pivotal in any planning method, be it Kanban, Re-order Point (ROP) or Material Requirement Planning (MRP) etc.

While some companies such as those in aviation typically hold high inventories of spare parts to assure high availability[8], this approach can result in an overinvestment in inventory and tie up working capital. High levels of inventory can have adverse effects for the firm such as concealing inefficiencies in the supply chain like transport delays and poor quality of raw

[1] Cf. (Kumar & Aouam 2019)

[2] Cf. (Sridharan & LaForge 1989)

[3] Cf. (Limère et al. 2012)

[4] Cf. (Greasley 2013)

[5] Cf. (Jain, Rudi & Wang 2015)

[6] Cf. (Monk & Wagner 2012)

[7] Cf. (Ruiz-Torres & Mahmoodi 2010)

[8] Cf. (Khajavi & Holmström 2017)

materials from suppliers[9]. These problems can be mitigated by effectively managing inventory levels[10]. The optimal safety stock level establishes a balance between penalties the firm would incur from unfulfilled and/or delayed orders and the holding costs of the safety stock it carries to avoid them[11]. Most safety stock calculation methods require a measure of the forecast error uncertainty and assume the errors to be Gaussian independently and identically distributed. A deviation from this property may further reduce the accuracy of the safety stock calculation[12].

There are several formulas that have been proposed for safety stock calculation. However, there is no universal safety stock formula because they all have their shortcomings. For example, the average Safety Stock formula offers a simple way to calculate the safety stock required per unit of stock. However, it fails to account for seasonal changes in demand[13]. Heizer and Render's approach addresses this flaw by considering standard deviation despite overlooking the effects of time[14]. Greasley came up with an elegant method of calculation that considers fluctuations in demand and lead times to compensate for inaccuracies in data on demand while still maintaining normal distribution[15]. The McKinsey & Company Method also considers the combined effects of demand and replenishment cycle variability[16].

While all these authors and several others like Alicke[17], Hermann[18] and Gudehus[19] have proposed different formulae and improvements for the calculation of safety stock, very little research has been carried out, to the author's best knowledge, to make a comparative analysis of these methods. In their paper, Schmidt, Hartmann and Nyhuis[20] made a simulation-based

[9] Cf. (SCMDojo 2017)

[10] Cf. (Laura 2019)

[11] Cf. (Chaturvedi & Martínez-de-Albéniz 2016)

[12] Cf. (Graves & Willems 2000)

[13] Cf. (SCMDojo 2017)

[14] Cf. (Emmanuel-Ebikake 2014)

[15] Cf. (Greasley 2013)

[16] Cf. (SCMDojo 2017)

[17] Cf. (Alicke 2005)

[18] Cf. (Herrmann 2011)

[19] Cf. (Gudehus & Kotzab 2012)

[20] Cf. (Schmidt, Hartmann & Nyhuis 2012)

analysis of safety stock formulae. However, their work focused more on investigating the effectiveness of different safety stock formulae on different distribution types of data rather than demand patterns. Therefore, a knowledge gap remains that must be filled. It is necessary to determine which demand patterns each of these formulae is best suited to. This knowledge would make it easier for supply chain managers to apply the correct method of safety stock calculation and thus optimize their inventory management.

1.2 Aims of the Study

The focus of the study is to conduct a comparative analysis of the most widely adopted methods of safety stock calculation. Firstly, it aims to identify the most widely adopted methods of safety stock calculation and investigate their strengths and weaknesses. Secondly, the thesis aims to analyse the demand patterns that operations managers often encounter and their behaviours. The safety stock calculations will then be compared to one another by running a simulation with different demand patterns using each of them. Finally, recommendations will be made on which demand patterns, if any, each of these methods is best applied to.

2 Literature Review

In this chapter the concept of safety stock is going to be further explained. The benefits and challenges of using safety stock are going to be discussed. Particular attention will be given to the uncertainties that supply chain managers encounter and the currently adopted approaches to compensate for them. There will also be a discussion about the techniques to calculate safety stock where their strengths and weaknesses will be analysed. Finally, the research gap will be established.

2.1 Safety Stock

There are several models that can be used to determine the ordering policy i.e. the quantity of inventory that is required and the frequency of ordering that yields the most efficiency[21]. The Reorder Point (ROP) model employs a predetermined level that marks the time to reorder. This level typically includes a quantity of inventory to cover for the Leadtime and delays[22]. The Economic Order Quantity (EOQ) model seeks to minimize the annual costs of ordering and holding inventory by calculating a fixed order volume[23]. However, its effectiveness has been questioned by some scholars because it makes several rather unrealistic assumptions including a stable demand, constant item cost regardless of order size and a linear relationship between the cost of holding inventory and the number of items held[24]. The Fixed Order Inventory (FOI) Model is used to calculate the amount to order when fixed intervals are used between orders. Maximum and minimum levels of inventory can be set where at a fixed period inventory can be replenished to the maximum level if it is below the minimum level[25].

It is evident that the more robust of these models consider uncertainties like demand and lead time and attempt to attune for them. A common approach is to carry safety stock. Essentially, safety stock is excess inventory that is carried to avoid the costs associated with uncertainties in supply and demand. Such costs include lost revenues from stock-outs and production delays

[21] Cf. (Zhang et al. 2016)

[22] Cf. (Gonzalez & González 2010)

[23] Cf. (Kostić 2009)

[24] Cf. (Friend, Swift & Ghobbar 2001)

[25] Cf. (Baker & Urban 1991)

due to depletion of necessary components[26]. The most apparent of these uncertainties tend to be demand and Leadtime[27]. Demand uncertainty differs between products where demand for perennial products like toilet paper is easier to forecast than demand for seasonal products like umbrellas. As a rule, products with more demand uncertainty require a stronger safety stock[28]. Leadtime uncertainty is influenced by a myriad of factors among them missing components, transport problems, customs clearances and hazards[29]. Also, an information delay due to the structure of supply chains can result in the "bullwhip" effect, whose severity is positively related to lead times[30].

The easiest methods used to set safety stock involve the use of gut feelings or hunches by operations managers. Others opt to base safety stock levels on a percentage of the cycle stock[31]. These techniques generally yield poor performances. Some techniques with better yields are going to be discussed below.

2.2 Safety Stock Calculation Techniques

Perhaps the simplest safety stock calculation technique is the aptly named Basic Safety Stock formula[32]. As previously alluded to above, the EOQ model seizes to be effective when there is unexpectedly high demand. It is therefore used in conjunction with the Basic Safety Stock formula. The average safety stock formula seeks to keep inventory required for a certain amount of days as a safety stock. The time to be covered by the safety stock can be arbitrarily chosen. For example, if a firm sold an average of 50 units per day and resolved to keep 10 days of inventory as safety stock, then they would carry 500 units of safety stock. The calculation for safety stock thus becomes:

$$\boldsymbol{Safety\ Stock} = Average\ Sale \times Safety\ Days \tag{1}$$

[26] Cf. (Holsenback & McGill 2007)

[27] Cf. (Dolgui & Prodhon 2007)

[28] Cf. (Landeta 2016)

[29] Cf. (Wazed, Ahmed & Nukman 2009)

[30] Cf. (Lee, Padmanabhan & Whang 1997)

[31] Cf. (Markovic & Arvid 2017)

[32] Cf. (Schwarz & Weng 2000)

Consequently, the reorder point, also known as the control point, in the EOQ model becomes:

$$\textbf{Reorder Point} = Safety\ Stock + Average\ \ Stock \times Leadtime$$

However, this technique does not take fluctuations in Leadtime or seasonal demand into account.

The Average Safety Stock Formula is a variation of this method is applicable in situations with low demand variability. It uses exponential smoothing or moving averages to create a curve of mean demand. The Average Safety Stock formula is as follows:

$$\boldsymbol{Safety\ Stock} = (D_{max} \times LT_{max}) - (D_{mean} \times LT_{mean}) \tag{2}$$

where:

LT_{mean} = Average lead time in days

LT_{max} = Maximum lead time in days

D_{mean} = Mean demand rate per item

D_{max} = Maximum demand rate

King (2011) proposed a technique that elegantly accounts for the variability in demand[33]. According to his approach, the safety stock that is required to guarantee a particular level of protection is the product of the standard deviation of demand and the Z-score. The Z-score is sometimes referred to as the standard score. Cycle stocks are those inventories that are expected to meet the demand before being resupplied[34]. While in an ideal world all operations managers would seek to achieve a Cycle Service Level (CSL) of 100%, higher cycle service levels require a disproportionately higher investment of resources. Thusly, typical goals lie within a range of between 90 and 98 percent[35]. In fact, it is statistically impossible to get a CSL of 100%. For example, to get a CSL of 95% that is generally considered acceptable, a company must carry safety stock equal to 1.65 standard deviations of demand variability. Figure 1 below shows

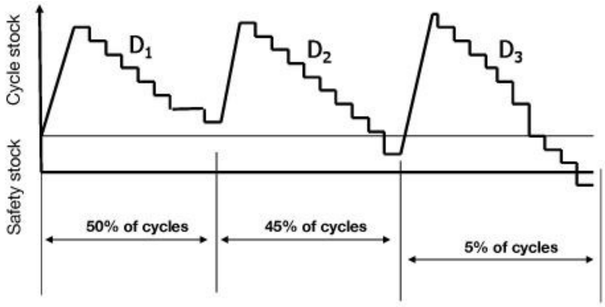
33 Cf. (King 2011)

34 Cf. (Beier 1995)

35 Cf. (Radasanu 2016)

inventory designed for a 95% CSL and figure 2 shows the relates the desired service level to the Z-score.

Figure 1: Inventory designed for 95% service level



Source: (King 2011, p33).

The results from this technique can be improved by carrying out an ABC analysis of the products based on criteria such as strategic importance and profit margin[36]. In the ABC analysis, Class A items are relatively few but constitute a relatively large amount of annual use value, while class C items are relatively large in number but constitute a relatively small amount of annual use value. Items between the above two classes constitute class B. The Z-scores can then be set independently in order to apportion more safety stock to products of more value to the business, in this case Class A items.

Figure 2:connection between CSL and Z-score

Desired cycle service level	Z-score
84	1
85	1.04
90	1.28
95	1.65
97	1.88
98	2.05
99	2.33
99.9	3.09

Source: (King 2011, p34).

[36] Cf. (Flores 1986)

King's safety stock formula is:

$$\boldsymbol{Safety\ Stock} = Z \times \sqrt{PC/T_1} \times \sigma_D \tag{3}$$

Where:

Z = Z-score

PC = performance cycle, another term for total Leadtime

T_1 = time increment used for calculating standard deviation of demand

σ_D = standard deviation of demand

Building upon this, the variability in Leadtime can be considered by using the following formula:

$$\boldsymbol{Safety\ Stock} = Z \times \sigma_{LT} \times D_{avg} \tag{4}$$

Where:

σ_{LT} = standard deviation of lead time

D_{avg}= average demand

When demand and Leadtime variability are not independent of each other, that is, when they are influenced by the same factors[37], safety stock equals the sum of these two individual calculations.

$$\boldsymbol{Safety\ Stock} = (Z \times \sigma_{LT} \times D_{avg}) + (Z \times \sqrt{PC/T_1} \times \sigma_D) \tag{5}$$

However, if they vary independent of each other and they are both normally distributed, the safety stock can be calculated by using the equation:

$$\boldsymbol{Safety\ Stock} = Z \times \sqrt{(PC/T_1\, \sigma_D{}^2) + (\sigma_{LT} \times D_{avg})^2} \tag{6}$$

Where:

Z= Z-score (a statistical figure based on the cycle service level)

PC = performance cycle or total lead time (including transport time)

T_1 = time increment used for calculating standard deviation of demand

[37] Cf. (Balakrishnan 1992)

σ_D = standard deviation of demand

Hermann[38] extended these safety stock techniques by introducing the concept of the undershoot into the calculation. In periodic review systems, the inventory position is checked at regular intervals. When using such a system, the inventory position is usually some amount below the reorder point at the time of order placement. This amount below the reorder point is referred to as the undershoot[39]. After introducing the concept of the undershoot into the above pair of formulae, they become:

$$\boldsymbol{Safety\ Stock} = Z \times \sqrt{Var(U) + LT \times {\sigma_D}^2} \qquad (7)$$

and:

$$\boldsymbol{Safety\ Stock} = Z \times \sqrt{Var(U) + ({}^{PC}/_{T_1}\, {\sigma_D}^2) + (\sigma_{LT} \times D_{avg})^2} \qquad (8)$$

Where:

Var(U) = variance of the undershoot

The effects of demand variability tend to influence safety stock requirements more significantly than the effects of Leadtime variability[40]. Consequently, it is usually more productive to reduce demand variability than Leadtime variability[41]. Another important distinction to note is the difference between CSL and fill rate. Many scholars regard fill rate as a better measure of inventory performance because it also measures the magnitudes of stockouts on top of just their frequency as in the case of cycle service level[42]. This means that when there are low standard deviations of demand and Leadtime, the fill rate is typically be higher than the cycle service

[38] Cf. (Hermann 2011)

[39] Cf. (Baganha et al. 1995)

[40] Cf. (Boute, Disney & Lambrecht 2007)

[41] Cf. (Kampen, Donk & Van Der Zee 2010)

[42] Cf. (Chopra, Dada & Reinhardt 2004)

level because the magnitude of the stockouts will be small. In contrast, fill rate tends to be lower than cycle service level when there is a high variability of demand and Leadtime[43].

Heizer and Render (2013) offered a technique that is significantly simpler but still takes standard deviation of demand into account[44]. According to them, safety stock can be calculated as follows:

$$\boldsymbol{Safety\ Stock} = Z\sigma_{dLT} \qquad (9)$$

Where:

Z= number of standard normal deviations (Z-score)

σ_{dLT} = standard deviation of demand during the lead time.

The approach by Greasley (2013) goes a step further by using lead time as a variable in the equation, while maintaining simplicity[45]. It therefore appears to not only be as comprehensive as King's method but also simpler. Greasley's equation is:

$$\boldsymbol{Safety\ Stock} = Z \times \sqrt{LT} \times \sigma_d \qquad (10)$$

Where:

Z = number of standard deviations from the mean (Z-score)

LT = lead time

σ_d = standard deviation of demand.

Alicke[46] proposed a related calculation rule for safety stock as a function of CSL that substitutes the standard deviation of demand with a standard deviation of forecast error. The standard deviation of forecast error can be computed from historical data by squaring the mean of the difference between forecasted demand and actual demand. This method can therefore be applied for any specific distribution of demand. His safety stock formula is:

$$\boldsymbol{Safety\ Stock} = Z \times \sigma_F \times \sqrt{LT} \qquad (11)$$

Where:

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[43] Cf. (King 2011)

[44] Cf. (Heizer, Render & Munson 2008)

[45] Cf. (Greasley 2013)

[46] Cf. (Alicke 2005)

Z = Z-score

σ_F = standard deviation of forecast error

LT = Lead time

Chopra and Meindl (2013) also proposed a different technique. It is particularly useful to optimize the calculation of safety stock in situations where assembly can be delayed until the customer confirms the orders[47]. This model significantly reduces the safety inventory required while maintaining a CSL of 95%. Below is the formula they came up with:

$$\boldsymbol{Safety\ Stock} = NORM.INV\ (CSL, D_L, \sigma_L) - D_L \tag{12}$$

Where:

CSL = Desired cycle service level

LT = lead time

D_L = mean demand during lead time

σ_L = standard deviation of demand during lead time

Another approach explained by Nahmias calculates safety stock using the following formula:

$$\boldsymbol{Safety\ Stock} = z_\beta \sigma \tag{13}$$

This formula uses the standardized unit loss integral L(z) which can be calculated by:

$$L(z) = \int_z^{+\infty} (t - z)\emptyset(t)dt$$

Where:

$\emptyset(t)$ = cumulative distribution function for the standard normal

β = proportion of demand met from stock

Q = the order quantity

σ = standard deviation of demand

The relationship between the variables is:

[47] Cf. (Chopra, Meindl & Kalra 2013)

$$L(z) = \frac{(1 - \beta)Q}{\sigma}$$

The expected number of units out of stock during an order cycle can be given by $\sigma L(z)$.

Finally, a common approach assumes that demand during successive time periods are independent and identically distributed random variables. It calculates safety stock by the formula:

$$\boldsymbol{Safety\,Stock} = z_{\alpha} \times \sqrt{E(L)\sigma^2{}_D + (E(D))^2\sigma^2}$$

Where:

α = service level

z_{α}= inverse distribution function of a normal distribution with cumulative probability

E(L) and σ_L= mean and standard deviation of lead time

E(D) and σ_D = mean and standard deviation of demand in each unit time period

Twelve of the fourteen techniques discussed in this section were used in a comparative simulation for the study in this paper. They are referred to in the later parts of the paper according to the numbers designated to them here. The last two formulae were excluded from the study as they are not widely used in inventory management.

2.3 Demand Forecasting

The concept of forecasting is vital in inventory management. It is usually "joined at the hip" with safety stock calculations because several safety stock formulae use the forecast as a variable. Demand forecasting is the process of estimating future demand of products or services[48]. It is especially useful when trying to predict the behaviour of intermittent demand. Intermittent demand refers to a series of random values that seem to appear at random intervals[49]. Production planners and inventory managers often face intermittent demand[50]. Forecasting techniques can be either historically oriented or future oriented. They can also be

[48] Cf. (Archer 1987)

[49] Cf. (Silver 1981)

[50] Cf. (Watson 1987)

either quantitative or qualitative in nature[51]. For the purposes of this paper, we will focus on historically oriented quantitative approaches. These include moving averages, exponential smoothing and regression. Moving averages are a technical indicator used to predict future data in a time series analysis[52]. Moving averages can be exponentially smoothed to increase accuracy of the estimation in some situations[53]. Regression is a widely used too in statistical forecasting[54]. However, it is important to note that forecasts are never accurate. Also, the more detailed and further into the future the look, the less reliable they become[55]. Forecast errors show the difference between the actual demand and the forecasted demand. In the calculations performed in this study, moving averages, exponential smoothing and regression were used for forecasting depending on the demand pattern. The demand patterns in question are discussed below

2.4 Demand Patterns

As alluded to above, demand variability appears to be the biggest influence on the amount of safety stock required. It is therefore essential to get a better understanding of the different patterns that firms encounter. There are five patterns that typically appear in time series data. These are trend, horizontal, seasonal, cyclical and random[56]. A trend is a pattern where there is growth or decline in the data over time. In contrast, a horizontal pattern has data that is more evenly distributed over the entire timeframe[57]. A seasonal pattern, on the other and, signifies that that the data is influenced by seasonal factors such as months of the year or days of the week. A seasonal pattern tends to repeat itself at regular intervals. Cyclical data is influenced by longer term economic fluctuations such as periods of boom or recession[58]. Finally, random data is data that does not follow any discernible pattern resulting from chance and cannot be

[51] Cf. (Goldstone 2008)

[52] Cf. (Hansun 2013)

[53] Cf. (Crane & Crotty 1967)

[54] Cf. (Pankratz 2012)

[55] Cf. (Penner 2002)

[56] Cf. (Bon & Ng 2017)

[57] Cf. (Malpass & Shah 2008)

[58] Cf. (Haltiwanger & Harrington 1991)

predicted. However, it is important to note that most real-world data exhibits combinations of these different patterns.

2.5 Research Gap

In this chapter some of the several approaches currently being used to calculate safety stock have been discussed. King's method appears to be the most comprehensive as it accounts for both demand and Leadtime variability. It also allows for the adjustment of safety stock levels to different demand levels and the determination of safety levels[59]. However, it assumes a normal distribution and a mean forecasting error close to zero and there is no consideration of incoming good variance. Heizer and Render's technique is simpler although it overlooks time as variable in the equation. This weakness also appears to be inherent in Greasley's formula which does not take seasonal fluctuations into account[60]. Although at first glance the Average Safety Stock formula appears too simplistic to be useful, it also offers a convenient way to quickly calculate Safety Stock. Finally, Chopra and Meindl's formula can have applications for online retailers whose industry is gaining traction and relevance today[61]. All these approaches have their strengths and weaknesses. However, it is not immediately obvious in which situations each formula's strengths offset its weaknesses enough to justify its use. This is the gap that this paper seeks to fill by looking at these approaches from an application point of view. The author's research and simulation-based analysis intends to ascertain which of these techniques is the best in different situations. This is particularly in the context of varying demand patterns.

[59] Cf. (Radasanu 2016)

[60] Cf. (Emmanuel-Ebikake 2014)

[61] Cf. (Liao et al 2017)

3 Methodology

This chapter describes the spreadsheet-based simulation model that was designed for this study. In the first part, the approach of the study and the context of the model will be elaborated along with the different variables under investigation. Afterwards, the Key Performance Indicators (KPIs) used to evaluate performance in the model will be explained.

3.1 Approach of the study

The approach of research that is adopted in a study determines the quality of the research results and must be therefore be tailored to suit the research problem. There are several approaches that a study can use including the analytical approach, the systems approach and the actor's approach[62]. This paper uses a balanced approach which is a hybrid of the Inductive approach and the deductive approach. The main aim of the inductive approach is to understand the phenomenon being researched in its undisturbed state[63]. The deductive approach typically commences with a study of available literature to establish a conceptual framework of the relevant variables and their expected relationships. Data is then collected and used to create a model[64]. This paper strives to stay consistent to the principles of the balanced approach whenever possible.

3.2 Spreadsheet-based simulation

A spreadsheet-based simulation is when a spreadsheet is used as a platform to represent models as well as to run simulation experiments[65]. Spreadsheets offer certain utilities that are especially useful for this study. The first of these is the ability to represent mathematical and logical relationships among variables in the form of computations and algorithms. This is necessary as this simulation relies on calculations using different formulae. Spreadsheets also allow for not only the repetition of the model's computations using a wide range of mathematical and

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[62] Cf. (Strömberg & Gustavsson 2018)

[63] Cf. (Hirschman 1986)

[64] Cf. (Golicic Davis & McCarthy 2005)

[65] Cf. (Seila 2005)

statistical functions but also the modification of individual variables for each run of the simulation. After completing the computations, spreadsheets offer charting and graphing capabilities that enable better visualization of the results. It is due these considerations that the Microsoft Excel spreadsheet platform was selected for the simulation.

3.3 Underlying Structure of the Simulation

The model required a company whose inventory management relies upon customer demand and supplier lead times to plan operations. It also required comprehensive data of the company's supply chain activities for at least five products, each following one of the different demand patterns that this paper strives to investigate. Unfortunately, companies generally prefer not to disclose information about the uncertain demand function to the public domain. This is because when confidentiality is maintained, both manufacturers and retailers have an incentive to engage in information sharing equally during negotiations where retail competition is intense. It allows the supply chain profit to achieve its equilibrium[66].

Due to the unavailability of real-world data, a dataset was created specifically for this study. Over the past two decades, the trend in the automotive industry has shifted towards mass customization. This requires complicated coordination between suppliers, equipment and logistics workers to ensure that the final assembly lines have an uninterrupted workflow[67]. This problem motivated the author to model the datasets for the study in the context of the automotive industry.

The model considers a hypothetical company that supplies tires to luxury automakers. It assumes that the company sells 5 types of tires, A, B, C, D and E. Each set of 4 tires, which is considered 1 unit in this case, has a price of 200 EUR. It costs 4.80 EUR to store each unit in the warehouse for a year. Every time an order is placed the company incurs ordering costs. Ordering costs are a flat fee, typically consisting of both fixed and varying expenses, that is charged for making an order[68]. In this case, the ordering costs are taken to be 450 EUR. The

[66] Cf. (Lode & Zhang 2008)

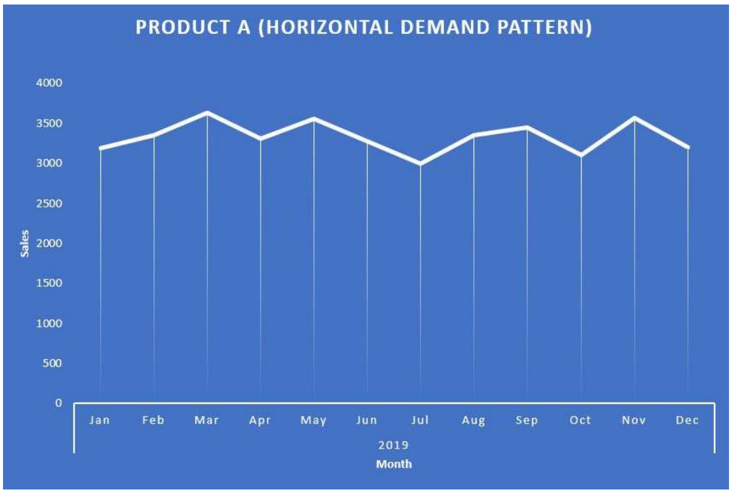
[67] Cf. (Boysen et al. 2015)

[68] Cf. (Islam 2013)

supplier lead time is assumed to be 15 days. However, the supplier is in the adjacent lot to the company therefore the transportation time is negligible. Consequently, the total replenishment time is equal to the production lead time of 15 days.

Each of the 5 products sold by the company in this model exhibits a different demand pattern. In order to be as true to life as possible, real world data that is available from independent sources was used as a proxy during the dataset creation process. This real-world data was then modified where necessary to fit the pattern that were required for the model. The data is in the form of a timeseries in which each period represents a month. At last 12 months of data was needed in order to capture the behaviour of the model over the full cycle of year. Also, another 12 periods of data were used to simulate historical data for the calculations in some of the equations. The first pattern under investigation is the horizontal pattern. As explained in the literature study, a horizontal demand pattern is signified by sales that are constant over time. The dataset used for the horizontal pattern was modelled after the sales for the Mercedes E class in the United States for the years 2018 and 2019[69]. Over that period the sales figures for this model of car fluctuated in a narrow range showing a horizontal pattern. The sales data was modified slightly for the purposes of this model. A line chart showing the sales as well as the pattern of the data is shown in figure. 3 below. The full spreadsheet of the dataset can be found in the appendix section of this paper.

Figure 3:Line graph showing pattern for Product A

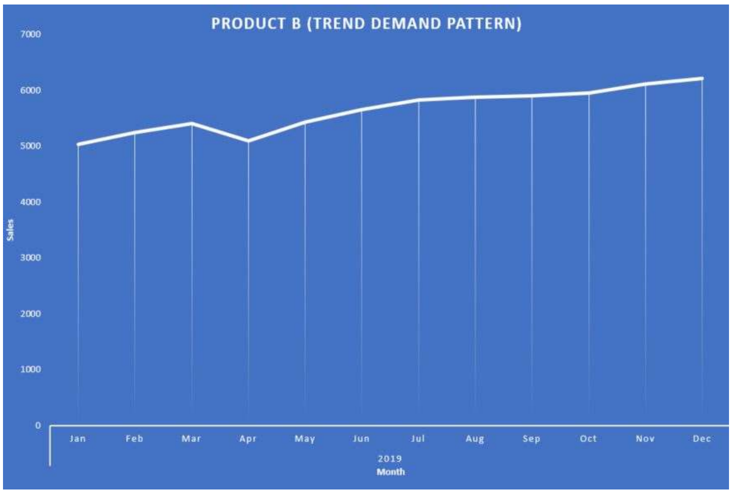


(Own Creation)

[69] Cf. (Demandt 2018)

The second pattern that is under investigation is the trend pattern. It was established in the literature study that a trend is when there is growth or decline over time. This pattern is especially relevant because in general, the number of light vehicles sold increases with Gross Domestic Product (GDP). Their sales in the United States tend to grow steadily by about 2 to 3% every year[70]. It is therefore necessary to capture how effectively different safety stock formulae protect automakers against stockouts for this endemic pattern. The line chart of the timeseries that was created for this purpose is shown in figure.4.

Figure 4:Line graph showing demand pattern for Product B



(Own Creation)

Thirdly, this study will look at seasonal trends. Seasonality involves predictable but uncontrollable variations in demand over time. These are trends in which are influenced by seasonal factors including days of the week, weeks of the months and months of the year. In the auto industry there is a distinct seasonal pattern that can be observed. The demand for cars in the United States, for example, typically has two peak seasons. The first one is in Spring from the end of February to the end of May. Sales experience another increase in Fall from September to November. This is because automakers normally release new models during this period. The

[70] Cf. (McKean 2020)

demand subsides in Demand as the holiday retail season rises to its peak[71]. This pattern was considered when the dataset for product C was generated. The resulting line chart is in figure.5.

Figure 5:Line graph showing demand pattern for Product C

(Own Creation)

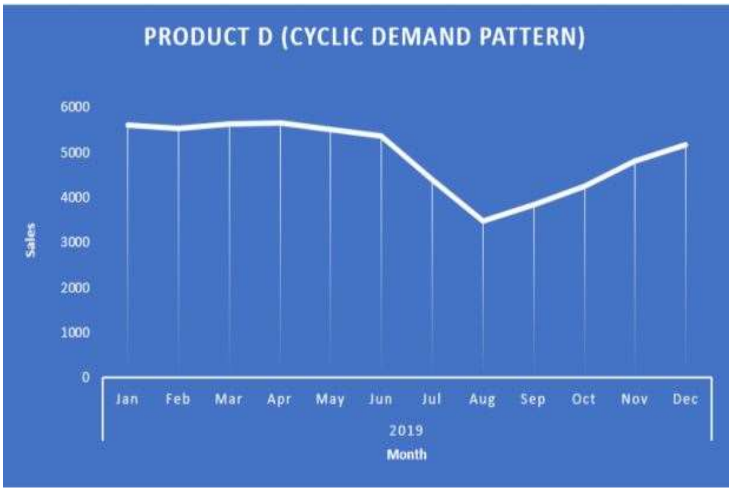
A cyclic pattern is one that is influenced by the rhythm of longer-term fluctuations in the economy such as recessions and booms. This pattern can also be observed in the automotive industry. An economic boom is usually followed by a surge in automobile sales while recessions affect sales negatively[72]. This correlation is so strong because demand for cars is elastic therefore changes in income has a significant effect on it. This cyclical behaviour can be observed in the annual sales of light vehicles in the United States from 1990 to the present day[73]. The timeseries for product D in this study was modelled after this data. Line chart is shown in figure. 6.

[71] Cf. (Shugan et al. 1999)

[72] Cf. (Barker 2011)

[73] Cf. (Blanchard & Melino 1986)

Figure 6:Line graph showing demand pattern for Product D



(Own Creation)

The final pattern under investigation is one of randomness. In some instances, there reason for the fluctuations in the demand cannot be explained by any of the above four patterns. A robust inventory management system should be able to keep stockouts at a minimum even in the event of random demand. During the creation of the dataset the objective was to create data that is comparable to the data for the other pattern while maintaining randomness. To achieve this the random number generator in Microsoft Excel was used. It was set to generate randomized discrete values between 500 and 4000. The resulting dataset was used to create the line chart in figure. 7.

Figure 7:Line graph showing demand pattern for Product E

(Own Creation)

During the creation of the timeseries for 2019, data for 2018 was also created. The 2018 timeseries was meant to act as historical data in the model. This means that the simulation was run for 2019 utilizing forecasts calculated using 2018 data. The details of the actual simulation run are elaborated below.

After generating demand data, attention was turned to the lead time data. As already discussed above, the expected lead time was assumed to be 15 days. During safety stock calculations, any granularity of time periods can be used for convenience. However, all terms must be expressed in the same time period to avoid inconsistency errors[74]. The lead times were therefore expressed as months in order to be consistent with the demand data. The expected lead time was set as 0.5 months. However, as was established in the literature study, the lead time tends to vary. It was also discussed that lead time tends to follow a normal distribution[75]. The random number generator in Microsoft Excel was therefore used again to create random numbers that represent lead variability. A mean of 0.5 was chosen along with a standard deviation of 0.03. The literature study also theorized that the effects of demand variability on safety stock levels outweigh those of lead time variability. A separate distribution of lead time was created in the same way, albeit with increased variability to investigate the substance of this thesis. In this case, the mean was set at 0.5 and the standard deviation at 0.25 in the random number generator. The two lead time timeseries are shown in figure 8. below.

[74] Cf. (De Kok, 2018)

[75] Cf. (Hoque, 2013)

Table 1:Leadtimes used in the simulation

Leadtime (Expecte	Leadtime (Actu	Leadtime (Expecte	Leadtime (Actu
0.5	0.44	0.5	0.90
0.5	0.50	0.5	0.27
0.5	0.51	0.5	0.25
0.5	0.44	0.5	0.46
0.5	0.43	0.5	0.78
0.5	0.59	0.5	0.99
0.5	0.57	0.5	0.58
0.5	0.58	0.5	0.50
0.5	0.38	0.5	0.66
0.5	0.51	0.5	0.52
0.5	0.53	0.5	0.07
0.5	0.41	0.5	0.81
0.5	0.43	0.5	0.44
0.5	0.41	0.5	1.00
0.5	0.60	0.5	0.42
0.5	0.40	0.5	0.22
0.5	0.50	0.5	0.31
0.5	0.43	0.5	0.95
0.5	0.43	0.5	0.20
0.5	0.54	0.5	0.18
0.5	0.47	0.5	0.46
0.5	0.49	0.5	0.55
0.5	0.42	0.5	0.32
0.5	0.51	0.5	0.91

(Own Creation)

3.4 Trial Plan

In this sub-section, the steps taken in each trial series of the simulation are going to be elaborated. Due to the nature of the study, the emphasis of this simulation was not on the number of simulation runs but on ensuring that each of the safety stock formulae was sampled with each demand pattern under different levels of lead time variability. To achieve this, six steps were taken. Firstly, the required safety stock level for 2019 for each of the products A, B, C, D and E was calculated using each of the formula. The demand information from 2018 available in the datasets was used as historical data necessary for the calculations. For example, the mean demand rate used in the calculations was taken from this historical data. Several safety stock formulae under investigation use forecasts as variables. The 2018 data was also used for the forecasting using an appropriate technique for each demand pattern. For product A which has a horizontal pattern, forecasting was done using a 3-period simple moving average. A linear trend line was utilized in the case of product B, which follows a trend pattern, to come up with a forecast. Regression was used to forecast for product C which follows a cyclical pattern. The forecasting for the seasonal product D was done using Winter's Method. Finally, a weighted moving average was used for the forecasting of product E. Using this information, the safety stock required for each product was calculated using 12 different formulae. The 12 safety stock formulae used in the study were all discussed in the literature study and are labelled according to the numbers designated to them in that section of this paper.

The simulation was conducted using a Reorder point (ROP) policy. As discussed in the literature study, the ROP determines a stock level at which a new order is triggered. Ideally, this threshold must give adequate time to make a new order before the stock runs out. Consequently, the ROP considers both safety stock and lead time. The formula for ROP used is:

$$\textbf{Reorder Point} = Safety\ Stock + Average\ \ Stock\ \times Leadtime$$

According to the ROP policy, a predetermined amount of stock is ordered every time the stock level reaches the ROP. This amount that is ordered must establish a balance between the ordering costs and the holding costs of the inventory. The amount is therefore called the Economic Order Quantity (EOQ)[76]. It is calculated by using the formula[77]:

$$\boldsymbol{EOQ} = \sqrt{\frac{2AD}{H}}$$

Where:

A = ordering costs per purchase order

D = demand per year

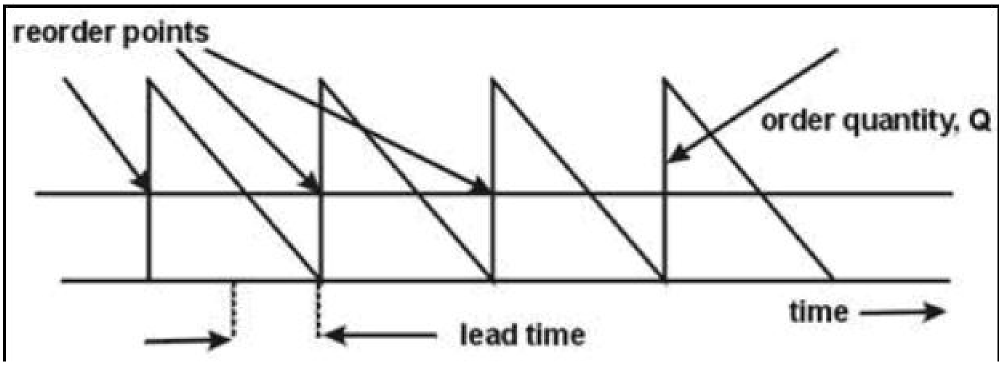
H = holding cost per unit per year

The figure below shows the stock level over time using the ROP policy.

[76] Cf. (Park 1987)

[77] Cf. (Cargal 2003)

Figure 8:Stock level graph in the ROP model



Source:(Islam 2013, p9)

The second and third steps of the study were to calculate the reorder point for each product-safety stock permutation and the EOQ for each product respectively. Afterwards an assumed initial inventory was calculated by summing the EOQ and the Safety Stock. This can be considered initializing the simulation as it ensured that each of the trial series that was conducted started with a full inventory. In the next step the mean weekly demand over 2019 was ascertained by dividing the monthly demand by four. This allowed the actual time the ROP threshold level was reached to be visualized easier.

Effectively, in each trial series that was conducted, the company started the year 2019 with a full inventory (combination of safety stock and EOQ). As time progressed the stock level began to decrease at a rate equal to the mean weekly demand that was calculated in step 5 above. Once the stock level reached the ROP, an order of a quantity equal to the EOQ was made. If at this moment the demand was such that the stock was below the ROP at the time that the order was made, an undershoot would be calculated. The concept of the undershoot was discussed in the literature study. It was calculated by subtracting the current stock level (If below the ROP) from the ROP. Since the expected lead time is 15 days, the stock would increase after about 2 weeks. This process was run over a period that was sufficiently long for the overall behaviour of the stock level under a set of parameters to be observed, in this case a full year. It is this stock level that was graphed and used to derive conclusions in this study.

In order to investigate the effects of the lead time variability, two trial runs were conducted for each combination of safety stock formula and demand pattern. All variables were kept constant between the two runs except for lead time which was the independent variable. The graphs created from the stock level yielded from the two cases were compared and analysed.

3.5 KPIs used in the study

Since the objective of this study is to investigate the effectiveness of different safety stock techniques in different demand and lead time environments, the KPIs used in the model must be able to distinguish the strengths and weaknesses of these techniques. The three main KPIs used are the cycle service level, order fill rate and the mean stock level. The difference between the CSL and the fill rate was established in the literature study. Essentially, the CSL measures the frequency of stock outs while the fill rate measures their severity. In both cases a higher result or percentage is considered better as it means a lower frequency of stock outs and less severe stock outs respectively. Both these scenarios typically imply that there is adequate safety stock to protect the company against most stock outs. The exception to this general rule is the reason a third KPI was also used. A good safety stock technique does not only strive to protect against stockouts, but it also tries to maintain very low levels of inventory. Consequently, the mean stock level was also considered in this study. In situations where there are no significant differences between the cycle stock levels and fill rates, the technique that yields the lower mean stock level is preferred.

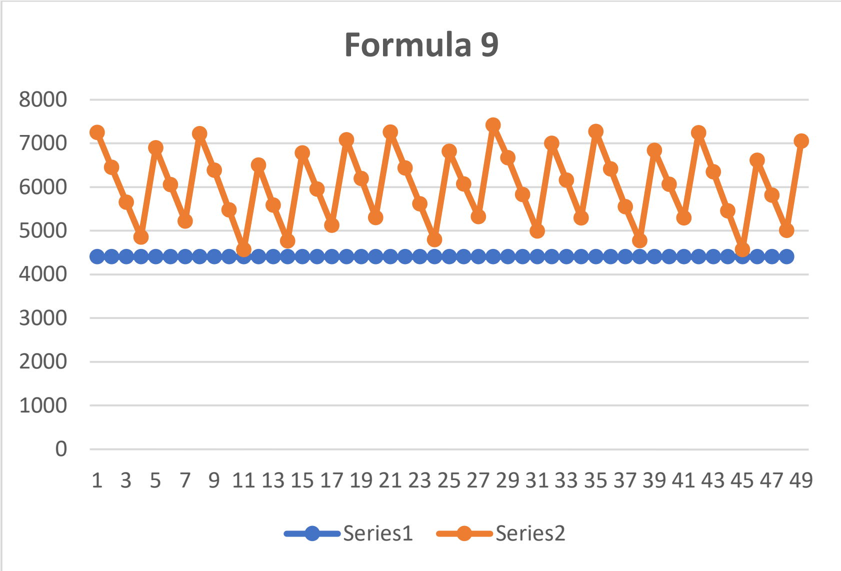
4 Results and Critical Reflection

In this chapter the results from the simulation that was conducted are going to be presented and critically analysed. Some trends that were observed will be discussed and explained. The chapter will look at the results one product or demand pattern at a time. Afterwards the results for the different levels of lead time variability will also be evaluated. Results will primarily be given in the form of cycle stock charts. Only the charts for the results on the extreme end of the spectrum will be presented in the primary text. In the charts, the cycle stock level is represented by the orange line and the safety stock is represented by the blue line. A table with a summary of the general behaviours of the different formulas in each situation is attached at the end of this chapter.

4.1 Horizontal Pattern (Product A)

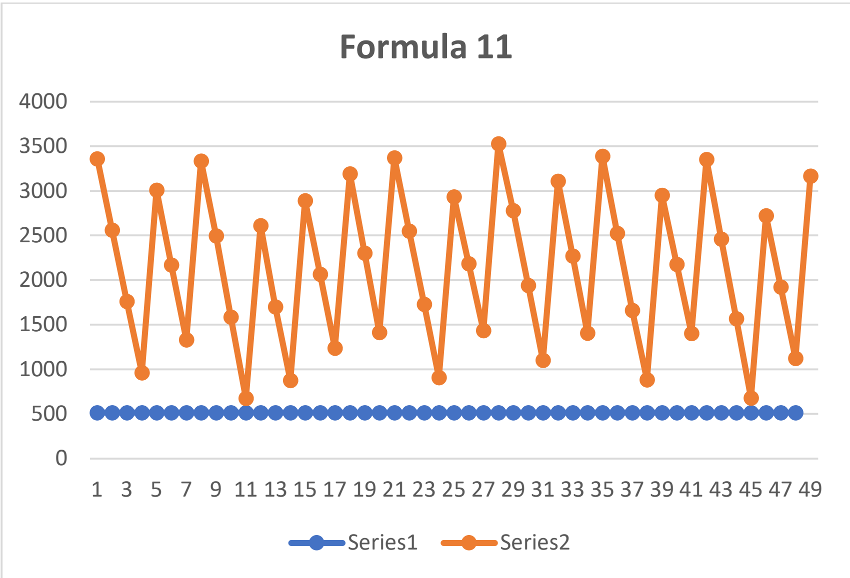
The results for the horizontal pattern are consistent with expectations. Since this pattern exhibits constant demand over the entire timeseries, it is well within expectations that this pattern be less complicated to carry safety stock for. The cycle stock charts show that all the formulae for calculating safety stock generally yield a good performance. In this study, none of them experienced stock outs for this pattern. All the charts followed the textbook pattern where the cycle stock graph only touches the safety stock line and finds support to go back up. This is the optimal inventory management scenario where everything is working as it should. However, it is important to note that despite the absence of stock outs across the board, some formulae still perform better than others. The mean stock level is the only KPI that can separate the formulas. Formula 9 yields an amount of safety stock that is too high and therefore would tie up too much of the company's capital as well as increase the inventory holding costs to an inefficient level. Therefore, in this case, formula 9 is the obvious worst performer while formula 11 is among the best performers as it yields a lower mean stock level.

Figure 9:Cycle Stock graph Formula 9 Horizontal Pattern



(Own Creation)

Figure 10: Cycle Stock graph Formula 11 Horizontal Pattern

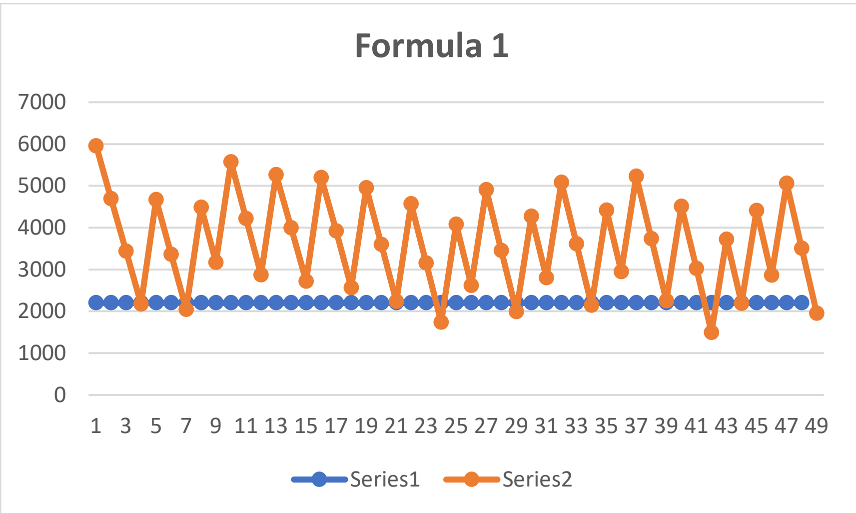


(Own Creation)

4.2 Trend Pattern (Product B)

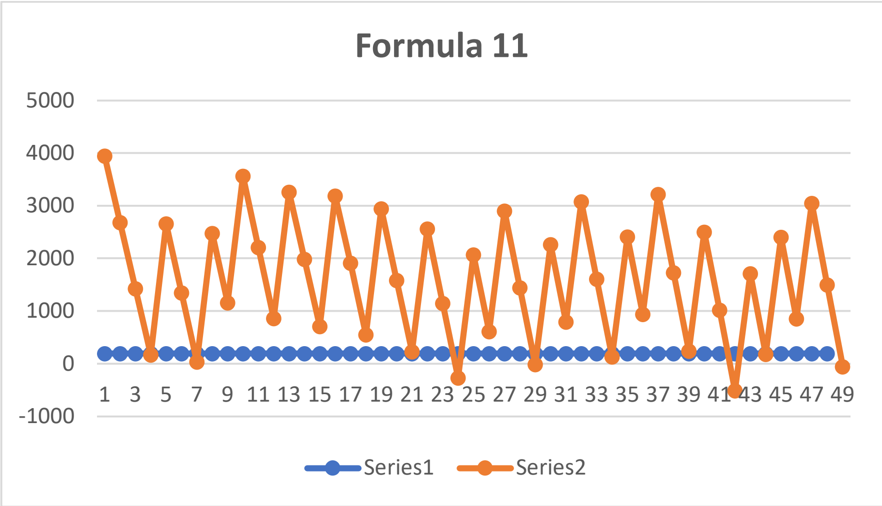
Meanwhile, the results for the trend pattern show a contrasting picture. Formula 1 and formula 4 still manage to maintain stable levels of inventory. In their case the stock level generally oscillated between the maximum level and the safety stock line as it should. For both formulae, the safety stock was enough to protect the company from stock outs in several instances when the demand was higher than normal. The behaviour of the stock level yielded by the remaining ten formulae can be divided into three distinct categories. The first is that of mild stock outs and critically low inventory (albeit with no stockouts). Such a result, as one displayed by formula 2 and 8 among others, can be arguably just as good as or even better than the stock out free scenario. This is because although mild stock outs have a significant effect on the cycle service level, their impact on the fill rate is not as critical. In some cases, it can be a good trade-off to deliver a few units short while maintaining a low inventory. However, this is usually subjective and dependent on the expectations of customers. The second category is that of severe stock outs. This can be observed in the graph of Formula 11. There are several stock outs and some of them fall short by a lot of units. Such a performance is not acceptable as it negatively influences customer satisfaction. Formulae that yield results in this category would generally be bad recommendations to use when planning inventory for products which exhibit the trend pattern. Finally, the final category is that of formulae that yield an inventory level that is inefficiently high. Formula 9 is an example of these.

Figure 11: Cycle Stock graph Formula 1 Trend Pattern



(Own Creation)

Figure 12:Cycle Stock graph Formula 11 Trend Pattern

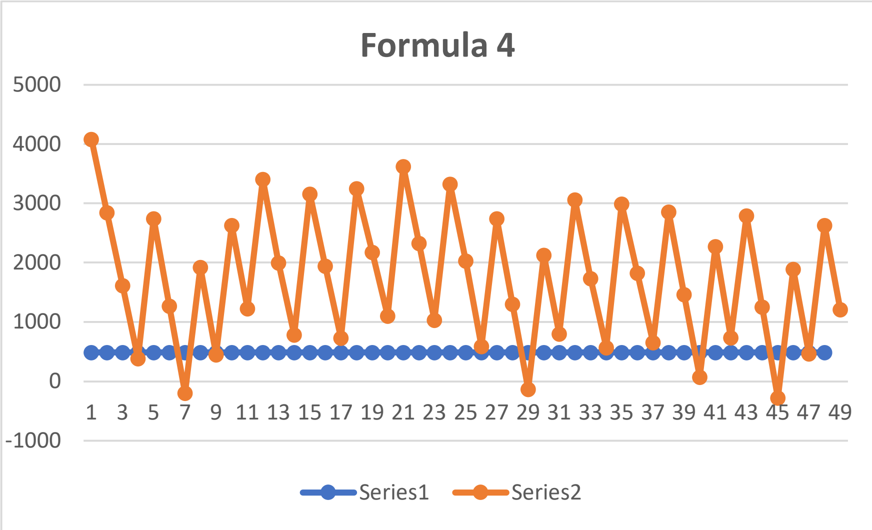


(Own Creation)

4.3 Seasonal Pattern (Product C)

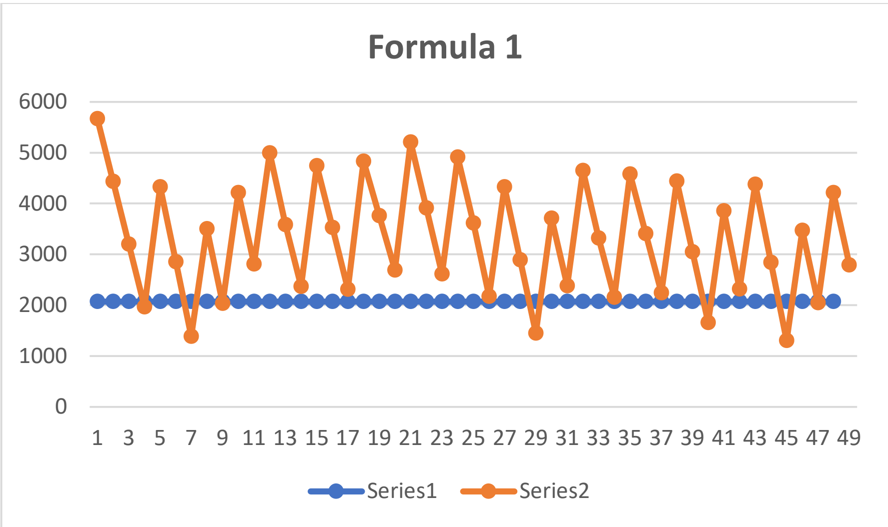
The results for the Seasonal pattern exhibit a comparable distribution of the categories discussed above to the Trend pattern. However, the formulae yielding these results have mostly changed. For example, while formula 4 yielded no stock outs in the Trend pattern, it yielded severe stock outs in this case. Formula 1 consistently maintained a desirable inventory level while formula 9 maintained its inefficiently high yields. The pattern of the results distribution is better summarized in the table and is further discussed in the final chapter of the paper.

Figure 13: Cycle Stock graph Formula 4 Seasonal Pattern



(Own Creation)

Figure 14: Cycle Stock graph Formula 1 Seasonal Pattern

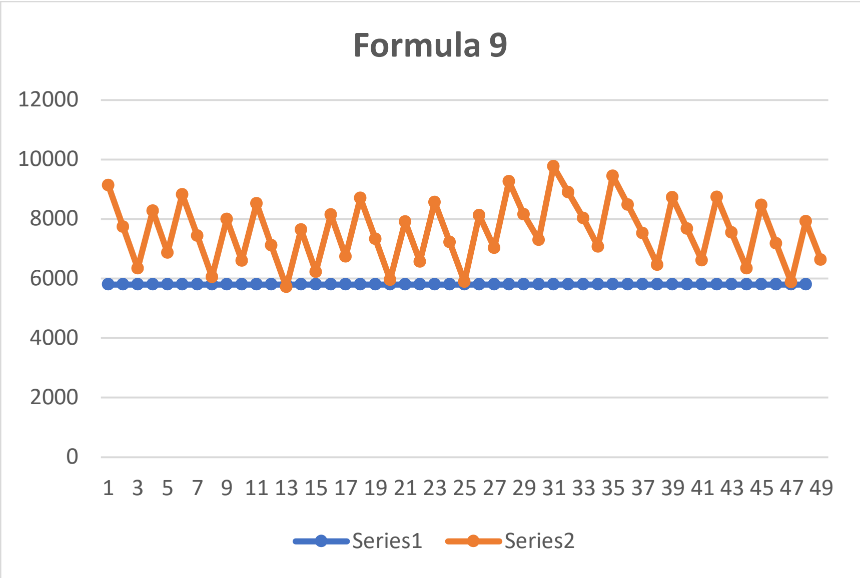


(Own Creation)

4.4 Cyclic Pattern (Product D)

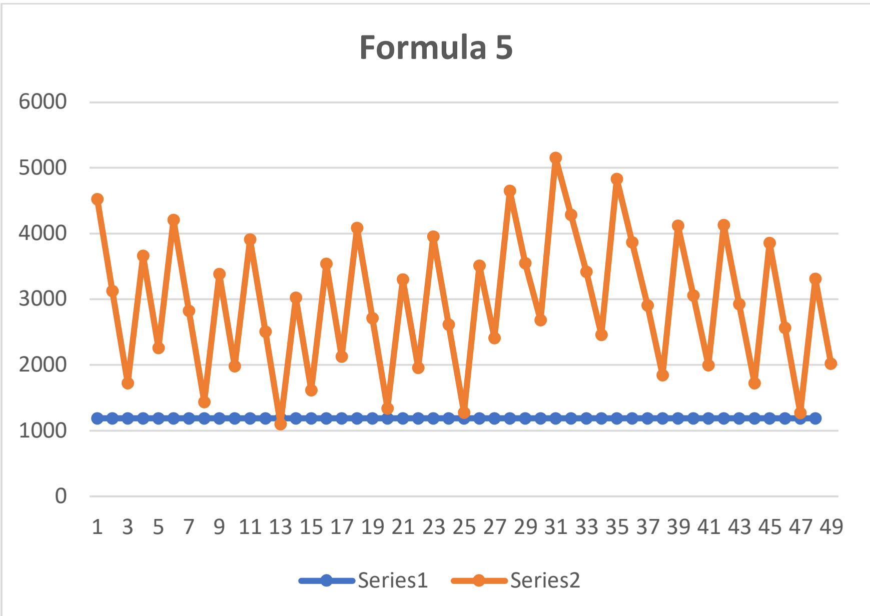
Interestingly, the results of the cyclic pattern bear a resemblance to those of the horizontal pattern. A possible explanation for this is that cyclic patterns usually follow a long-term cycle that tends to change gradually rather than drastically. Gradual change is typically easier to predict and has less spikes in demand that can cause stock outs. Consequently, most safety stock formulae yield an acceptable result. In this case formula 5 bears the best results while formula 9 continues its streak of inefficiently high inventory levels.

Figure 15: Cycle Stock graph Formula 9 Cyclical Pattern



(Own Creation)

Figure 16: Cycle Stock graph Formula 5 Cyclical Pattern

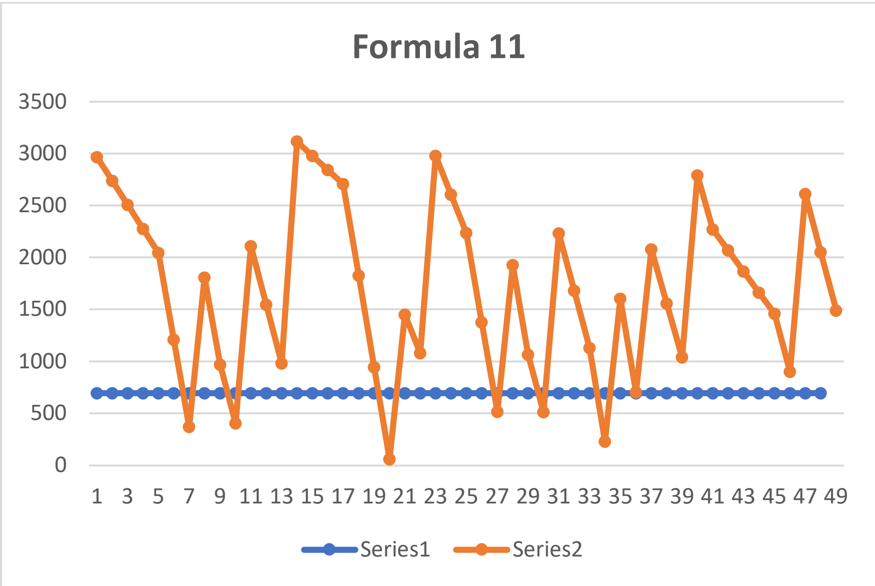


(Own Creation)

4.5 Random Pattern (Product E)

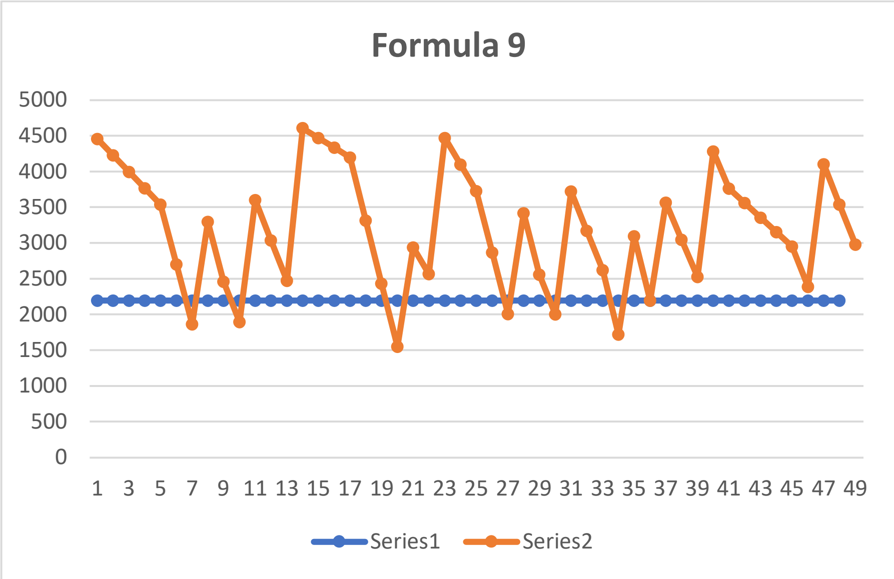
Due to the randomness and unpredictability of, expectations were for these results to display some form of chaos. Perhaps staying true to its spontaneous nature, this pattern yielded results that were generally more subdued than expected. Most of the formulae performed well with only formula 11 experiencing a stock out. An interesting observation is the results of formula 9 which in this case are closer to the range the other formulae are in than in other patterns.

Figure 17: Cycle Stock graph Formula 11 Random Pattern



(Own Creation)

Figure 18: Cycle Stock graph Formula 9 Random Pattern



(Own Creation)

4.6 Effects of Leadtime Variability

Notwithstanding the fact that the literature study had hypothesized that the effects of lead time variability on safety stock levels are negligible, this study sought to investigate the weight of this proposition. To achieve this, the trial run was conducted for a second time albeit using lead time data that showed increased variability over the timeseries. The proposition held for four of the formulae which do not include the actual lead time, its mean or standard deviation as a variable for the computation of safety stock. For these formulae, the safety stock level remained constant between the two variabilities of lead time. Contrarily, the safety stock level was significantly impacted by the increase in lead time variability in the case of the other eight formulae. This is because lead time and its derivatives such as the standard deviation of lead time are variables in all these formulae. In general, an increase of 0.2 in the standard deviation of lead time translated into an increase in safety stock level of about 13 to 15 percent. This is perhaps expected as an increase in lead time variability typically implies lower supplier reliability which means that a greater amount of safety stock is required to protect against stock outs. Figure 20 that is attached below shows an example of the difference in behaviour of the safety stock formulae under different lead time variabilities.

Table 2:General behaviour of all the formulae

Behaviour	High CSL + High fill rate	Low CSL + High fill rate	Low CSL + Low fill rate	Overstocking
Horizontal	1,2,3,4,5,6,7,8,10,11,12			9
Trend	1,4	2,7,8,12	3,5,6,10,11	9
Seasonal	1,5,2,7	12,8,6	3,4,10,11	9
Cyclic	2,3,4,5,7	1,6,8,10,11,12		9
Random	9,12	1,2,3,5,6,7,8,10	4,11	

(Own Creation)

Table 3: Behavior of Safety Stock Formulae after increased leadtime variability

Behaviour	Decreases Required Safety Stock	No Effect on required Safety Stock	Increases Required Safety Stock
Formula	2	3, 7, 10, 11, 12	1, 4, 5, 6, 8, 9

5 Conclusion

In this study, a comparison was made between the performances of different safety stock techniques under different demand patterns and lead time variabilities. This paper further substantiated the proposition that there is no universal safety stock formula. To conclude, the implications of this paper for not only further study but also practice are going to be explored.

5.1 Implications for further research

Although this paper and its underlying study sufficed to bridge the research gap that it strived to fill, it was not without its limitations. These limitations can be corrected by making improvements in future research. The simulation for this study was conducted using a dataset that was created by the author. This was necessitated by the author's limited access to real-world supply chain data from companies. The dataset created had all the characteristics that were required for the study. However, real-world data seldom exhibits idealistic patterns as in the artificial dataset. Actual demand typically shows a combination of two or more patterns. Therefore, a more reliable and relevant set of results can be attained from a partnership between real companies and researchers. Some of the formulae that were investigated in this study included forecasts as variables. Safety stock and forecasting tend to work hand in hand in inventory management. Effort was made to match demand patterns to appropriate forecasting techniques without digressing too far from the focus of this paper. In these cases, the effectiveness of the forecasting technique that was employed will have an impact, however minimal, on the results of this study. Safety stock considerations and forecasting are connected topics that still require a significant amount of research to optimize. Thusly, an integrated research of both topics has the potential to yield results that could profoundly improve inventory management practices. The methodology of this study focused on simulating the behaviour of inventory levels over a long period of time when a safety stock technique is used. While this approach is effective for most demand patterns, it has limitations when investigating random patterns. Since the values generated by a random number generator can differ drastically between trial runs, the reliability of results for random data can be improved by running the simulation many times. Finally, this simulation was also conducted using the ROP policy for inventory management. The results of this study can therefore not be extrapolated to other inventory management policies such as MRP and FOI without reservations. This can be addressed in the future by running the simulation using different policies.

5.2 Implications for practice

In their paper, Schmidt, Hartmann and Nyhuis[78] made a supposition that safety stock is not meant to protect against uncertainties brought about by demand patterns such as seasonality. This is a sentiment that several other scholars share. The most important contribution of this paper is the identification of the impact of safety stock techniques in protecting against demand variability due to patterns like seasonality. While it is widely accepted that there is no universal safety stock formula, this paper has made significant inroads towards the development of a comprehensive roadmap that guides operations managers to select the best performing safety stock technique for the demand pattern of their inventory. It was found that the simplest patterns to conduct inventory management for are the horizontal and cyclic patterns. For these two patterns all safety stock techniques generally perform well. Formula 11 and Formula 5 are likely to yield the best results for horizontal and cyclic patterns respectively. On the other hand, the trend and seasonal patterns were shown to be the most difficult to manage inventory for. It was observed that Formula 5 and 11 tend to yield the best results for each of these two patterns respectively. Based on the results of the study, the author would recommend avoiding the use of Formula 11 for both patterns as well as formula 4 and 10 for the seasonal pattern. Since

Formula 9 typically yields an overstocking of inventory in all patterns; it is recommended to avoid using it as a safety stock technique unless it is for a product that requires a very high delivery reliability. For operations managers who prefer to use a single formula regardless of the pattern, the paper would recommend using formula 1 as it yields acceptable results across the board. It also has the added advantage of being the simplest of all the formulae during computations. Finally, the study confirmed that the lead time variability has a significant impact on the levels of safety stock and by extension inventory. Consequently, efforts should be made to either negotiate a higher delivery date reliability with suppliers or switch to more reliable suppliers with less lead time variability. As a disclaimer, it should be noted that the

[78] Cf. (Schmidt, Hartmann & Nyhuis 2012)

recommendations made in this paper are subject to several variables such as the expectations of the customer.

For further reading of the Logistics Engineering and Technologies Group please refer to Auerbach & Uygun, 2007; Keßler et al., 2007; Keßler & Uygun, 2007; Kortmann & Uygun, 2007; Droste et al., 2008; Uygun, 2008; Kuhn et al., 2009; Uygun & Wötzel, 2009, Jungmann & Uygun, 2010; Keßler & Uygun, 2010; Uygun & Kuhn, 2010; Uygun & Luft 2010; Uygun & Schmidt, 2011; Uygun & Wagner, 2011; Liesebach et al., 2012; Uygun et al., 2012; Uygun, 2012a; Uygun, 2012b; Uygun, 2012c; Uygun & Straub, 2012, Besenfelder et al, 2013a; Besenfelder et al 2013b; Güller et al., 2013; Scholz et al., 2013; Uygun, 2013; Uygun & Straub, 2013; Güller et al., 2015; Mevenkamp et al., 2015; Uygun et al., 2015; Karakaya et al., 2016; Uygun & Reynolds, 2016; Güller et al., 2017; Reynolds, & Uygun, 2018; Uygun & Ilie, 2018; Lyutov et al., 2019; Nosheen & Uygun, 2020; Sommerfeld & Uygun, 2020; Uygun & Jafri, 2020; Uygun, 2020.

Table of references

Archer, B., 1987. Demand forecasting and estimation. *Demand forecasting and estimation.*, pp.77-85.

Alexandra Markovic, M. and Arvid, E., 2017. An evaluation of current calculations for safety stock levels.

Alicke, K., 2005. *Planung und Betrieb von Logistiknetzwerken*. Springer-Verlag Berlin Heidelberg.

Baganha, Manuel P., David F. Pyke, and Geraldo Ferrer. *The undershoot of the reorder point: Tests of an approximation*. INSEAD, 1995.

Baker, R.C. and Urban, T.L., 1991. Deterministic fixed order-level inventory models: An application for replenishment of radioactive source material for irradiation sterilizers. *European journal of operational research*, *50*(3), pp.249-256

Balakrishnan, N., Bendre, S.M. and Malik, H.J., 1992. General relations and identities for order statistics from non-independent non-identical variables. *Annals of the Institute of Statistical Mathematics*, *44*(1), pp.177-183.

Barker, M.M., 2011. Manufacturing employment hard hit during the 2007–09 recession. *Monthly Labor Review*, *134*(4), pp.28-33.

Beier, F.J., 1995. The management of the supply chain for hospital pharmacies: a focus on inventory management practices. *Journal of Business Logistics*, *16*(2), p.153.

Blanchard, O.J. and Melino, A., 1986. The cyclical behavior of prices and quantities: the case of the automobile market. *Journal of Monetary Economics*, *17*(3), pp.379-407.

Bon, A.T. and Ng, T.K., 2017, January. An optimization of inventory demand forecasting in university healthcare centre. In *IOP Conference Series: Materials Science and Engineering* (Vol. 166, No. 1, p. 012035). IOP Publishing.

Boute, R.N., Disney, S.M., Lambrecht, M.R. and Van Houdt, B., 2007. An integrated production and inventory model to dampen upstream demand variability in the supply chain. *European Journal of Operational Research*, *178*(1), pp.121-142.

Boysen, N., Emde, S., Hoeck, M. and Kauderer, M., 2015. Part logistics in the automotive industry: Decision problems, literature review and research agenda. *European Journal of Operational Research*, *242*(1), pp.107-120.

Cargal, J.M., 2003. The EOQ inventory formula. *Mathematical Sciences*, *1*.

Chaturvedi, A. and Martínez-de-Albéniz, V., 2016. Safety stock, excess capacity or diversification: Trade-offs under supply and demand uncertainty. *Production and operations management*, *25*(1), pp.77-95.

Chopra, S., Meindl, P. and Kalra, D.V., 2013. *Supply chain management: strategy, planning, and operation* (Vol. 232). Boston, MA: Pearson.

Chopra, S., Reinhardt, G. and Dada, M., 2004. The effect of lead time uncertainty on safety stocks. *Decision Sciences*, *35*(1), pp.1-24.

Crane, Dwight B., and James R. Crotty. "A two-stage forecasting model: Exponential smoothing and multiple regression." *Management Science* 13, no. 8 (1967): B-501.

De Kok, S. (2018) "A New Safety Stock Formula – Part 1", LinkedIn, 18 September. Available at: https://www.linkedin.com/pulse/new-safety-stock-formula-part-1-stefan-de-kok (Accessed: 28 May 2020)

Demandt, B. (2018)"Mercedes-Benz E-class US Sales Figures", *Carsalesbase*, Available at: https://carsalesbase.com/us-mercedes-benz-e-class/ (Accessed: 28 May 2020)

Dolgui, A. and Prodhon, C., 2007. Supply planning under uncertainties in MRP environments: A state of the art. *Annual Reviews in Control*, *31*(2), pp.269-279.

Emmanuel-Ebikake, O., 2014, September. Safety Stock Provision Amid Fluctuating Demand In The UK Automotive Industry. In *Logistics Research Network*.

Flores, B.E. and Whybark, D.C., 1986. Multiple criteria ABC analysis. *International Journal of Operations & Production Management*.

Friend, C.H., Swift, A.L. and Ghobbar, A.A., 2001. A predictive cost model in lot-sizing methodology, with specific reference to aircraft parts inventory: an appraisal. *Production and Inventory Management Journal*, *42*(3/4), p.24.

Gonzalez, J.L. and González, D., 2010. Analysis of an economic order quantity and reorder point inventory control model for company XYZ.

Graves, S.C. and Willems, S.P., 2000. Optimizing strategic safety stock placement in supply chains. Manufacturing & Service Operations Management, 2(1), pp.68-83.

Goldstone, J.A., 2008. *Using quantitative and qualitative models to forecast instability* (Vol. 204). United States Institute of Peace.

Golicic, S.L., Davis, D.F. and McCarthy, T.M., 2005. A balanced approach to research in supply chain management. In *Research methodologies in supply chain management* (pp. 15-29). Physica-Verlag HD.

Greasley, A., 2013. *Operations management*. John Wiley & Sons Limited.

Gudehus, T. and Kotzab, H., 2012. Comprehensive logistics. Springer Science & Business Media.

Haltiwanger, J. and Harrington Jr, J.E., 1991. The impact of cyclical demand movements on collusive behavior. *The RAND Journal of Economics*, pp.89-106.Heizer, J., Render, B. and Munson, C., 2008. *Operations management*. Prentice-Hall.

Hansun, S., 2013, November. A new approach of moving average method in time series analysis. In *2013 conference on new media studies (CoNMedia)* (pp. 1-4). IEEE.

Herrmann, F., 2011. Operative Planung in IT-Systemen für die Produktionsplanung und-steuerung: Wirkung, Auswahl und Einstellhinweise von Verfahren und Parametern. Springer-Verlag.

Hirschman, E.C., 1986. Humanistic inquiry in marketing research: philosophy, method, and criteria. *Journal of marketing Research*, *23*(3), pp.237-249.

Holsenback, J.E. and McGill, H.J., 2007. A SURVEY OF INVENTORY HOLDING COST ASSESSMENT AND SAFETY STOCK ALLOCATION. *Academy of Accounting & Financial Studies Journal*, *11*(1).

Hoque, M.A., 2013. A vendor–buyer integrated production–inventory model with normal distribution of lead time. *International Journal of Production Economics*, *144*(2), pp.409-417.

Islam, N.S., 2013. A Variant Deterministic Model of Classical EOQ Formula. *IOSR Journal of Business and Management (IOSR-JBM) e-ISSN*, pp.09-11.

Jain, A., Rudi, N. and Wang, T., 2015. Demand estimation and ordering under censoring: Stock-out timing is (almost) all you need. *Operations Research*, *63*(1), pp.134-150.

Khajavi, S.H. and Holmström, J., 2017, September. Production capacity pooling in additive manufacturing, possibilities and challenges. In IFIP International Conference on Advances in Production Management Systems (pp. 501-508). Springer, Cham.

King 2011, *Understanding safety stock and mastering its equations*, ASCM, viewed 24 April 2020, <https://www.apics.org/apics-for-individuals/apics-magazine-home/magazine-detail-page/2011/09/12/crack-the-code>.

Kostić, K., 2009. Inventory control as a discrete system control for the fixed-order quantity system. *Applied Mathematical Modelling*, *33*(11), pp.4201-4214.

Kumar, K. and Aouam, T., 2019. Extending the strategic safety stock placement model to consider tactical production smoothing. European Journal of Operational Research, 279(2), pp.429-448.

Landeta, J.M.I., Cortés, C.B.Y. and García, O.G., 2016. Lead time demand variability, safety stock and the inventory cost. *Contaduria y Administracion*, *61*(3), pp.499-513.

Laura, T., 2019. Optimizing working capital tied into inventories by efficient inventory management: case study in a Finnish manufacturing company.

Lee, H.L., Padmanabhan, V. and Whang, S., 1997. Information distortion in a supply chain: The bullwhip effect. *Management science*, *43*(4), pp.546-558.

Li, Lode, and Hongtao Zhang. "Confidentiality and information sharing in supply chain coordination." *Management science* 54, no. 8 (2008): 1467-1481.

Liao, C., Lin, H.N., Luo, M.M. and Chea, S., 2017. Factors influencing online shoppers' repurchase intentions: The roles of satisfaction and regret. *Information & Management*, *54*(5), pp.651-668.

Limère, V., Landeghem, H.V., Goetschalckx, M., Aghezzaf, E.H. and McGinnis, L.F., 2012. Optimising part feeding in the automotive assembly industry: deciding between kitting and line stocking. *International Journal of Production Research*, *50*(15), pp.4046-4060.

Malpass, J. and Shah, M., 2008. Forecasting and demand planning. In *Service Chain Management* (pp. 51-64). Springer, Berlin, Heidelberg.

Makridakis, S. and Wheelwright, S., 1973. Integrating forecasting and planning. *Long Range Planning*, *6*(3), pp.53-63.

McKean, M. (2020) "Be wary of forecasts in cyclical industry", *Automotive News*, 27 January. Available at: https://www.autonews.com/letter-editor/be-wary-forecasts-cyclical-industry (Accessed: 28 May 2020)

Monk, E. and Wagner, B., 2012. Concepts in enterprise resource planning. Cengage Learning, pp.11

NAHMIAS, S., Production and Operations Analysis, Irwin, Homnewood, IL, 1989. *NahmiasProduction and Operations Analysis1989*.

Pankratz, A., 2012. *Forecasting with dynamic regression models* (Vol. 935). John Wiley & Sons.

Park, K.S., 1987. Fuzzy-set theoretic interpretation of economic order quantity. *IEEE Transactions on systems, Man, and Cybernetics*, *17*(6), pp.1082-1084.

Penner, R.G., 2002. Dealing with uncertain budget forecasts. *Public Budgeting & Finance*, *22*(1), pp.1-18.

Radasanu, A.C., 2016. Inventory management, service level and safety stock. *Journal of Public Administration, Finance and Law*, (09), pp.145-153.

Ruiz-Torres, A.J. and Mahmoodi, F., 2010. Safety stock determination based on parametric lead time and demand information. International Journal of Production Research, 48(10), pp.2841-2857.

SCMDojo. 2017. *Safety Stock Formula And Safety Stock Calculation- The Ultimate Guide*. [online] Available at: <http://www.scmdojo.com/safety-stock-formula/> [Accessed 15 March 2020]

Schmidt, M., Hartmann, W. and Nyhuis, P., 2012. Simulation based comparison of safety-stock calculation methods. *CIRP annals*, *61*(1), pp.403-406.

Schwarz, L.B. and Weng, Z.K., 2000. The design of a JIT supply chain: The effect of leadtime uncertainty on safety stock. *Journal of Business Logistics*, *21*(2), p.231.

Seila, A.F., 2005, December. Spreadsheet simulation. In *Proceedings of the Winter Simulation Conference, 2005.* (pp. 8-pp). IEEE.

Shugan, S.M., Radas, S., Swartz, T.A. and Iacobucci, D., 1999. Services and seasonal demand. *Handbook of services marketing and management*, pp.147-170.

Snyder, R.D., Koehler, A.B., Hyndman, R.J. and Ord, J.K., 2004. Exponential smoothing models: Means and variances for lead-time demand. *European Journal of Operational Research*, *158*(2), pp.444-455.

Strömberg, O. and Gustavsson, O., 2018. Direct Material Safety Stock Standard-A Study at IKEA Industry.Sridharan, V. and Lawrence LaForge, R., 1989. The impact of safety stock on schedule instability, cost and service. Journal of Operations Management, 8(4), pp.327-347.

Van Kampen, T.J., Van Donk, D.P. and Van Der Zee, D.J., 2010. Safety stock or safety lead time: coping with unreliability in demand and supply. *International Journal of Production Research*, *48*(24), pp.7463-7481.

Wazed, M., Ahmed, S. and Nukman, Y., 2009. Uncertainty factors in real manufacturing environment. *Australian Journal of Basic and Applied Sciences*, *3*(2), pp.342-351.

Zhang, Q., Zhang, D., Tsao, Y.C. and Luo, J., 2016. Optimal ordering policy in a two-stage supply chain with advance payment for stable supply capacity. *International Journal of Production Economics*, *177*, pp.34-43.

Auerbach, M. & Uygun, Y. (2007). Data Security in RFID on Item Level. 3rd European Workshop on RFID Systems and Technologies, VDE, pp. 1-9

Besenfelder, C.; Kaczmarek, S. & Uygun, Y. (2013a). Process-based Cooperation Support for Complementary Outtasking in Production Networks of SME. In: International Journal of Integrated Supply Management. Vol. 8, Nos. 1/2/3, pp. 121-137, 2013. https://doi.org/10.1504/IJISM.2013.055072

Besenfelder, C.; Uygun, Y.; Kaczmarek, S. (2013b). Service-Oriented Integration of Intercompany Coordination into the Tactical Production Planning Process. In: K. Windt (Ed.): Robust Manufacturing Control - Lecture Notes in Production Engineering. Springer: Berlin & Heidelberg, pp. 301-314.

Droste, M., Kessler, S., Uygun, Y. (2008): Ganzheitliche Produktionssysteme für Logistikdienstleister - Folgen und Übertragungsmöglichkeiten der industriellen Anwendung methodischer Ordnungsrahmen auf die Dienstleistungsbranche. In: Zeitschrift für wirtschaftlichen Fabrikbetrieb, Volume 103, 9, pp. 594-597. https://doi.org/10.3139/104.101330

Güller, M.; Karakaya, E.; Uygun, Y.; Hegmanns, T. (2017): Simulation-based performance evaluation of the cellular transport system. In: Journal of Simulation. https://doi.org/10.1057/s41273-017-0061-1

Güller, M.; Uygun, Y.; Karakaya, E. (2013). Multi-Agent Simulation for Concept of Cellular Transport System in Intralogistics. In: Azevedo A. (eds): Advances in Sustainable and Competitive Manufacturing Systems. Lecture Notes in Mechanical Engineering. Springer: Heidelberg, pp. 233-244.

Güller, M.; Uygun, Y.; Noche, B. (2015): Simulation-based Optimization for a Capacitated Multi-Echelon Production-Inventory System. In: Journal of Simulation. Vol. 9 No. 4., pp. 325-336. https://doi.org/10.1057/s41273-017-0061-1

Jungmann, T. & Uygun, Y. (2010): Das Dortmunder Prozesskettenmodell in der Intralogistik. In: G. Bandow & H. H. Holzmüller (Eds.): "Das ist gar kein Modell" - Unterschiedliche Modelle und Modellierungen in Betriebswirtschaftslehre und Ingenieurwissenschaften. Gabler: Wiesbaden, pp. 357-382.

Karakaya, E.; Uygun, Y.; Güller, M. & Kuhn, A. (2016). Development of an Agent-based Simulation for the Cellular Transport System and Scenario-based Performance Analysis. In: International Journal of Electrical, Electronics, and Data Communication. Vol. 4 No. 1, pp. 17-20, 2016.

Keßler, S. & Uygun, Y. (2007). Ganzheitliche Produktionssysteme. Systematische Entscheidungsunterstützung beim Implementieren. In: Industrie Management.

Keßler, S. & Uygun, Y. (2010). Nutzenpotenziale des Einsatzes des Dortmunder Prozessketteninstrumentariums in Ganzheitlichen Produktionssystemen. In: M. ten Hompel & U. Clausen (Eds.): Facetten des Prozesskettenparadigmas. Praxiswissen: Dortmund, pp. 19-40.

Kessler, S., Uygun, Y., Stausberg, J. (2007). Ganzheitliche Produktionssysteme entlang der Wertschöpfungskette. In: PPS MANAGEMENT, Volume 12 Issue 1, GITO, pp. 58-60.

Kortmann, C. & Uygun, Y. (2007). Ablauforganisatorische Gestaltung der Implementierung von Ganzheitlichen Produktionssystemen. In: ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, Volume 102 Issue 10, pp. 635-638. https://doi.org/10.3139/104.101195

Kuhn, A., Bandow, G., Uygun, Y., Wötzel, A. (2009). Grundmethodik der Antizipativen Veränderungsplanung intralogistischer Systeme. In: ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb. Volume 104 Issue 3, pp. 136-140, De Gruyter. https://doi.org/10.3139/104.110012

Mevenkamp, A., Uygun, Y. & Straub, N. (2015): Ganzheitliche Produktionssysteme in der Pharma-Industrie. In: U. Dombrowski & T.Mielke (Eds.): Ganzheitliche Produktionssysteme – Aktueller Stand und zukünftige Entwicklungen. Springer: Berlin, pp. 269-284.

Reynolds, E.B. & Uygun, Y. (2018). Strengthening Advanced Manufacturing Innovation Ecosystems: The Case of Massachusetts. In: Technological Forecasting and Social Change – An International Journal. https://doi.org/10.1016/j.techfore.2017.06.003

Scholz, D., Liesebach, T., Uygun, Y. (2013). Hybride Anpassungsplanung zur Konfiguration von Netzwerkfabriken. In: Industrie Management 4/2013, pp. 49-52. https://books.google.de/books?hl=en&lr=&id=FMYA5bu3juYC&oi=fnd&pg=PA49&ots=ZkSFzat2tA&sig=muo_YKIGCOxo-Ul5KJDgumexplo#v=onepage&q&f=false

Uygun Y. & Ilie, M. (2018). Autonomous Manufacturing-related Procurement in the Era of Industry 4.0. In: Schupp, F & Woehner, H. (eds): Digitalisierung im Einkauf. Springer, Wiesbaden, pp. 81-97. ISBN: 978-3-658-16909-1

Uygun Y. & Straub N. (2013). Supply Chain Integration by Human-Centred Alignment of Lean Production Systems. In: Kreowski HJ., Scholz-Reiter B., Thoben KD. (eds) Dynamics in Logistics. Lecture Notes in Logistics. Springer, Berlin, Heidelberg, pp. 93-112.

Uygun, Y. (2008). Datensicherheit beim RFID-Item-Tagging: Grundlagen-Anforderungen-Maßnahmen. VDM Verlag Dr. Müller.

Uygun, Y. (2012a). Realisation of Flow Production by the Example of an Automotive OEM – A Case Study. In: H. Nylund, S. Kantti, V. Toivonen, S. Torvinen (Eds.): Proceedings of 22nd International Conference on Flexible Automation and Intelligent Manufacturing. Tampere, pp. 743-750.

Uygun, Y. (2012b). Ein praxisorientierter Leitfaden zur Verschlankung der Produktion – Die VDI-Richtlinie 2870. In: D. Spee & J. Beuth (Eds.): Lagerprozesse effizient gestalten - Lean Warehousing in der Praxis erfolgreich umsetzen. Huss Verlag: München, pp. 51-57.

Uygun, Y. (2012c). Integrierte Kapazitätsbörse - Entwicklung eines Instrumentariums für den Handel mit Maschinenkapazitäten in regional-lateralen Unternehmensnetzen. Praxiswissen: Dortmund, 2012. ISBN: 978-3-86975-063-7

Uygun, Y. (2013). Entwicklung eines Diagnosesystems für Ganzheitliche Produktionssysteme. Dissertation. Shaker: Aachen, 2013. ISBN: 978-3-8440-2117-2

Uygun, Y. & Kuhn, A. (2010). Life-cycle Oriented Postponement in International Supply Chains. In: K.S. Pawar & A.T. Potter (Eds.): Proceedings of the 15th International Symposium on Logistics: Configuring Next Generation Supply Chains, pp. 13 - 21.

Uygun, Y. & Luft, N. (2010). Vorgehensmodell zur Maßnahmenselektion - Das Maßnahmenfilter-Modell. In: G. Bandow & H. H. Holzmüller (Eds.): "Das ist gar kein Modell" - Unterschiedliche Modelle und Modellierungen in Betriebswirtschaftslehre und Ingenieurwissenschaften. Gabler: Wiesbaden, pp. 213-232.

Uygun, Y. & Reynolds, E. B. (2016). Advanced Manufacturing Ecosystems. In: C. Brecher & S. Jeschke (Eds.): Industrial Internet of Things - Cybermanufacturing Systems. Springer: Berlin, pp. 691-715.

Uygun, Y. & Schmidt, A. (2011). „Performance Measurement for Interorganisational Collaborations of SMEs“. In: H.-J. Kreowski, B. Scholz-Reiter, K.-D. Thoben (Eds.): Dynamics in Logistics. Springer: Berlin et al., pp. 169-190, 2011.

Uygun, Y. & Straub, N. (2012). Human-centred Model for Application of Lean Production in Networks. In: H. ElMaraghy (Ed.): Enabling Manufacturing Competitiveness and Economic Sustainability. Springer: New York, pp. 660-665.

Uygun, Y. & Wagner, S. U. (2011). Guidelines for Human-based Implementation of Lean Production. In: N. Duffie (Ed.): Proceedings of 44th CIRP International Conference on Manufacturing Systems - New Worlds of Manufacturing. Omnipress: Madison, Wisconsin.

Uygun, Y. & Wötzel, A. (2009). Antizipative Veränderungsplanung intralogistischer Systeme - Eigenschaften und Handlungsfelder. In: ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, Volume 104 Issue 12, pp. 1131-1134, https://doi.org/10.3139/104.110223

Uygun, Y., Ringeln, M. & Straub, N. (2015): Pull-Prinzip. In: U. Dombrowski & T.Mielke (Eds.): Ganzheitliche Produktionssysteme – Aktueller Stand und zukünftige Entwicklungen. Springer: Berlin, pp. 110-128.

Uygun, Y.; Luft, N.; Woetzel, A. (2012). A Model to Select Specific Measures for Adaptability of Logistics and Production Systems. In: K.S. Pawar & A.T. Potter (Eds.): Proceedings of the 17th International Symposium on Logistics: New Horizons in Logistics and Supply Chain Management. Centre for Concurrent Enterprise: Nottingham, pp. 195-203.

Lyutov, A., Uygun, Y. & Hütt, M.-T. (2019): Managing workflow of customer requirements using machine learning. In: Computers in Industry. 2019. Volume 109, pp. 215-225. https://doi.org/10.1016/j.compind.2019.04.010

Liesebach, T.J., Scholz, D., Uygun, Y. (2012). Die Netzwerkfabrik - Ein Beitrag zur Synchronisation von Produkt- und Fabriklebenszyklus. In: ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, Volume 107 Issue 9, pp.613-616. https://doi.org/10.3139/104.110825

Uygun, Y. & Jafri, A. (2020): Controlling Risks in Sea Transportation of Cocoa Beans. In: Cogent Business & Management. Open Access. Vol. 7, No. 1. https://doi.org/10.1080/23311975.2020.1778894

Sommerfeld, D. & Uygun, Y. (2020): Digitalization Applications in the Automotive Value Chain – Summary and Outlook. In: Industry 4.0: Principles, Effects and Challenges. Y. Uygun (Ed.). Nova Science: Hauppauge, NY, pp. 219-245.

Nosheen, S. & Uygun, Y. (2020): The Effects of Industry 4.0 on Employment – How Reliable are the Current Jobs Reports? In: Industry 4.0: Principles, Effects and Challenges. Y. Uygun (Ed.). Nova Science: Hauppauge, NY, pp. 133-157.

Uygun, Y. (2020): The Current State of Research & Application of Industry 4.0 in Germany. In: Industry 4.0: Principles, Effects and Challenges. Y. Uygun (Ed.). Nova Science: Hauppauge, NY, pp. 3-15.