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A NOVEL MODEL FOR THE CALCULATION OF SAFETY STOCK OF PERISHABLE PRODUCTS WITH A TOTAL WASTE CONSTRAINT

Fatih Yigit[1, *] and Sakir Esnaf[2]

[1]Department of Industrial Engineering
Altinbas University
Istanbul, Turkey
[*]Corresponding author's e-mail: fatih.yigit@altinbas.edu.tr

[2]Department of Industrial Engineering
Istanbul University- Cerrahpasa
Istanbul, Turkey

Perishable products cover a high percentage of all goods. The variability, long lead times, risk period, and high service level increase the safety stock level. An increase in safety stock will also increase the probability of perished products because of the increased probability of sales of less than stock during shelf life. This study proposes a model for calculating safety stocks of perishable products besides showing the effect of perishability on service level. The effects of long lead times, risk periods, high sales and lead-time variance, and short shelf life adversely affect perished products. The study investigates and proposes a novel model for calculating total expected waste and costs with a waste quantity constraint. A real-life example compares a proposed model with waste constraints and the traditional safety stock model based on costs and waste quantity. The case study shows the better results of the proposed models.

Keywords: Safety Stock, Shelf Life, Perishable Inventory, Waste Reduction, Inventory Management

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1 INTRODUCTION

The deterioration of products is an area that has drawn significant attention in modern academic literature. The reason is that the deterioration of products is a common occurrence. As stated in the literature, the deterioration of products is a part of commercial activity. According to a study, 54% of total store sales and 57% of total inventory is perishable products in the supermarket sector of the US (NSSS, 2005). 31% of foods at the retail and consumer level were wasted in the United States, 10% at the retail level, and 21% at the consumer level (Buzby *et al*., 2014). Such wasted products increase costs, undermine the service level, and cause the loss of valuable resources. In today's globally competitive market environment, suppliers of perishable products face tremendous pressure to maintain inventory and supply optimum order quantity to fulfill customer demands, thus minimizing the cost (Mallidis *et al*., 2018). Improper management of inventory may lead to dissatisfaction among customers. Effective inventory management would increase customer satisfaction and revenue (Ovezmyradov and Kurata, 2019).

In contrast, about 15% of the perishable products in a supermarket are lost by retailers due to spoilage and damage (Ferguson and Ketzenberg, 2006). The effect of perishability would further be amplified when products that do not perish but lose value are also investigated. As a result, perishable products are an essential aspect of accurate inventory management.

Many studies have been in the literature regarding perishable products and safety stocks. Most of the studies focus on the two topics separately. A recent study investigates the literature regarding the safety stock. In the mentioned study, a detailed search is conducted using keywords; however, no keyword is associated with shelf life, perishability, or expiry date. (Gonçalves *et* al., 2020). Similarly, a recent study reported that safety stocks are essentially affected by six factors: service level, lead time, demand volatility, order policy, component commonality, and holding costs (Gonçalves *et al*., 2020). As a result, it is assumed that the shelf life does not affect safety stock.

On the other hand, a high service level combined with high variability would increase the safety stock. High safety stock would increase the possibility of perishing due to the increased risk of selling less than safety stock during shelf life. Ignoring the shelf life of products would undermine both service-level and total costs.

The study first investigated the effects of lead time, variance, and shelf life on service level and costs for perishable products. Then, by using this information, the authors developed a new model. The study calculated the actual service level

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considering shelf life. The proposed model considers shelf life, calculates the probability of perishing, and formulates the accurate waste and total cost. The waste quantity calculated according to the proposed model is vital as it allows the integration of green constraints into the model. The proposed model will represent the total cost for perishable products with a waste constraint (TCMPP). Comparisons are shown in a real case study based on the data received from a distribution company.

The study aims to propose a new methodology to integrate the perishability of products in safety stock calculation. The motivation of this study is to analyze the relationship of product perishing with safety stock levels and propose a model to integrate the relevant waste quantity and costs into the model. The study develops a model that calculates the optimum quantities considering perishability. This aspect is also essential, especially when green concerns regarding sustainability are an increasing trend. A case study validates the assumptions and shows the proposed and traditional models.

Some of the significant contributions of this research paper are as follows.

- Assess the impact of lead times, risk period, variability, and shelf life on the service level of perishable products
- A real-life example compares the traditional and proposed models based on total cost and service level.
- To show the effect of service level and safety stock on products with shelf life.
- To show the relationship between perished product quantity and cost with the service level and shelf life.
- Using adjusted safety stocks, a novel model to achieve lower cost and higher service levels for perishable products.
- Meeting the service level and, at the same time lowering inventory and the total cost is a challenging task. The proposed model serves the following purposes.
- Service level is recalculated based on perished product quantity. The recalculation shows the actual and planned service level.
- Total cost and quantity are calculated, considering perished products' cost due to high safety stock. The additional cost would significantly differ between TCMPP and the traditional model (TM).

The proposed model integrates waste quantity into the decision model. As a result, the decision model integrates the green constraint. The increased waste is an essential aspect of decisions. It allows the integration of concerns that may not be converted as cost. The sections of the study are as follows. Section 2 deals with the literature review of separately proposed safety stock, perishable products, and relevant models. The authors assume that neglecting shelf life for safety stock undermines the service level and deserves a novel model to represent accurate cost and service level. Therefore, Section 3's model formulation represents the safety stock level for perishable products with short shelf life. To underline the need for the proposed study, a simple example to show the comparison between the TCMPP and TM is given in Section 4. In addition, in the same section, the study uses a real-life example from a distribution company with high demand variability, short shelf life, and long lead times. Finally, the proposed model and standard safety stock calculation are compared. In section 5, a conclusion is given to summarize the outcomes of this study, limitations, and areas for further research.

2 LITERATURE REVIEW

Perishable products inventory management is complex and deserves a specific focus. Forecasting all perishable products' consumption becomes difficult and time-consuming (Holmström, 1997). Financial-wise, this focus is also essential, as a yearly loss of millions of dollars occurred in the European grocery store from products not consumed by the end of their shelf life (Beck, 2004). It is also vital for business performance due to emerging green concerns. Such losses undermine the profitability of a company but also damage the sustainability of the environment.

Therefore, studies emerged to model perishability since 1963, starting with the problem of modeling the deterioration process by Ghare and Schrader (1963). Ghare and Schrader (1963) developed an exponentially decaying inventory model. Covert and Philip (1973) contributed considerable work on deteriorating inventory systems that deal with continuously deteriorating items. As an extension, Misra (1979) developed an inventory system for deteriorating items. Regarding the studies associated with perishable items, the researcher may check detailed studies associated with the literature review. Bakker *et al*. (2012) published such a study. The study investigates a review of the advances made in inventory control of perishable items (deteriorating inventory). A recent study by Chaudhary *et al*. (2018) investigates the literature on perishable products. According to the study, the literature review covers 419 studies published between 1990-2016 for perishable products.

Multiple studies focus on effectively managing perishable products as a topic that draws attention in the literature. A recent study on perishable products focused on the decision support model of perishable products. The study concluded that successfully controlling distribution operations according to weather conditions can significantly reduce energy consumption and costs (Accorsi *et al*., 2017). Another study also focused on the integrated approach for production-inventory routing coordination of perishable products. The study suggested two heuristic and meta-heuristic algorithms to solve the problem (Vahdani *et al*., 2017).

Similarly, constraints are a part of the decision models. A recent study used a simulation model to analyze the inventory model with service level constraints (Alizadeh *et al*., 2017). The proposed model in this study has a legal aspect due to this constraint integration with the proposed study. Additional studies focus on some decisions regarding perishable products' inventory. Perishable product tracking is another important topic in order to reduce waste. Traceability systems of perishable products are also analyzed in the literature (Zhu and Lee, 2018). A model using an integer linear programming type simultaneously minimizes the sum of production, inventory holding, wastage, freshness-related, and transportation costs proposed (Alipour *et al*., 2020). A different study focused on the lot sizing of perishable products (Sinha and Anand, 2020). However, an essential aspect of inventory, safety stock, is not considered for the proposed decision model.

Effective inventory management employs safety stock. Safety stock is a vital countermeasure to secure supply chain performance against forecast inaccuracy and sales variance. The amount of safety stocks required to satisfy a specific customer service level depends on the demand uncertainty and the corresponding forecast errors (Hosoda and Disney, 2009). Therefore, ignoring the aspect of safety stock often increases the risk of high costs and product waste (Mallidis *et* al., 2020). It is vital to develop a further understanding of correctly determining safety stocks for each product (Gonçalves *et al*., 2020). As a result, accurate safety stock levels are essential in today's business world. The business world is defined as Volatile, Uncertain, Complex, and Ambiguous (VUCA) (Popova *et al*., 2018).

Safety stock is essential for business performance and customer satisfaction. However, high safety stock increases the possibility of perishing for products with a short shelf life. Safety stock is an essential aspect of an efficient inventory policy and is vital for dealing with demand and lead time variation. This aspect is considered a countermeasure against forecast and risk period variability. Mainstream inventory management models require the specification of a demand distribution and are solved using calculus to derive required safety inventory levels (Beutel and Minner, 2012). The safety stock is calculated according to the demand variance and the risk period's length and variability. Typically, the risk period covers the lead time and review period. Generally, when the variance increases, the safety stock level increases to overcome the possibility of above-average sales.

Similarly, lower variability thus reduces the risk associated with an inventory decision (Beutel and Minner, 2012). A study by Sonntag and Kiesmüller (2017) combined the number and positions of inspections with inventory control strategies in a warehouse. The goal was achieved by reducing the safety stock levels by 30% with the defined parameters.

There are many studies associated with the inventory management of perishable products. Econometrics provides an extensive toolbox for estimation and statistical analysis, especially concerning forecast errors. Furthermore, these models decrease safety stock by explaining a significant portion of the demand variability (Beutel and Minner, 2012). Muriana (2016) proposed an Economic Order Quantity (EOQ) model for perishable products with fixed shelf life under stochastic demand. For deteriorating products, e.g., Perishable products, literature mainly focuses on defining optimal batch sizes. A detailed literature study regarding the impact of perishability and shelf life is given by Muriana (2016).

Minner and Transchel (2017) analyzed the impact of perishability on a tactical level, expressed in shelf life, retailers' order variability, and demand managing perishables: replenishment and issuance. The question generally dealt with in the perishable inventory research field is determining the optimal batch to stock under either deterministic or stochastic demand conditions and possibly considering constant or time-dependent deterioration (e.g., exponential, Weibull, or Gamma deterioration distribution) and shortage costs. A recent study focused on products with concise shelf life. The study focused on cut flowers with only two periods of shelf life (Fu *et al*., 2019). On the other hand, a small research effort deals with the inventory planning problem of perishable products under a stochastic customer demand assumption (Mallidis *et al*., 2020). The study proposed by Noble *et al*. (2023) underlined the importance of effectively managing perishable products. The study presented an efficient inventory model for a perishable product. The study focused on two cases following order-up-to-S, and (s, S) were compared. The proposed model can help retailers meet customer requirements while reducing shortages and expired products. The safety stock aspect is also not covered in the mentioned models.

The study by Riezebos and Zhu (2020) focused on the seasonality effects and showed the importance of focusing on prediction rather than allocating safety stocks. In the same study, the perishability of products is also ignored. This cost reduction is an essential aspect of the proper management of inventory. The cost also increases when safety stock costs cover added perishability costs. Also, a reduced service level would dramatically affect inventory management decisions. The study by Mallidis *et al*. (2018) considers the shelf life of products. The study proposes a social responsibility model for the ideal donation period of goods. This study is one of the studies covering the shelf life or perishability of products in inventory management studies. As seen from the studies on perishable products, the safety stock aspect is ignored (Reio and Ghosh, 2009; Minner and Transchel, 2017; Chaudhary *et al*., 2018; Gonçalves *et al*., 2020; Mallidis *et al*., 2020; Riezebos and Zhu, 2020). Decisions regarding the management of safety stock are vital decisions.

There are recent studies associated with managing safety stocks. Aouam *et al*. (2021) proposed a study employing a critical constraint in safety stock management. Different constraints are typical in business life, as no company has unlimited resources for inventory management. The study compared the guaranteed and chance-constraint approaches and analyzed their effects on safety stock placement. The decisions are complex regarding safety stock. Da Silva *et al*. (2021) proposed a decision support system (DSS) that considers safety stocks and time. The study also proposed improving service levels while minimizing inventory-related costs. The study is essential as it links costs with service levels. Again in the recent study, shelf life is not integrated into the decision model.

From the business perspective, efficient inventory management, including decisions about safety stocks, is an important aspect. Reducing safety stocks can contribute to the total inventory level reduction but may sacrifice service level. An increase would benefit customer satisfaction but increase the cost simultaneously. However, as long as variability exists, safety stocks will be a part of inventory systems, so the relevant study about safety stocks of perishable items is prepared.

Safety stocks increase with both variability and increase in the lead period. So, the safety stock level is increased to overcome the expected deviations from historical data or forecasts and the time needed to react to the underperformance. This characteristic of safety stock has a potential adverse effect if the product is perishable. When the variance is high and the perishable product has a short shelf life, the possibility of lower total sales during the shelf life period increases. This risk increases when the risk period is extended. This risk would cause increased waste. Based on the mentioned studies, it has been observed that the specific topic of safety stock for perishable products is an under-investigated area. To the best of our research, increased perishability is not a part of safety stock calculations. TM does not fulfill the specific constraints of perishable products.

A recent study investigates 95 papers regarding safety stocks from 1977 to 2019. The study employs modeling techniques and main performance criteria (Gonçalves *et al*., 2020). Similarly, in the mentioned study, no relationship between safety stock and perishable products is mentioned. Therefore, this study proposes a novel model to fill this gap. In the proposed model, TCMPP calculates the total inventory cost while considering shelf life and possible perished products quantity and cost. Polotski and Gharbi (2021) addressed in their study the difficulty of finding a trade-off between having an inventory level that satisfies the demand and perished products that are kept in inventory exceeding shelf life. The study proposed a solution to solve this trade-off. Although the model has limitations, the authors suggested that obtained results may serve as valuable guidelines for more complex problems. Li *et al*. (2021) focused on the effective placement of safety stock in a supply chain for perishable products. The results indicate that the proposed solution performed better compared to the alternatives.

A more recent study also underlines the importance of both aspects for determining safety stocks (Polotski *et al*., 2022). The study underlines the importance of considering shelf life for inventory management. The study proposed s 3-step procedure that causes no perished products. On the other hand, the goal is to develop a model with no perished products. Under probabilistic demand and lead-time, statistically, it may be possible to always achieve no perished products without sacrificing customers' service level. Besides, the study focuses on the production environment in contrast with the proposed study on distribution business with deterministic shelf life.

The study by Nematollahi *et al*. (2022) proposed a model to solve a common problem. The case covers an actual case where products have limited shelf life and demand variation. The study results reveal that the proposed coordination policy not only coordinates the SC of products with fixed shelf life but also significantly improves the customer service level (CSL) and the profits of the entire supply chain. Polotski *et al*. (2022) study focused on perishable products with limited and random shelf lives. The proposed optimal control policy aims to minimize the total cost. The numerical studies showed that total cost is lowered compared to other policies.

As can be seen from the literature, the deterioration of products is a common characteristic of products. The topic is extensively investigated in literature in line with the common occurrence of perishability. Similarly, safety stock is an essential tool to counter variability. Therefore, efficient inventory management should employ safety stock and consider perishability. According to the existing literature review, the proposed model aims to cover this gap. This study offers an analytical model to calculate appropriate customer service levels, accurate total costs, and waste quantity for perishable products associated with safety stocks. The extensive literature review of the safety stock calculation of perishable products shows that it is an important gap. The study aims to propose a model that can contribute to the efficient inventory management of perishable products. In the following section, 3, the model formulation of the proposed model represents the safety stock level model for perishable products with short shelf life.

3 MODEL FORMULATION OF THE PROPOSED MODELS

In Section 3, details of the proposed models will be given. The proposed model is a multi-period model of a company selling n products with probabilistic customer demand that fits a normal distribution. The company uses a periodic review model. The inventory model is a periodic review and Order Up-to Level (R, S) model. Order up to level is calculated based on mean demand during the risk period. The supply chain is a two-stage supply chain covering the seller and customers. The objectives of the two models are calculating the actual service level and minimizing the total cost, respectively. Inventory aims to satisfy customer demand. sl_x are the variables in the model. The primary assumption regarding the supplier is that the supply is unconstrained and lead times are deterministic. The model has been formulated by considering the following assumptions and notations. Some assumptions and notations are used from the study by Muriana (2016).

- The item's shelf life equal to *p* is deterministic and constant.
- *rp* covers lead time and review period. It is denoted as a risk period. This value is considered deterministic.
- The demand rate is probabilistic and fits the normal distribution with the mean d_t and variance σ_t^2. *t* is denoted as a time unit.
- The safety stock aims to satisfy service level (*sl*). This rate is fixed for each *t*. In normally distributed demand, such a quantity can be approximated by $k\sigma_t$, where *k* is the safety factor. see (Alstrøm, 2001)
- *A* is the ordering cost per order
- h_{xy} is the inventory holding cost per unit value held in stock per period y for product *x*
- C_{px} is the cost of perished products per unit for product *x*
- C_{ox} is the shortage cost per unit per time for product *x*
- The initial stock level is raised to the order level at the beginning of the risk period. Deterministic and constant lt_x assumes that new order is to be placed after the review period for product *x*.
- First in, First Out (FIFO) principles are applied to the inventory on hand.
- Sales and inventory values have integer values. This assumption is due to the packaging quantities of products.

Notations:

μ_{sl}	: Mean service level
σ_{sl}	: Standard deviation of service level
μ_p	: Mean of perished products percentage of the total quantity
σ_p	: Standard deviation of perished products percentage of the total quantity
σ_{tx}^2	: Variance of demand per period for product x
σ_{tx}	: Standard deviation of demand per period for product x
σ_{rpx}	: Standard deviation of demand in risk period for product x
σ_{slx}	: Standard deviation of demand in shelf life for product x
A	: Ordering cost per order
c_p	: Waste quantity coefficient for product x
C_{px}	: Cost of perished products per unit for product x
C_{ox}	: Shortage cost per unit per time for product x
d_{rpx}	: Mean demand per lead time for product x
d_{px}	: Mean demand during p period for product x
d_{tx}	: Mean demand per period for product x
h_{xy}	: The inventory holding cost per unit value per period y for product x
k_x	: Safety factor of the service level for product x
k_{rx}	: Revised safety factor of the service level for product x
k_{px}	: Cost coefficient of perished products based on the value of products for product x
k_{sx}	: Storage cost coefficient for product x
k_{so}	: Cost coefficient of a stock-out product based on value (>1)
k_w	: Waste cost coefficient
lt_x	: Lead Time for product x
MT	: Metric Ton
n	: Number of products
p	: Shelf life period
$P(d_{xy})$	: Probability of demand of product x in period y
$P(SS_p)$	: Probability of perishing
$P_{so}(1-sl)$	: Probability of stock-out based on sl
rp	: Risk period
sl_x	: Service level for product x
sl_{rx}	: Service level revised for product x
ss_{px}	: Stock perished for product x
ss_{rx}	: Revised safety stock for product x
ss_x	: Safety stock for the product x
ss_{xy}	: Safety stock for the product x per period y
t	: Time unit

TC_f	: Total financial cost of inventory
TC_h	: Total holding cost
TC_s	: Total storage cost
TC_w	: Total waste cost
TC_p	: Total cost of perished products
TC_{so}	: Total cost of a stock-out
TS	: Total stock
TS_x	: Total stock of x
TS_p	: Total stock perished
x	: Indices of products
v_x	: Cost of the item x
y	: Indice of period y

The primary assumption of the study is that the probability of product perishing is associated with the safety stock quantity and shelf life. Eq. (1) and Eq. (2) represent the mean and standard deviation of demand during the risk period (*rp*). In Eq. (1) and Eq. (2), rp represents the risk period, σ_x represents the standard deviation of demand, d_{tx} represents the demand in period $t\ for\ product\ x$. rp_x covers the total period of the review period and lead time of the product x (Silver, Pyke and Peterson, 1998).

$$d_{rpx} = d_{tx} * rp_x \tag{1}$$
$$\sigma_{rpx} = \sigma_x * \sqrt{rp_x}\ . \tag{2}$$

Safety stock calculation is directly relevant to the deviation of sales and, therefore, set to cover the variance during the risk period. The common assumption used for the calculation of safety stock is that these errors have a normal distribution with no bias (that is, the average value of the error is zero) and a known standard deviation (σ_{rpx}) for a period of rp (Silver *et al*., 1998). Figure 1 represents the normal distribution and relevant forecast errors in *rp*.

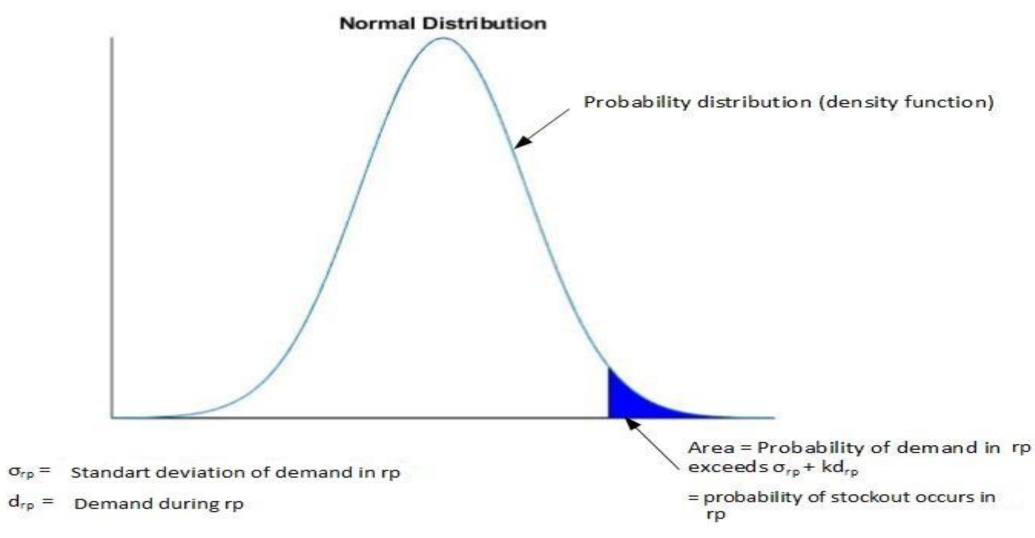

Figure 1. Normally Distributed Forecast Errors (Silver, Pyke and Peterson, 1998)

Traditional safety stock calculations and models in the literature, as given in Section 2, ignore the shelf life aspect of products. Ignoring shelf life is an essential drawback of the safety stock models because perishable products cover a high portion of sales, therefore, inventory (Sinha and Anand, 2020).

There is a higher probability of perishing when the safety stock level is set to a high level due to long lead time, high variance, or service level. When shelf life is short and, at the same time, the safety stock level is high, the probability of perishing increases. The high safety stock reflects the probability of lower sales than products in inventory during shelf life. In order to integrate the effect of perishability, accurate models should reflect this aspect accordingly.

The amount of perished products is calculated according to the probability of lower sales than inventory during the shelf life. The formula of safety stock is given in Eq. (3) (Silver, Pyke and Peterson, 1998).

$$ss_x = k_x * \sigma_{rpx} , \quad (3)$$

where

ss_x = safety stock for the product x

k_x = safety factor of the service level for product x

σ_{rpx} = standard deviation of demand during rp for product x

In Eq. (3), although the safety stock level increases in parallel with lead time, the shelf life of products is not considered. In order to integrate this factor into safety stock, the study focused on two different goals. The first goal is to incorporate the effect of perishability on service levels. Service level is defined as the expected probability of not hitting a stock-out during the next replenishment cycle or the probability of not losing sales (Radasanu, 2016). This effect is critical due to two reasons. The first concern is the lowered customer service level due to perished products resulting from lower sales than anticipated. Lower sales cause an increased possibility of perished products. The amount of perished products decreases the quantity of usable safety stock; therefore, it has an adverse effect on customer service levels (Silver *et al*., 1998). Service level, risk period, standard deviation, and demand are the primary inputs for the calculation. The proposed model reevaluates this issue and comes with a revised calculation for the safety stock level. The revised service level is calculated based on perished products. The possibility and effect on service level are given in Section 3.1, which aims to show the effects of shelf life on safety stocks and perishability.

The proposed model in Section 3.2 incorporates the amount of perished products into the decision model. This aspect is also integrated as a constraint to reflect a real-life case. The additional cost is essential as total cost calculation is a standard model used for safety stocks (Silver *et al*., 1998). The proposed model incorporating waste quantity and value is given in Section 3.2.

3.1 Actual Customer Service Level Due to Perished Products

The amount of safety stock increases with increased risk period, demand variability, and defined service level. The safety factor correlates positively with increased variability. The total demand during shelf life may be lower than the total safety stock and order quantity. Low sales are an increased possibility when the variance and service level increase. In this case, the products that are not sold will perish. The inventory kept as a part of safety stock that perished will affect the service level negatively. All goods that perished have no commercial value. The goods are not transferred to the next period when they perish. Total stock (*TS*) at the beginning of the risk period equals the total safety stock and order quantity. Eq. (4) represents the calculation of TS.

$$TS_x = ss_x + d_{rpx} \ . \quad (4)$$

The probability of demand for product x in a period of y in Eq. (5) is given as $P(d_{xy})$ according to demand that fits normal distribution ($\sim N(d_{tx}, \sigma_{tx}^2)$).The amount of perished products is proportional to the inventory and the probability of lower sales during shelf life. The primary assumption is that the demand should be rounded to the next upper integer value as the goods are given in integer values. When the total demand can be denoted as $P(d_{xy}) * \ d_{xy}$ is less than the total stock, the goods will perish. After the shelf life of products, all stock goods will perish. The expected amount of perished product is given in Eq. (6).

$$P(d_{xy}) = f\mathcal{N}(k;\ d_{tx}, \sigma_{tx}). \quad (5)$$

$$ss_{px} = \ TS_x - \sum_{y=1}^{sl} P(d_{xy}) * \ d_{xy} \ ;\text{ when } TS_x \geq P(d_{xy}) * d_{xy} \quad (6)$$

Accordingly, the revised safety stock is given in Eq. (7).

$$ss_{rx} = ss_x - ss_{px}. \quad (7)$$

The revised service level for product x is calculated based on Eq. (8) and Eq. (9).

$$ss_{rx} = k_{rx} * \ \sigma_{slx} \quad (8)$$

$$krx = \frac{SSrx}{\sigma slx}\ . \quad (9)$$

The difference between ss_{rx} and ss_x shows the variance between expected and actual safety stocks. $sl_{rx,}$ defined as the revised service level, can be calculated with a normal distribution function using the k_{rx}. sl_{rx} is an important outcome. The difference between sl_{rx} and sl_x is essential. Low service levels will undermine the desired customer satisfaction. Without satisfied customers, a company's long-term objectives are hard to achieve. sl_r is an essential objective in determining the service level.

3.2 Total Cost Based on Shelf Life and Safety Stock

An alternative model to define the safety stock level is to set the safety stock level to minimize the total cost. The total cost is the main objective to be minimized. Typical costs are ordering costs, holding costs, stock-out costs, perished product costs, and waste disposal.

Ordering costs are mostly one-time costs associated with the ordering decision but do not change with the quantity. Instead, the costs are fixed and include the cost of order form processing, receiving, inspection, following up on unexpected situations, and handling vendor invoices (Silver *et al*., 1998).

The variable costs associated with the quantities ordered are called holding costs. These are typical costs incurred during the management of inventory. Such costs are storing, handling, transportation, and the financial cost of money tied to inventory, insurance, and inventory obsolescence. In case there is a stock-out incident, costs of stock-out also occur. Such costs are relevant to inventory but occur when insufficient inventory matches the demand. Also, the costs of perished products are essential costs associated with inventory decisions for perishable products. These costs occur when the product's age exceeds the shelf life. Additional costs of disposal of waste also occur. The disposal of waste is strictly regulated in many countries. As a result, disposal is managed by specialized companies with additional costs. Disposal of waste costs is associated with the mentioned disposal activities.

In the rest of the section, a model is proposed to accurately calculate total costs while calculating the increased perished product quantity and using this quantity as a constraint. The goal of minimizing total cost is to lower the total cost of inventory level, including safety stock level, by balancing the cost of inventory holding and stock-out costs and perished product costs. The constraint is used to incorporate waste quantity in the model.
Inventory holding cost equals the sum of the financial cost and the total storage cost. This calculation is given in Eq. (10)

$$TC_h = TC_f + TC_s \,. \tag{10}$$

The total cost of finance is given in Eq. (11). This cost is associated with the financial value of inventory. The total cost of finance also represents the opportunity cost associated with the money tied to inventory.

$$TC_f = \sum_{x=1}^{n} \sum_{y=1}^{rp} ss_{xy} * h_{xy} * v_x \,. \tag{11}$$

The total cost of storage of safety stock is given in Eq. (12), associated with the stock quantity. It is represented with a coefficient proportional to safety stock quantity.

$$TC_S = \sum_{x=1}^{n} \sum_{y=1}^{rp} ss_{xy} * k_{sx} \,. \tag{12}$$

The total inventory cost also covers the expected cost of perished products not sold during the shelf life. Since it is a probability rather than a deterministic value, this cost should be calculated as given in Eq. (13). The perished products cost also covers the waste cost. For the proposed model's simplicity, the waste cost is added to the k_{px}.

$$TC_p = \sum_{x=1}^{n} \sum_{y=1}^{rp} ss_{px} * v_x * (k_{px} + 1) \,. \tag{13}$$

The total cost of a stock-out is given in Eq. (14). In Eq. (14), the stock-out cost is proportional to the value of goods. Therefore, the cost coefficient is given as k_{so}.

$$TC_{so} = \sum_{x=1}^{n} \sum_{y=1}^{rp} (1 - P(sl_{rx})) * v_x * k_{so} \,. \tag{14}$$

Therefore, according to the abovementioned costs, the goal is to minimize inventory, holding, and stock-out costs.
The total objective of cost is given in Eq. (15)

$$Min\,(TC_h + TC_p + TC_{so}). \tag{15}$$

Total waste is a significant concern for sustainability. Even when recycling is in place, waste means sacrificing human effort, raw material, and energy. Green concerns should play an essential role in our decisions. As a result, this study integrates this concern into the decision on safety stock. The study integrates total waste quantity as a constraint in the decision.
In Eq.(16), waste is integrated into the decision. c_p represents the value used for constraints. The total proportion of waste products can not exceed that amount.

$$TS_p < TS * c_p \ . \tag{16}$$

So the model is defined as:

$$Min \sum_{x=1}^{n}\sum_{y=1}^{rp}(ss_{xy} * h_{xy} * v_{xy}) + (ss_{xy} * k_{sx}) + (ss_{px} * v_x * k_{px}) + (ss_{px} * v_x) + (P(1 - sl_{rx}) * v_x * k_{so})) \tag{17}$$

s.t.

$$TS_p < TS * c_p$$
$$0 \leq c_{px} \leq 1$$
$$0 \leq sl_x \leq 1$$
$$ss_{xy}, h_{xy}, v_{xy} \geq 0 \ \forall x, y$$
$$k_{sx}, k_{px}, k_{so} \geq 0$$

4 NUMERICAL EXAMPLE AND CASE STUDY IN A DISTRIBUTION COMPANY

In subsection 4.1, an illustrative example shows the probability of a product perishing when safety stock is high. This example is important because it shows the effect of long lead times, short shelf life, high variability on service level, and decreased safety stock due to perished products. Another aspect is the increased waste and cost. Traditional approaches ignore the increased risk of perishing associated with short shelf life and high safety stock.

4.1 Single Product Example

The effect of a long risk period, high variability, and short shelf life are shown. Table 1 shows the safety stocks based on calculation for a basic example with d_1=100 and σ_1=55. The demand and standard deviation are assumed to be constant for all periods. Table 2 shows the probability of product perishing based on shelf life and risk period calculated on $d_1=100$ and $\sigma_1=55$. The calculations are based on Eq. (3). The order quantity is another critical factor in calculating perished products. The amount of perished product is associated with the initial inventory levels. In order to integrate this decision, the fixed order period principle is applied.

The traditional approach gives monthly orders based on average sales and calculated safety stock. The shelf life is calculated based on the additional time after lead time. Lead time and risk periods are in months for simplifications. The simplification represents longer shelf life, particularly for products with long lead times.

Table 1. Safety Stocks Based on rp_1 and sl_1 with a $d_1=100$ and $\sigma_1=55$

		Risk Period in Months											
		1	2	3	4	5	6	7	8	9	10	11	12
Service Level	0.900	70.49	99.68	122.08	140.97	157.61	172.65	186.49	199.36	211.46	222.89	233.77	244.17
	0.950	90.47	127.94	156.69	180.93	202.29	221.60	239.35	255.88	271.40	286.08	300.04	313.39
	0.990	127.95	180.95	221.61	255.90	286.10	313.41	338.52	361.89	383.85	404.61	424.36	443.23
	0.995	141.67	200.35	245.38	283.34	316.79	347.02	374.83	400.71	425.01	448.00	469.87	490.76
	0.999	169.96	240.36	294.38	339.93	380.05	416.32	449.68	480.73	509.89	537.47	563.70	588.77

As seen in Table 1, the safety stock levels increase with variance, lead times, and service levels. Based on these figures, Table 2 shows the probability of product expiration based on different order quantities and shelf life with an $rp=1$.

Figure 2 also represents the product expiry probability based on changing order quantities and shelf life for goods with a lead time of 3 months. Order quantities in months represent the quantity sufficient for average consumption for given months. As seen in Figure 2, the products with shorter shelf life (x-axis) and order in months (z-axis) increase the probability of expired products.

Based on Table 2, the increase in service level and, accordingly, safety stock causes an increase in perishability probability, e.g., the service level of 99% is used for safety stocks for an item with an rp=1 with an average sale of 100 and a standard deviation of 55. As a result, there is a probability that 0.69 of the safety stock kept in inventory may perish. Considering that the sales figures are taken from a real-life example, the service level of 99% is used, as given in Radasanu's study (2016). Table 3 represents the revised service level when perished products are reduced from the available inventory. Table 3 also represents the importance of integrating shelf life for safety calculations. As expected, short shelf life combined with high order quantity in months increases the risk and reduces the service level.

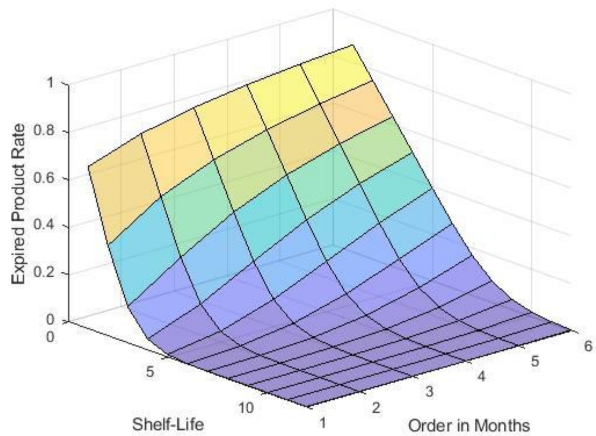

Figure 2. Shelf life, Order in Months, and Expired Product Rate Relationship

Table 2. Expiry Probability Based on Different Order Quantity and Shelf Life

		Shelf Life in Months											
Order Quantity in Months		1	2	3	4	5	6	7	8	9	10	11	12
	1	0.69	0.38	0.15	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.76	0.52	0.30	0.13	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	3	0.81	0.62	0.42	0.25	0.12	0.04	0.01	0.00	0.00	0.00	0.00	0.00
	4	0.84	0.68	0.52	0.36	0.21	0.10	0.04	0.02	0.01	0.00	0.00	0.00
	5	0.86	0.72	0.58	0.45	0.31	0.19	0.10	0.04	0.02	0.01	0.00	0.00
	6	0.88	0.76	0.63	0.51	0.39	0.27	0.17	0.09	0.04	0.02	0.01	0.00

Table 3. Revised SL Based on Expired Products

		Shelf Life in Months											
		1	2	3	4	5	6	7	8	9	10	11	12
Order Quantity in Months	1	0.51	0.96	1	1	1	1	1	1	1	1	1	1
	2	0.1	0.5	0.89	0.98	1	1	1	1	1	1	1	1
	3	0.02	0.15	0.5	0.84	0.95	0.98	0.99	0.99	0.99	0.99	0.99	0.99
	4	0	0.03	0.18	0.5	0.79	0.92	0.96	0.97	0.98	0.98	0.98	0.98
	5	0	0.01	0.05	0.21	0.5	0.76	0.89	0.94	0.96	0.96	0.96	0.96
	6	0	0	0.01	0.07	0.23	0.49	0.73	0.86	0.92	0.94	0.95	0.95

4.2 Real-Life Example

The authors assume a relationship between safety stocks and expired products for goods with high variability, long lead times, and short shelf life. A real-life example consisting of 20 items is given in this section to validate our assumption. The service level for products is 99%. The service level of products is taken high as the products considered for the case are under Class

A according to the ABC classification of the company inventory. Products, especially with a short shelf life, are subject to perishing.

The data is received from a distribution company specializing in the chemical business. The products distributed and sold have a short shelf life as they are subject to chemical decomposition. Due to harsh competition, products have a high variance in sales and a long risk period. The products have an average shelf life of 2.85 and a standard deviation of 0.66 months.

The cost of safety stock is calculated according to Eq. (14). The following variables are used for the calculation of stock costs;

$$h_x = 2\%/\text{yr}$$

This amount is equal to the finance cost of USD at the time of the study. Finance cost is a part of the inventory holding cost.

$$k_{sx} = 0.25 \text{ USD* day * MT}$$

This formula represents the storage cost for all products.

$$k_w = 285 \text{ USD/MT}$$

The amount is equal to the cost of disposal of products. According to regulations, accredited authorities should dispose of a chemical product.

$$cp = 0.01$$

The total waste is limited with cp.

The stock cost of both original and revised safety stock costs is calculated. Stock-out costs are calculated according to Eq. (13).

This value is partly due to the B2B environment in which the company works. When customers are unsatisfied, they are very likely to switch to an alternative provider. As a result,

$$k_{so} = 3$$

Matlab 2018a and a computer with an i7 processor with 16 MB RAM running on Windows 10 are used to calculate. As a result of these calculations, the outcomes are summarized in Table 4. Table 4 compares the total cost model(TCM) that calculates fixed service levels for all products and the proposed TCMPP approach.

Table 4. Service Level and Expired Products

		TM	TCM	TCMPP
Service Level	μ_{sl}	97%	86.2%	90.1%
	σ_{sl}	8.5%	6.1%	15.1%
Expired Products	μ_p	8.1%	5.2%	0.9%
	σ_p	13.6%	9.5%	0.6%
Expired Products (Kg)	Total	331,593	140,340	5,288

Table 5 shows the cost based on the TM, TCM, and TCMPP models. The TM's calculation detail is given in Eq. (3). Costs associated with waste and perished products are not considered in the classical model for calculation.

Table 5. Cost Comparisons of Models

	TM (USD)	TCM (USD)	TCMPP (USD)
Cost of Safety Stock (Revised)	82,067	29,682	7,421
Cost of Finance	3,510	1,826	2,602
Cost of Storage	4,422	2,457	2,350

Cost of Expired Product	49,346	15,217	2,006
Cost of Waste	24,789	10,183	462
Cost of Stock-Out	13,101	32,675	25,872
Total Cost	95,169	62,358	33,293

In order to reduce the total cost of inventory using stock-out costs and perished product costs, the proposed model achieved a 65% and 46.5% reduction in total costs compared to other models. When traditional safety stock is calculated based on fixed service level for all products, out of 839,000 kg of all safety stock, 331,593 kg will perish due to lower sales than the safety stock quantities during the shelf life. Due to perished safety stocks, the service level desired of 99% cannot be achieved. Therefore, after the perished products, the service level decreased to an average of 96.96%, with a standard deviation of 8.55%.

The proposed model calculates the total cost without waste constraint with total cost minimization and achieves better results. The service level will have a mean of 86.2%, with a standard deviation of 6.1%. At the same time, the total waste will be lower. The proposed TCMPP model with waste constraint achieves better results compared to TM. Table 5 and Table 4 show that costs and quantity were dramatically reduced. The proposed model also calculated the service level achieved according to Eq. (8) and Eq. (9). The set service level and achieved service level, including perished products, are summarized in Table 4. The results show that under the circumstances of our case study, setting the service level high may increase the cost dramatically due to perished products' cost. Also, it will increase the total amount of waste dramatically, as shown in Table 4.

4.3 Sensitivity analysis

A sensitivity analysis was performed to validate the applicability of the proposed model. The main variables for the model are associated with safety stock and shelf life. 12 scenarios are performed, each by changing a variable. The behavior of the proposed methodology is observed afterward.

Service level is essential since it affects the safety stock level and business perspective due to customer retention. Different service levels are used to see the possible effects of different service levels. As expected, increased service levels adversely affect the total cost as expired products increase. The proposed TCMPP performs better than alternative models, as the goal is to minimize the total cost by covering all factors. When the service level is reduced to 0.90 and 0.70, respectively, the total cost of the TM is lower due to lower expired products. In all cases, TCMPP performed better compared to TM. The performance increased for a higher service level, 0.999. The cost improvement became 78.7%. The improvement still is valid for other service levels. For the service level of 0.90, the improvement is 50.4%; for the service level of 0.70, the improvement is 57.4%. The primary outcome of these cases, as the expected increase in service level, will increase the inventory cost mainly due to perished goods. Setting the correct service level and the existence of perishable products are essential.

Shelf life directly affects inventory decisions. In order to assess this assumption, we performed three adjustments to the shelf life of products. In the first case, we increased the shelf life of products by multiplication of 2; in the other two cases, the shelf life of products decreased by multiplication of 0.5 and 0.25, respectively. As expected, total costs increased dramatically in the two latter cases and decreased in the first. The primary outcome of these changes, the proposed model could not find a feasible solution due to waste constraints. For all three cases, the proposed TCMPP performed better than TM. The improvements are 35.6%, 71.3%, and 64.1%, respectively. The quantity of waste could not be lower than the constraint as products expired due to high service levels. This outcome is important to show that short shelf life and high service levels are conflicting as expected. The decision-makers should be aware of these cases. In such cases, make-to-order instead of make-to-stock can be a better alternative. Goods with a short shelf life will not be kept in inventory. As a result, the risk of perishing will diminish.

The cost of disposal is an essential cost for particular cases. For some goods, the cost of disposal can be very high, namely explosives, toxic waste, and infectious waste. Disposal cost is reduced by 50% for one case and increased by 200% and 400% for two cases. The TCMPP model performed better for all cases than the TM and TCM models. All models' total cost was reduced when the disposal cost was amended to 50%. However, when the disposal cost is increased by 200% and 400%, TM performed much worse than TCM and TCMPP models. The improvement of the proposed model increased to 73.4% and %80.4, respectively. When the cost of disposal is reduced by 50%, the difference between TM and TCMPP is reduced to 62.7%. The results underline the importance of the cost of disposal. For goods with high disposal costs, the inventory management decisions should integrate the risk of perishing.

Table 6. Sensitivity Analysis Results and Costs

Variable Revision		Amendments	TM (USD)	TCM (USD)	TCMPP (USD)
	Base Results		95,169	62,358	31,285
Service Level	Scenario-1a	Revised Service Level 99.9%	145,563	62,358	31,020
	Scenario-1b	Revised Service Level 90%	63,091	62,358	31,285
	Scenario-1c	Revised Service Level 70%	73,516	62,354	31,285
Shelf life	Scenario-2a	Increased to 200%	23,926	20,904	15,392
	Scenario-2b	Decreased by 50%	477,510	149,965	136,942
	Scenario-2c	Decreased by 75%	1,438,885	506,847	517,248
Cost of Disposal	Scenario-3a	Increased to 400%	169,535	82,974	33,172
	Scenario-3b	Increased to 200%	119,957	71,424	31,865
	Scenario-3c	Decreased by 50%	82,774	56,913	30,915
Lead Time	Scenario-4a	Increased to 400%	283,521	89,767	42,199
	Scenario-4b	Increased to 200%	163,866	77,326	36,700
	Scenario-4c	Decreased by 50%	78,922	59,459	27,352

Lead times affect the safety stock and also inventory decisions. Increased safety stocks will increase the possibility of perishing. To validate this assumption, we performed three cases by amending the lead times of the actual case. In the first two cases, lead times are increased by 4 and 2, respectively. The TM model's total cost dramatically increased for these two cases. When the lead time is increased by 2, the total cost of inventory for the TM model increases by 72.2%, and when the lead time is increased by 4, the TM's total cost increases by 197.2%.

On the other hand, the TCMPP model performs 77.6% and 85.1% compared to the TM model. When the lead times are changed by 50%, the TCMPP performs 65.4% better compared to TM Model. These outcomes are essential as lead time is subject to changes in the real business case. The proposed TCMPP model still performs better compared to TM under these circumstances. The graphical representation of Table 6 is given in Figure 3. As can be seen, the shelf-life has a major effect on total costs in all models.

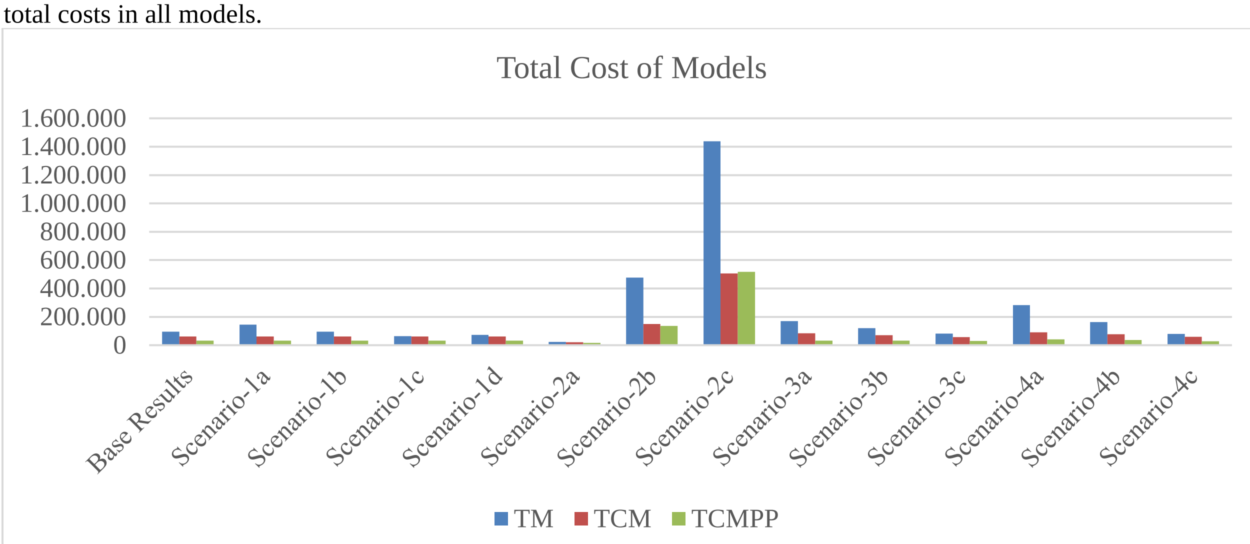

Figure 3. Total Cost of Models after Sensitivity Analysis

5 CONCLUSION

The increasing trend for sustainability and devotion to nature protection increased the importance of the efficiency of supply chains. Therefore, the level of perished products became an essential key performance indicator (KPI) not only in economics but also in particular energy and waste management and, thus, overall environmental impact.

The studies in the literature consider safety stock and perishability as two areas that do not have a relation. This study has a goal to cover this gap. The first illustrative example shows the effect of shelf life on the service level. The example shows that the extended risk period, the higher variability, and the shorter shelf life undermine customer service levels. The factors also increase perished products. The first example is essential to validate our assumption.

The second example covers a real-life case. The data from a distribution company reflects the high variability, long lead times and risk period, and short shelf life. In return, the typical safety stock calculation ends with a high quantity of perished products, high costs, lower service levels, and high waste. The proposed model shows higher performance compared to the traditional approach.

In conclusion, the revised service level represents 90.1%, whereas the TM's goal was 99% based on TM and 86.2% based on a model that ignores the waste quantity constraint. The difference is a significant gap between the goal and the achieved service level. Therefore, the products classified under the A-class achieve much lower service levels than desired. On the other hand, the quantity of perished products equals 0.9% of the total stock. TCMPP model reduced the waste quantity dramatically. Based on the traditional approach, the waste quantity is 331,593 kg, whereas the proposed TCMPP reduced it to 5,288 kg. The results show the importance of the perishability factor on safety stock.

The proposed model calculated that the optimum value for service level is 90.1%, while there is an average waste constraint per product. Thus, the total cost is significantly lower than the original model based on service level only. The proposed model and alternatives' cost differences are 65% and 46.5%, respectively.

As the results show, the traditional by-the-book approaches may not be suitable for perishable products. Considering the number of perishable products compared to non-perishable products, the importance of integration of shelf life can be better understood. In this research, we developed a model that integrates the shelf life into the model. Integration of the shelf life would be necessary for inventory decisions due to increased risk, particularly for products with short shelf life. The detailed sensitivity analysis validated the importance of shelf life, service level, and lead times on inventory costs. The proposed TCMPP model performed better than TM in all cases with different variable values.

The study has some limitations due to application areas. The shelf life is considered deterministic; this assumption is parallel with the case study. On the other hand, in literature, the shelf life may be stochastic. Although the products may not wholly deteriorate for fresh foods, they may lose some value. As a result, the proposed model needs to be revised to cover such cases. Our assumption that shelf life and safety stock are closely linked is based on our future studies. Other methods can develop analytical solutions to the developed model. Similarity with newsvendor problems or linear programming methods may provide better results. The study focused on providing a new area in safety stock for perishable products. Alternative solutions to the same problem by different methods can benefit future studies.

In some cases, low variability and long shelf life may cause our assumption to be inaccurate. Although our study has limitations, the authors assume that applying the shelf life of products for the safety stock calculation would be valuable when the additional workload is justified. Even when the additional workload becomes a limitation for the application, integration with inventory classification may help to overcome such limitations.

The areas for future research are integrating dynamic sales price changes subject to the remaining shelf life. Also, a DSS to help decision-makers will be developed. This DSS will contribute to real-time decision-making in a highly complex and volatile business environment of perishable products. In our opinion, DSS in inventory management should cover the perishable characteristics of products. Similarly, the same DSS system should integrate safety stock calculations as a part of DSS. Future works will cover similar sub-areas for the effective development of inventory management.

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