Optimal Inventory Stock Policy Detection for a SME with High Perishability Constraints

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Abstract: In recent years, the supply chain management discipline has attracted an increasing set of challenges. Supply process sustainability issue, the increasingly competitive level registered within and between industries and unexpected catastrophic events – such as COVID-19 pandemic – have generated the essential need for every kind of manufacturing enterprise to increase resilience and to rely on robust decision-making tools. The digital solutions introduced nowadays aim at making companies extremely agile facing different demand behaviours, shaping production, and warehousing policies. Unfortunately, enabling technologies are not easily accessible to every company, especially for a SME. In order to ease the access to those technologies' potential benefits, in this article we develop a model that helps to identify the best inventory stock policy for every product, considering economic aspects, the uncertainty tied to the sell-out price trend, the production system features and parameters, focusing on SMEs afflicted by high perishability problems. After reviewing the current literature, we first classify different demand trends into specific categories, according to their singular behaviour. Thus, both unexpected and usual demand's influencing factors are defined, such as seasonality and commercial actions in general. Simultaneously, the main stock policies are examined and set as the outcome of the model. After a concise production strategy evaluation, a series of simulations leads to the most efficient and effective stock policy. Basing on the demand class and considering the specific production approach, the model elaborates the best policy which allows the company both to minimize wastes, stockout and overstock events, and to maximize the operational efficiency and effectiveness from an economic and temporal perspective, focusing on perishability and shelf-life constraints. The model allows the company to increase its resilience facing unexpected events, constantly aiming at enhancing the company awareness about its own capability to react with the best strategy to the supply chain challenges.

Keywords: Stock policy, Warehouse Management, Efficiency, Resilience, Operational Excellence.

1. Introduction

It is well known that the expanding need for food is the result of some worldwide phenomenon such as the population increase. Thus, markets and industries are experiencing a level of competitiveness never seen before, in which technology plays a key role. Furthermore, customers' expectations to quality and traceability of products are continuously increasing their level, with an ever more careful look to environmental, economic, and social implications. Just these aspects generate a reasonable pressure onto supply chains issues, especially on inventory and production decisions. Wrong choices in these fields can lead to inefficiencies, translated into wastes, shortages, and destruction of value with heavy consequences under multiple points of view. Each of these issues are emphasized when an unexpected catastrophic event arises – such as COVID-19 pandemic – and every single supply chain knot is stressed, from the procurement to the material flow control.

In food industry, the importance of the above-mentioned kind of decisions increases because of the perishable nature of the products. This variable makes the system more complex transferring a trouble much more rapidly to every supply chain node with respect to other industries (Wang, et al., 2017). Indeed, shelf life of foods is one of the main aspects that should be focused on both in storage and in delivery phase. Losing their functionality and therefore their market value, at the end of their useful life goods must be scrapped and the whole effort allocated on the production is lost. On the one hand, an overstock event will imply an extra-cost and a sure waste; on the other hand, a stockout will be translated in a demand loss. These scenarios must be absolutely avoided because of its brutal consequences on environment and economic systems (Huang, et al., 2018). What really generate inefficiency, uncertainty and imbalance along the supply chain is the variable length of the Delivery Lead Time (DLT), the amount of available information, decisions about policies, process optimization approaches and final customers' demand variability. Each of these elements affect the supply chain efficiency, influencing raw materials (RM) procurement processes, production planning and strategies, inventory management activities and finished product (FP) delivery.

Since this, food production enterprises have to set among their objectives the minimizing of food waste, as well as maximizing efficiency and resilience, beyond the essential profit. Keeping scrapping to a minimum level, both the enterprise and society will take advantage. Enterprise will be able to minimize production and stockholding costs with the same demand fulfilment level, while environment will benefit suffering a lower impact in terms of carbon footprint (Sel, et al., 2017). The production capacity –

earned by the inefficiency reduction – will carry welfare to society, allowing to better fulfil the growing demand. In order to achieve this purpose, both large enterprises and small-medium sized enterprises (SMEs) should rely on robust and fast decision-making tools, able to reduce uncertainties and to support their management about inventory and production issues.

This paper primarily aims at elaborating a model that should be involved to determine the optimal inventory stock policy basing on the demand behaviour and considering economic aspects, such as the minimization of stockholding and production costs. In dynamic contexts – where demand is subject to seasonality, trends, and other fluctuation elements – it is fundamental to continuously observe the system performances and to re-evaluate the control parameters in order to adopt the best possible approach. In addition to this, the model also evaluates the stock policy sustainability in terms of food waste quantity and value. The best matching between demand type and stock policy is led also including the product perishability constraints and the production strategy parameters. The resulting decision-support tool should be used recurrently – especially when the boundary conditions change – in order to minimize stockout events and to switch to the most efficient policy.

2. Literature review

In this section, we provide a brief overview of the main features which characterise the studies focused on inventory management concerning perishable goods. A deep analysis about the current state-of-the-art literature is rigorously presented by Janssen (Janssen, et al., 2016). Because of the topic complexity – due to the wide supply chain management scope – many research areas are identified, related to different time span: perishable inventory models, continuosly deteriorating models, inventory systems, blood bank models, production-distributing planning, traceability and so on. It is usual that, within the single work, the reader can find several topics including the optimal production lot-sizing coupled with the best stock policy or the optimization of the order quantity tied to the minimization of the payback period of the investment. Basically, two main factors operate as first principal watershed: the demand and the products' shelf-life nature. The first one generates two major categories according to how it is treated. Indeed, it may be considered as definite and consequently the work is based on deterministic assumptions. This kind of approach can be used to lead ex-post analysis or to validate a certain mathematical model to help production planning activities. In fact, in this case demand is already known. Quite the opposite, when several sources of uncertainty and variability are taken into account, demand assumes a stochastic characterization. In particular, the demand forecasting – performed with the usage of a wide variety of statistical approaches – is implemented to foresee as well as possible the future events – i.e. often trying to minimize the mean standard error (MSE) – and to take advantage with regards to inventory stock policy decisions or whatever critical-to-success choices. Shelf-life issue is approached by modeling the useful life of product either as known, i.e. with a fixed life-time, or with a random function. In particular, in the latter case a Weibull distribution is often used in order to describe the deterioration function of perishable goods. The relevance of the studies focused on foods is witnessed by the large and increasing number of works published concerning this topic. Indeed, while Bakker's literature review (Bakker, et al., 2012) analysed 227 papers produced in eleven years, Janssen traced 393 in just three years (2012-2015).

Even Maihami (Maihami, et al., 2021) provides an effective way to classify literaure works, in line with this paper's needs. Four main criteria are proposed to distinguish relevant works. Demand has a decisive impact on procurement planning, lot-sizing and many cost items. Since this, the demand function type must be considered in order to optimize decisions. In particular, they suggest to refer to multiple demand functions in which one or more variables among time, price and stock level influence the evolution of sales volumes. The second variable to take into account consists in shortage events. Even if this could be considered as a predictable aspect in inventory management issues, Maihami proposes an interesting vision about this kind of events. In fact, it is detailed in a more precise way, presenting three different scenarios. Shortages can be considered as lost sales since the vendor loses the customer because of the unfulfilled demand. If the latter is more loyal, then the shortage will cause only a backlog, and the customer will wait until the next replenishment cycle. The third case proposes a mixed situation, in which a portion of customers will turn to a direct competitor, while the remaning will patiently wait until the next replenishment cycle. Therefore, beyond the immediate sustainability and economic troubles, shortages could also lead to long-term inefficiencies, causing a hardly recoverable share of market loss, especially concerning the food industry. The third aspect to evaluate, in order to contextualize a paper, are marketing and commercial influencing factors. They are able to modify the demand trend, and consequently all technical decisions about inventories. The last feature focuses on the so-called "greenness" of the inventory model. With this expression, the author means the attention paid to the impact that a specific inventory policy or system has onto the environment, mainly in terms of food waste and carbon footprint.

Many studies have focused their efforts in modeling the impact of pricing and production capacity on inventory control decisions (Rezagholifam, et al., 2020), always including advanced mathematical tecniques to determine the optimal solutions, but overlooking the ease of use, especially for industrial realities in which sophisticated knowledges are not always available (Müller, 2017). In this paper, we face a scenario in which many of the above-mentioned features are taken in consideration. A set made up by four different perishables are analysed. Their 2019 daily demand is known and each of them have a fixed shelf-life. Traceability is a basic assumption on which the model is based. It will not imply a generality loss, since HACCP and ISO 22005 have become mandatory. After having characterized the demand, according to a specific model specifically developed by Williams and illustrated by Syntetos (Syntetos, et al., 2005), and after having pointed out the influence that promotions had on the demand pattern, the best inventory stock control policy is highlighted basing on a specific transfer function which takes into account some peculiar production and logistic parameters. In particular, stockholding costs and production costs must be minimized, and simultaneously the service level (SL) has to be optimized. In line with the no longer negligible importance of sustainability of every acitvity involved in supply chain scope, many authors have included in their works the role of environmental impact, embodying those aspects into the objective function of the mathematical model. Bortolini (Bortolini, et al., 2019) succeded in optimizing a bi-objective model in a logistic network under sustainability and efficiency of stocks. Even in this work sustainability plays a main role in evaluating the best stock policy. The minimization of the food waste is at least as important as the reduction of the two main cost items taken into account.

3. Model architecture and entities

Inventory management is a challenging topic within the supply chain management. This discipline – strictly tied to the production management – can be considered as a systematic approach that involves RM sourcing and the FP storing and delivery. The existence of inventories is due to essential needs expressed by a company to meet as many times as possible the customer demand. Indeed, inventories allow to protect companies from uncertainties tied to a long list of sources, such as demand and supply lead time. Inventories' decoupling function allows the production company to continue the manufacturing activities, despite the supplier delays in RM delivery or to continuously fulfil the final customer demand, regardless its nervousness and unpredictability. RM and FP warehouses protect the company from external unexpected events coming from the task environment in which it operates, avoiding stock-out and overstock cases. Within the manufacturing company, some warehouses – or simply buffers – are put between the above-mentioned structures in order to grant as much as possible the smoothness of production pace, bypassing starving and blocking events on the production floor. Meanwhile, inventories are sources of stockholding costs i.e., that cost item generated by the only presence of stocks within warehouses, by their assurance and all the other general cost elements incurred to keep them – e.g., shelves, energy to keep the right environmental conditions. Regardless their position along the supply chain or the production process, when we talk about perishable goods, it gets more complicated. Inventories not only perform the mentioned duties, but they are also called on to correctly keep the physical and chemical conditions within certain limits. This can also result in a greater use of energy and a consequent higher keeping cost. The model's purpose is to provide a simple and user-friendly tool, but that includes as many aspects as possible for the determination of the best stock keeping policy, also taking into account the goods' shelf-life constraints and implications.

3.1 Stock policies

An inventory system has the duty to provide operational policies in order to control and to keep the right stock level, at the right time and at the right place. The system is in charge of the timing concerning the order placement and of its tracking. It is essential to track and trace what has been ordered, its quantity and its supply lead time. Applying this concept to a FP warehouse, the previous supplier turns into the production line, because it is just the entity which provides the stock keeping unit (SKU) stored towards the final warehouse. In perishable goods' industries, the matter become more complex. In fact, the deteriorating constraint is added to the just wide pre-existing set.

In order to better manage these issues, many stock control policies have been modelled over the last decades (Eilon & Elmaleh, 2007). We reviewed those schemes and adapted them to the specific case of a FP warehouse concerning decomposable goods. The model evaluates and returns the best solution basing on demand pattern and a series of specific parameters. The scenario considers the warehouse that is from the one hand supplied by the production system and from the other hand depleted by the customer demand. In particular, we have considered:

- Re-Order Level (ROL): the order must be launched when a certain stock level is reached – that is the re-order level (RL). The re-ordered quantity is considered to be the economic batch quantity (EBQ), computed evaluating the best trade-off between the stockholding costs and the production cost. In order to protect from uncertainty tied to production lead times and to the final demand, a safety stock (SS) has been considered. It is important to highlight that this policy can be implemented if inventory is subject to a continuous check. The latter would favour a better control of the single product's deterioration state.
- Re-Order Cycle (ROC): the order can be launched only every re-order interval (RI) and only if the stock level is below an "augmented" re-order level (RL'). Indeed, the stock control is blind during the RI and both the RL and SS must also include RI as a source of uncertainty. The re-order quantity is fixed, and it is equal to the EBQ. In this case the inventory control becomes periodic. The rigidity in reordering time could cause serious problems if RI is different from the product's useful life. Even the higher SS do not work in favour of perishable goods.
- Base Stock Policy (BSP): the order must be launched every RI, but the quantity ordered varies with respect to the previous cases. In fact, the lot is equal to the difference between a target stock level (TSL) – previously planned and fixed – and the current stock level. TSL and SS include RI in their own computations and inventory control is periodic. This policy is often used when the physical storage space is limited. The "augmented" SS and the mandatory reorder penalise this policy with respect to the perishable goods management.
- Min-Max Policy (l, L): in this case two levels are set, that are a minimum (l) and a maximum (L). As in the

previous case, the lot size depends on the current inventory level and the order is launched if the stock goes below l and every RI. Even in this case SS are "augmented" with respect to the ROL policy and perishable goods would be disadvantaged.

- Two-bin Policy (TBP): this is the simplest case, and it is often implemented for low-value SKUs. This policy considers a trivial dynamic, basing on the computing of the bin dimension (B): having available two bins of equal size, the order is launched every time the first one is completely depleted and, while the supply chain starts, the demand depletes the second bin. If B is conveniently right-sized, this policy will favour the shelf-life constraints management.

Basically, every time a policy fixes one of the considered parameters, invalidating its flexibility, it reduces its capability to fulfil the perishable goods requirements.

3.2 Demand classification

This work aims at matching a certain demand pattern to the best stock policy, considering the values assumed by a set of specified indicators concerning the inventory system performance under multiple perspectives. In this paragraph, we illustrate the model which we based on in order to categorise the model's main input behaviour: the customer demand. It is the cause of the stock level lowering and its uncertainty sources are the main entities which the model wants to protect the inventory from. Many authors have focused their studies on the categorization of demand patterns in order to match the best forecasting method. Williams (Williams, 1984) is the author of the system on which the model is based in order to assess the time series behaviour. He based his idea on the partition of the demand variance during lead time into its main constituent parts. The variables to consider are:

- λ – the mean demand arrival rate.
- APLT – average production lead time.
- SVC – demand size squared variation coefficient, computed as the ratio between the demand standard deviation and its average.

The $1/\lambda \cdot SVC$ (1) ratio characterizes how intermittent the demand is, since the rate can be also read as the number of lead times between successive demands. The higher is the ratio, the more intermittent the demand is. The $SVC/\lambda \cdot APLT$ (2) indicates the lumpiness of the demand. These two ratios determine the dimensions of the matrix in which demand patterns can be allocated. As reported in the figure below Figure 1: Williams' demand categorization matrixFigure 1), the matrix is made up by five areas, delimited by some defined cut-off values. Williams indicates them with alphabetic letter from A to D, but detailing the latter in two further sub-categories, D1 and D2. Area A represents the smooth demand patterns; B is referred to the slow-moving category; C is the area dedicated to the irregular ones; D1 and D2 are respectively addressed to erratic and highly erratic demand patterns.

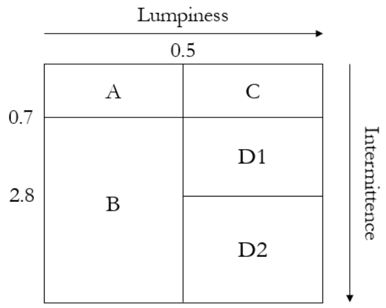

Figure 1: Williams' demand categorization matrix

In addition to the classification, the model also receives as input further information about the demand pattern in order to better understand what really influences its allocation to a specific stock policy. In particular, some influencing factors (IF) are detected. They can be primarily divided into two main categories: intrinsic IF and extrinsic IF. The first class includes entities like trend, seasonality and cyclicity, embedded inside the demand pattern and out of the company direct control. In the second cluster, we could consider variables directly controllable by the company. Commercial and marketing actions are clearly a prime example of extrinsic demand IF.

3.3 Production system characterization

This model is structured by look-back stock policies. These procedures work in production systems in which the finished product warehouse (FPW) – that is downstream with respect to the production line – is decreased by the final demand and then it has to "pull" the needed quantity, according to specific production parameters. That quantity will be produced in a certain production lead time (PLT), identified by an average (APLT) and a variance (σ^2PLT), and depending on a certain production rate. The production strategy can be referred to the job shop category, in which batches – opportunely sized – follow a specific activity sequence.

The model makes a step forward also including a tight constraint concerning the products' deteriorating nature. Many goods lose their quality or value over time because of physical condition changes or monetary value issues. In this model the user set the perishability lifetime (PL) parameter, setting the product's useful life. If the good exhausts its whole useful life while stocked, then it must be destroyed, and it will lose its entire value. That value is considered to be equal to its production cost. This is a direct consequence of an overstock event in presence of perishable goods. During the whole material flow, products generate cost elements, which are typically counterbalanced by the value produced and acknowledged by the market through the price. In this model we take into account two cost items: the periodic stockholding cost and the production cost. The first one is typically computed as a percentage of the stocked value, while the second one is typically computed summing the unitary RM cost and the labour one – following a direct costing accounting method. Taking inspiration from the Maihami's work (Maihami, et al., 2021), shortages are considered in the same manner as a lost sale, quantified by multiplying the unitary selling price and the quantity of lost demand

The framework relies both on the Hadley-Whitin model concerning SS and on the EBQ one, conveniently re-adapted to the reference framework. For instance, in both the models the variance tied to the supply lead time has been turned into the variance tied to the PLT.

4. The model proposal: how it works

The model aims at recurrently support decisions concerning the inventory management area. External influencing factors, such as unexpected and upsetting events – as COVID-19 pandemic, may dangerously affect the company business, causing great economic losses. In addition to this, production and inventory systems must aim at revolutionizing their paradigm towards sustainable goals. In food industry, overstocks and bad inventory managing practices cause a great amount of product waste, in addition to a devastating impact onto the environment. In addition to these objectives, the model is designed to be the as easy-to-use and user-friendly as possible. The user activities are thought to be minimized and they only consist in explicating in the model some essential parameters. The dynamic nature of the model allows the inventory manager to have a continuous advice about which is the best inventory stock policy to implement in that specific period, basing on the demand trend and on the boundary conditions.

The data flow starts from the upload of the demand time series database. Data must be organized following the same temporal unit and must refer to the same time horizon. The information associated to each of the time bucket must be the sold quantity, the unitary sell-out price, and average promotional discount. The granularity must be the same. The data upload will automatically allow the model to compute the whole parameters needed both to categorize the demand pattern into a specific cluster – from A to D2 – according to the criteria expressed in paragraph 3.2 and to compute all the essential components for each policy – SS, RI, RL, etc. Once the user has completed this demand upload activity, he is asked to entry the values of a precise set of production parameters for each of the analysed product, among which we can highlight:

- PR - production rate referred to the temporal time bucket.
- ISL – initial stock level.
- TSerL – target service level, expressed in k, i.e., the number of standard deviations needed to reach a certain SL.
- PL – perishability lifetime.
- Pc – production cost of the single batch.
- %VAL – percentage to multiply with the average unitary sell-out price (AUP) in order to compute the stockholding cost per period.

Once these data are entered, the model first automatically elaborates the whole set of descriptive parameters to classify the demand pattern (1) (2), previously introduced in paragraph 3.2. Williams' classification method has been validated on data series coming from automotive industry, but the cut-off values can be calibrated according to the specific need and to the peculiar industry in which the company operates, including perishable goods industries. Simultaneously, the model elaborates the production parameters needed. Every single stock policy is simulated from the order launches to the over-stock – wasted product - and stock-out events – demand loss. In every single policy framework, all the order launch rules – illustrated in the 3.1 paragraph list – are observed according to the specific case and all the related sawtooth diagrams are elaborated, evaluating the inventory stock level during the entire time horizon. Every result is immediately accessible, and it can be modified to simulate a different scenario from the real one, meeting the eventual needs to lead what-if analysis. The results are stored into a definite table in which some specific computations are executed. In fact, the next step followed by the model is the computing of the principal indicators that the transfer function will take into account in order to state which is the best stock policy for that specific demand behaviour. In detail, the following indicators are computed (in particular (3) (4) (5) (6) (7) (8) and Table 1):

- ASL – actual service level (%).
- AStL – average stock level.
- STC – stockholding cost (total).
- PC – production cost (total).
- DL – demand loss, that is computed both in the unit of measurement and in terms of economic value. In particular, it is equal to the integral of the whole stock-out (SO) events during the entire time horizon T.
- FW – total product waste (Wa). It is the total amount of goods which overcame the PL during its warehouse stay. Thus, they must be destroyed. Even in this case, it is computed both in the unit of measurement and in terms of economic value. Even in this case, it is computed as in the previous case.

Table 1: Model parameters computation formulas

Indicator	Formula	Ref.
ASL	$\mathrm{ASL} = 1 - \frac{\text{StockOut Events}}{\text{Sell Events}}$	(3)
AStL	$\mathrm{AStL} = \frac{\sum_{i=1}^{T} V_i}{\mathrm{T}}$ where Vi = Volume sold at time i; T is the entire time horizon	(4)
STC	$\mathrm{STC} = \mathrm{ST_c} \cdot \mathrm{AStL}$	(5)
PC	$\mathrm{PC} = \mathrm{P_c} \cdot \text{Total Production Orders}$	(6)
DL	$\mathrm{DL}[€] = \sum_{i=1}^{T} \mathrm{SO_i} \cdot \text{Average Unitary Sell} - \text{Out Price}$	(7)
FW	$\mathrm{FW}[€] = \sum_{i=1}^{T} \mathrm{Wa_i} \cdot \text{Average Unitary Sell} - \text{In Price}$	(8)

Every product is evaluated in each of the five considered stock policies. Thus, a matrix of results values will be structured as follow: on the rows the just exposed evaluation criteria are put. On the columns the different policies. The matrix data are appropriately normalised in order to homogenise the values. Thus, a weight vector W is associated to each criterion in order of importance of the specific scenario. In this way, every stock policy, for each product, has a certain mark assigned by the transfer function. The latter sums the factors which negatively contribute to the mark – AStL, STC, PC, DL and FW – and subtracts the positive contribution of the ASL. The policy that will reach the lowest score, will be the best solution for a product characterized by certain parameters of perishability and a certain type of demand. Basically, we could consider the just presented model's computations as the transfer function which, receiving in input the user parameters and the actual state of the inventory system, returns the best inventory stock policy according to some specific KPIs and their relative importance. The output will point out the next state of the system that will be recursively assessed by the transfer function.

5. A model simulation in fresh food industry

In order to validate the model efficiency and to clarify the process, we decided to implement the proposed scheme to a database made up by four different products – P1, P2, P3 and P4 – characterised by different production, perishability, and demand pattern features. The scenario is typified by a multi-period inventory system. In this paragraph, the whole analysis process will be evaluated referring to the product P1, with PL equal to 5 days. The demand pattern consists of the active invoices tied to P1, as far 2019 year is concerned. The same path is valid for the other products.

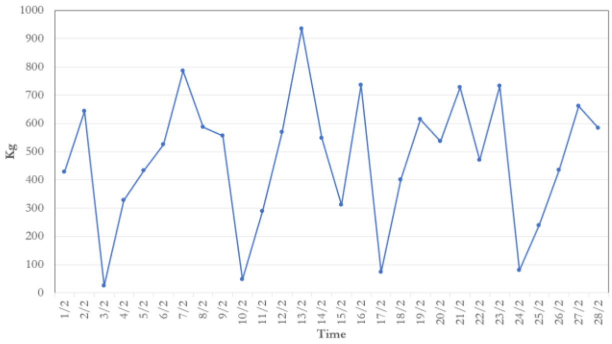

Figure 2: P1 demand in February 2019

In addition to the sales volume – partially reported in Figure 2 as far P1 is concerned, database also provides the unitary sell-out price and the discount applied in that specific period. The model immediately computes the entity of the latter as an extrinsic influencing factor. Trend and seasonality – intrinsic IF – are elaborated through the usage of an extrapolation method (Shumway & Stoffer, 2011) able to isolate these time series components. Simultaneously, the model elaborates a table in which the key variables are computed in order to categorise the demand pattern within the right cluster. After the cut-off parameters have been set, the model elaborates the data and outputs a table as the following (Table 2).

Table 2: P1 demand pattern class: B

Variable	Value
λ	0,97
APLT	0,50
SVC	0,32

At this point, the model receives as input the production parameters introduced in section 4. Thus, the stock policy simulation starts. The demand pattern is elaborated, and the re-order rules and parameters are set according to the stock policy analysed. The stock level is computed for each time bucket considering the waste food to be destroyed if the PL is overcome and the replenishment events coming from the EBQ arrival. The model takes into account all the stock-out and the over-stock events, also considering the SS level. The model returns the table in which the above-mentioned performance indicators are summarized for each product and for each stock policy. The P1 stock level and recap table is reported below, respectively in Figure 3 and in Table 3.

Figure 3: P1 stock level in February 2019

Table 3: P1 policy assessment table

Indicator	ROL	ROC	BSP	l, L	TBP
ASL [%]	82,2%	83,8%	83,0%	80,5%	84,1%
AStL [Kg]	1,05K	1,46K	1,33K	2,17K	2,55K
STC [K€]	18,8	26,7	24,5	39,8	46,9
PC [K€]	11,9	15,1	18,2	18,2	15,5
DL [K€]	63,4	69,5	55,9	85,8	32,1
FW [K€]	4.9	9.5	7.4	11.9	12.5

Passing through a normalization of each vector associated to the single criterion, the table is transformed such that the sum of the row gives 1. After criteria have been assigned to each indicator, the previous normalized table is multiplied with the W vector and a table of weighted values is obtained. The grade of the stock policy – referred to the product taken into account – is given by the sum of the values reported in the related column, except for the first element, which is subtracted. That is exactly how the transfer function works in this model: by computing in a certain way the stock policy mark and considering the influence of several factors, it connects the demand pattern class to the best stock policy. In the P1 case, the best stock policy returned by the model is the ROL. Even if the ASL is lower than the one proposed by TBP, the ROL policy allows to have lower costs in terms of production, stockholding, and food waste. In conclusion, the model suggests adopting a ROL policy for a perishable good like P1, characterized by a 5-day PL and by a certain demand behaviour classified in the B cluster.

Fore completeness, the results associated to the other 3 products are reported below. P2, has a D1 demand pattern and a 10-day PL. The model suggests a ROL policy. P3, has a B demand pattern and a 2-day PL. The model suggests a TBP policy. Finally, P4 has a C demand pattern and a 12-day PL. The model suggests a ROL policy.

6. Conclusions and future development

In the last decades, supply chain management became a central discipline in business management, regardless the company size. It is clear how decisions taken in this company function heavily impact on the whole company fate. One of the main tasks it has to address to is the inventory management, that is the systematic material flow management both within the company warehouses and along the whole supply chain. In this work we propose a model that aims at supporting the warehouse manager to choose about the best stock control policy, according to the product demand pattern. Exploiting some information extrapolated through time series analysis techniques and using some well-known model in operations management, the model links the best stock policy control for the specific product. Since its design, this tool has been thought to be easily used by the responsible of the inventory. Beyond the optimization of the ASL and the minimization of the whole set of warehouse item cost, the model sets among its objectives to keep track of the impact that the goods waste has both on the business and on the environment, introducing a sustainability view of the inventory operations.

From a technical perspective, this model could be improved by enhancing the SS model. The ASL is often far from the target one because of other uncertainty sources, not considered in the actual model. The same matter is for the demand classification model considered: it would be a great improvement to enhance the model, aiming to understand the widest possible set of patterns. In order to improve the model performance, a demand forecasting module could be implemented. In fact, the user can actually use the model only to execute ex-post analysis. Knowing in advance the best policy to be applied, benefits could increase, causing positive effects on the entire company. It could be very insightful to provide the possibility to translate the food waste amount into carbon foot-print equivalent. This could help the company to better account its social and environmental responsibility to its stakeholder, and it would be a stimulus towards the operations continuous improvement. Beyond these technical improvements, further validation could be executed. It would be a great success to see how the model reacts to an unexpected and catastrophic event – such as COVID-19 pandemic. The actual model is just able to make more resilient the inventory stock control system, allowing to switch to the best policy according to the scenario, just in few steps. If the model succeeded in facing a so devasting phenomenon, its robustness would be extremely verified. In order to further validate the model, it would be extremely interesting to implement the tool also in other industries with the same perishability problems. With these improvements and adaptations, the model would express its whole potential, and it could become a very effective tool towards the operational excellence.

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