Operations research models and methods for safety stock determination: A review

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ABSTRACT

In supply chain inventory management it is generally accepted that safety stocks are a suitable strategy to deal with demand and supply uncertainty aiming to prevent inventory stock-outs. Safety stocks have been the subject of intensive research, typically covering the problems of dimensioning, positioning, managing and placement. Here, we narrow the scope of the discussion to the safety stock dimensioning problem, consisting in determining the proper safety stock level for each product. This paper reports the results of a recent in-depth systematic literature review (SLR) of operations research (OR) models and methods for dimensioning safety stocks. To the best of our knowledge, this is the first systematic review of the application of OR-based approaches to investigate this problem. A set of 95 papers published from 1977 to 2019 has been reviewed to identify the type of model being employed, as well as the modeling techniques and main performance criteria used. At the end, we highlight current literature gaps and discuss potential research directions and trends that may help to guide researchers and practitioners interested in the development of new OR-based approaches for safety stock determination.

1. Introduction

Global market competitiveness and the need to meet customer requirements have triggered an increase in uncertainty factors within the organizations [1]. These factors are frequently related to manufacturing, transportation, demand, supply, or even external events, and can assume a short-term nature (e.g., increase, reduction, cancelation or even forward-backward movements of orders) or a long-term nature (e.g., price volatility) [2]. Coping with uncertainty is, therefore, relevant given that in addition to its unavoidably presence in real-world operational contexts [3], it is one of the major issues in supply chain management (SCM). A number of research studies, especially in the field of supply chain risk management (SCRM) [4], have been focusing on the development of techniques able to manage uncertainty phenomena and their repercussions throughout the SC. In particular, as a "*function of the cycle service level, demand uncertainty, the replenishment lead time, and the lead time uncertainty*" [5], safety stocks are considered to be a suitable strategy to prevent stock-outs [6] and to deal with supply and demand variability [7,8]. In fact, in spite of the challenges inherent to their management, Koh et al. [9] emphasize that safety stocks are one of the most robust strategies to soften supply and demand uncertainty.

Typically, the research works on safety stock methods cover the problems of dimensioning, positioning, managing and placement. Within these main problems, this research narrows its scope to strategies for dimensioning safety stocks, consisting in determining the proper safety stock level for each product [10]. It is known that no SC can operate without safety stocks [11] which, together with adequate financial flows and funds, are deemed relevant to the prevention of massive SC disruptions [12]. In effect, given the current concerns with the impact of SC disruptions on business performance, a recent Forbes' report [13] points out that companies will tend to be less tolerant to risk and uncertainty. It particularly highlights the importance of safety stock planning to cope with SC risks coming from scenarios related with natural disasters (e.g., hurricanes, tsunamis, floods) or mass epidemic infections (e.g., 2019-nCoV), which have been increasing across the world. As a first and important step before moving on to more advanced safety stock problems, such as determining the optimal locations and quantities of safety stocks so as to maintain target service levels whilst minimizing costs (commonly referred as to safety stock placement [14]), we consider that it is fundamentally important to develop further understanding on how to correctly determine safety stocks for each product.

The goal of this paper is to provide a concise overview on how

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academics working in SCM have been addressing the safety stocks dimensioning problem, from an operations research (OR) perspective. Although there is a large body of literature on safety stocks dimensioning models, scarce attention has been given to review articles in this particular field. For instance, the work of Guide Jr and Srivastava [3] discusses a set of methodologies and techniques to cope with uncertainty in material requirements planning (MRP) environments. It points out several gaps in the context of the previous literature. Caridi and Cigolini [10] provided an overall perspective on dampening methods used to dwindle uncertainty within manufacturing systems. The authors discussed 14 papers related to the safety stock dimensioning problem as a basis to propose a novel safety stock model encompassing two buffer strategies: one to face demand peaks for a given service level (by taking into account their probability distribution) and another to address the variability of steady demand (by analyzing the statistical distribution of forecasting errors). Later, Schmidt et al. [15] compiled several stochastic approaches currently used for dimensioning safety stocks, and conducted a set of controlled simulation studies in order to assess the performance of the proposed methods in terms of the variance of demand and replenishment lead time. Of note, the need for dynamic approaches to compute safety stocks is underscored by the authors.

However, upon searching the literature related to the use of OR models and methods to tackle the safety stock dimensioning problem, we found that there is a lack of studies providing a replicable and structured process of gathering around all the relevant scientific works on this topic in an objective way. Thus, motivated by the alleged difficulty [15] regarding the survey of dimensioning safety stock works, perhaps due to their wide application in the SCRM field, this paper presents a systematic literature review (SLR), from 1977 to 2019, of OR-based approaches for dimensioning safety stocks. The contribution of our research is threefold. In the first place, it compiles and summarizes the state-of-the-art modeling efforts and techniques that have been studied for dimensioning safety stocks. At this point, the sampled papers were classified, in terms of the proposed OR model/method, into four distinct categories. Each paper is further discussed and characterized according to the type of model employed, as well as the modeling technique(s) and main performance criteria considered. Second, the drawbacks and limitations of the current dimensioning safety stocks approaches are stressed. Third, based on the identified gaps, we provide suggestions that could serve as gateways of opportunity for future research in this topic, both in a scholarly and business context.

The remainder of this paper is organized as follows. The next section explicitly recalls some standard approaches commonly adopted to treat the safety stock dimensioning problem and that serve as foundations for many current research studies on this topic. Section 3 presents the review methodology and objectives, and describes the paper selection phase. Section 4 performs a descriptive analysis on the selected papers. In Section 5, the selected papers are categorized according to the proposed strategy for dimensioning safety stocks. This process forms the basis for the material evaluation. Then, we conclude in Section 6, highlighting some important literature gaps and potential directions for future research.

2. Traditional dimensioning safety stock strategies

Safety stocks are essentially affected by six factors, including service level, lead time, demand volatility, order policy, component commonality and holding costs. The reasons are quite intuitive. An optimal safety stock strategy should be small enough to reduce inventory-related costs while satisfying demand and high service level customers on time. This naturally depends on how to cope with different levels of demand volatility, and how large is the lead time variance. On the other hand, the size of order releases and the degree of component commonality may also suggest opportunities to optimize safety levels. This

section recalls standard stochastic approaches for dimensioning safety stocks, based on normally distributed parameters, which embody some of the aforementioned factors. For a comprehensive knowledge on this topic, the reader is referred to the fundamental texts of [16–20] and to the review of [15].

Assuming that the total demand during a lead time $L > 0$ is normally distributed with mean μL and standard deviation $\sigma_D \sqrt{L}$, the most simple approach for dimensioning safety stocks for a fixed target service level α is set as:

$$SS = \Phi^{-1}(\alpha)\sigma_D \sqrt{L} \tag{1}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $\Phi^{-1}(\alpha)$ is the safety factor, and σ_D is the standard deviation of demand D per unit time. If L and D are assumed to be independent random variables, the safety stock Eq. (1) can be rewritten as:

$$SS = \Phi^{-1}(\alpha)\sqrt{L \cdot \sigma_D^2 + (\sigma_L \cdot \overline{D})^2} \tag{2}$$

where $\overline{D}$ is the average demand per unit time, and σ_L is the standard deviation for the lead time L. At this point, it is clear that safety stocks are composed by two dimensions: the first to cover demand uncertainty and the second to deal supply lead time variability.

A surrogate approach to consider the calculation of safety stocks for a given item as a function of the service level and the past lead time demand forecast errors is defined as:

$$SS = \Phi^{-1}(\alpha)\sigma_F \tag{3}$$

where σ_F is the standard deviation of the forecasting errors for the respective lead time L, which in its turn is typically assumed to be deterministic and known. Here, the central problem relies on the estimation of σ_F. For that, one can follow a theoretical approach, in which an estimation of σ_1 (the standard deviation of demand forecasting errors made for a unit period) is provided and further converted into an estimate of σ_F. On the other hand, parametric and non-parametric empirical approaches can also be employed, where σ_F is directly estimated from the lead time forecasting error [see 19, for details]. When demand distributions do not follow the common normality assumption, one can adopt a non-parametric forecasting approach to estimate safety stocks:

$$SS = Q_L(\alpha) \tag{4}$$

where $Q_L(\alpha)$ is the lead time forecast error quantile at the target service level α. This quantile can be obtained, in a non-parametrical fashion, from the empirical distribution of the lead time forecast errors [21].

Further research studies have been presented to show scientific improvements on the previous closed-form stochastic formulations, either via new safety stock formulations or incorporation of current traditional approaches into more realistic albeit more complex inventory control systems. Our aim is to provide a comprehensive review on how OR has been contributing to the safety stock dimensioning problem, by exploring what OR-based models and methods have been employed to tackle it and what type of performance criteria have been applied in such modeling approaches.

3. Research methodology and objectives

In this paper we propose a SLR [22] to identify relevant papers on OR-based models and methods for dimensioning safety stocks and to provide useful insights for future research in this field. This type of review is particularly helpful to handle with large volumes of scientific literature, as well as to reduce the bias inherent to the selection of research studies [23]. The review methodology herein proposed is based on the following steps: material comprehensive search and selection criteria; descriptive analysis, category selection; and material evaluation. These steps are deeply characterized throughout the subsequent sections. In a nutshell, the main purposes of this review are to:

i. Compile and explore the state-of-the-art modeling approaches and techniques which have been proposed for dimensioning safety stocks;

ii. Understand what industrial sectors have been explored as application domains to safety stocks;

iii. Highlight the drawbacks and limitations of the current safety stock dimensioning techniques;

iv. Discuss research opportunities that may help to guide future researchers and practitioners interested in the development of new OR-based approaches for dimensioning safety stocks.

3.1. Material comprehensive search

Purposing to collect the most relevant papers to this research, the search process was conducted on *Scopus* and *Web of Science* (*WoS*) scholarly databases, from 1977 to January 2020, under the fields "title, abstract, keywords". The search query firstly considers the context keywords *"safety stock"* and *"safety inventory"* in combination with the broader keywords *inventory* and *stock*, to capture all possible inventory management nomenclatures (e.g., inventory/stock planning, inventory/stock control), as well as with the uncertainty/risk keywords *uncertain*; variation; variability; volatile; volatility; fluctuate* and *fluctuation.* The use of the wildcard character in the search string *uncertain** makes it possible to identify papers with the terms *uncertain* and *uncertainty*. Finally, broader modeling keywords together with topics that, according to INFORMS and EURO organizations, characterize OR methods were also added to the search query. The search was then narrowed only to peer-reviewed scientific journals written in English, as most of the high-quality research is typically published in journals. This resulted in a total of 696 papers in *Scopus* and 506 in *WoS*. At the end, the number of papers resultant of excluding duplicates is 813. Table 1 summarizes the material collection process.

3.2. Selection criteria

As a way of excluding papers which did not meet the purpose of this investigation, all 813 documents were subjected to a scan analysis of the content based on a complete reading of the abstracts. In this process, papers that did not focus on the safety stock dimensioning problem in a quantitative fashion have been excluded. After this procedure, a final sample of 95 papers from 1977 to 2019 was derived. This set of articles formed the basis for the analyses presented hereinafter.

In order to validate the filtering process and papers selection

criteria, a keyword bibliometric analysis based on co-occurrence data was performed in both initial (813 papers) and final (95 papers) sets of papers, by taking advantage of the software VOSviewer [24]. The left and right of Fig. 1 depict co-occurrence maps of keywords present in the papers of the initial and final samples, respectively. In both maps, the bigger the circle of a keyword, the more frequently that keyword occurs in the respective sample. Moreover, the smaller the distance between two or more keywords, the larger the number of co-occurrences of such keywords in the same paper. A closer examination of the keywords presented in the final sample (right of Fig. 1) reveals that the papers included therein match with the objective of this paper, in the sense that core keywords such as *"inventory control"* and *"safety stock"* are not excluded during the process of refining the initial sample into the final one.

4. Descriptive analysis

The selected papers were descriptively characterized according to: the number of publications over time and per international peer-reviewed journal; the modeling methodology employed; and the sector of application. In what concerns the evolution of the number of published articles from 1977 to 2019, there appears to be an upward trend over the time window considered (see Fig. 2). Particularly, we note a significant increase in the number of published papers from the year 2005 onwards. Fig. 2 also shows the main journals that published the highest number of papers contained in our final sample. The International Journal of Production Economics lists the maximum number of published papers over the time window considered (24 papers), followed by the International Journal of Production Research (10 papers), the European Journal of Operational Research (9 papers), the Management Science (5 papers) and the Production Planning and Control ex-aequo with the Expert Systems and Applications journal (4 papers).

Table 2 presents the ten most cited papers so far in the safety stock dimensioning literature. Here, we use the *Scopus* database as it is the largest abstract and citation database of peer-reviewed research literature [25]. Yet, we found that not all papers listed on our sample appeared in *Scopus*. In these particular cases (marked with *), we take advantage of the *WoS* database to collect the number of citations. The most cited paper was published by Collier, D. [26] with 171 citations. This paper studies the relationship of safety stocks with the component commonality index, a fundamental concept in the material requirement planning (MRP) systems also introduced by Collier, D. [27] in the early 1980s.

Table 1
Material comprehensive search.

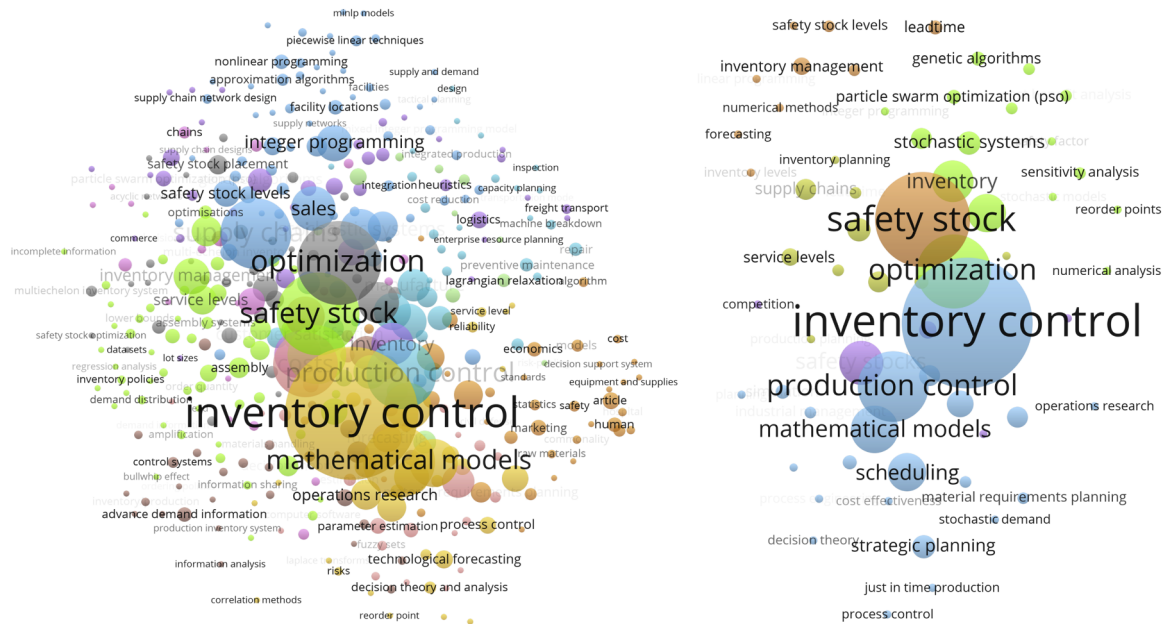| Research query	("safety stock" OR "safety inventory")
	AND
	(inventory OR stock OR uncertain* OR variation OR
	variability OR volatile OR volatility OR fluctuate OR fluctuation)
	AND
	("mathematical model" OR "numerical method" OR
	"numerical model" OR "decision tool" OR "decision model"
	OR "decision analysis" OR simulation OR heuristic OR
	metaheuristic OR "meta-heuristic" OR optimization OR optimisation OR "multi-objective" OR multiobjective
	OR "multi-attribute" OR multiattribute OR stochastic OR
	probabilistic OR probability OR programming
	OR MINLP OR MILP OR MCDM OR "multi-criteria decision making" OR
	MCDA OR "multi-criteria decision analysis" OR markov OR
	queuing OR statistics OR "neural networks" OR "data analysis" OR "expert systems" OR parametric
	OR "non-parametric" OR "data mining" OR "data analytics" OR
	"machine learning" OR "artificial intelligence")
Time span	All papers published up to January 2020
Article type	Only peer-reviewed academic journals
Language	English
Hits in Scopus	696
Hits in Web of Science	506
Hits excluding duplicates	**813**

Fig. 1. Co-occurrence maps for author and indexed keywords.

As to the distribution of publications according to the modeling methodology employed, we found that the safety stocks dimensioning problem is often treated by using analytical/optimization models (e.g., stochastic, dynamic and goal programming; robust optimization, linear (nonlinear) programming, mixed integer linear (nonlinear) programming); simulation models (e.g., Monte Carlo simulation, discrete event simulation); or hybrid models, via simulation-based optimization techniques. In particular, we found that analytical/optimization approaches play a pivotal role on the dimensioning of safety stocks, inasmuch as they represent the vast majority of techniques used for that purpose (88%). Concerning the remaining modeling methodologies, 6% of the papers take advantage of hybrid (simulation-based optimization) approaches and another 6% employ simulation methodologies (Fig. 3). Regarding the practical applicability of the selected papers, it was found that in 62 out of the 95 papers (65%) there is no reference to real case studies or industrial applications. The remaining 33 papers (35%) consider case studies in diverse industrial/practical contexts, with a higher concentration in the pharmaceutical (6 papers), automotive (6 papers), retail (3 papers) and electronics (3 papers) industry sectors.

Section 5.5 provides details on the case-based studies that have been explored when applying OR methods to safety stock determination.

5. Category selection and material evaluation

We found that the majority of the selected papers can be characterized into four distinct categories:

1. Papers in which safety stock dimensioning decisions are based on the variation of demand, typically modeled as normally distributed;
2. Papers in which safety stock dimensioning decisions are based on the variation of the forecasting errors;
3. Papers that study how product structure and component standardization affect the safety stock dimensioning problem;
4. Papers that do not follow, explicitly, neither of the three foregoing categories but accommodate, for instance, modeling approaches that do not settle as a whole on normally distributed parameters or that encompass additional uncertainty factors apart from demand and supply. This category of papers is referred to hereinafter as
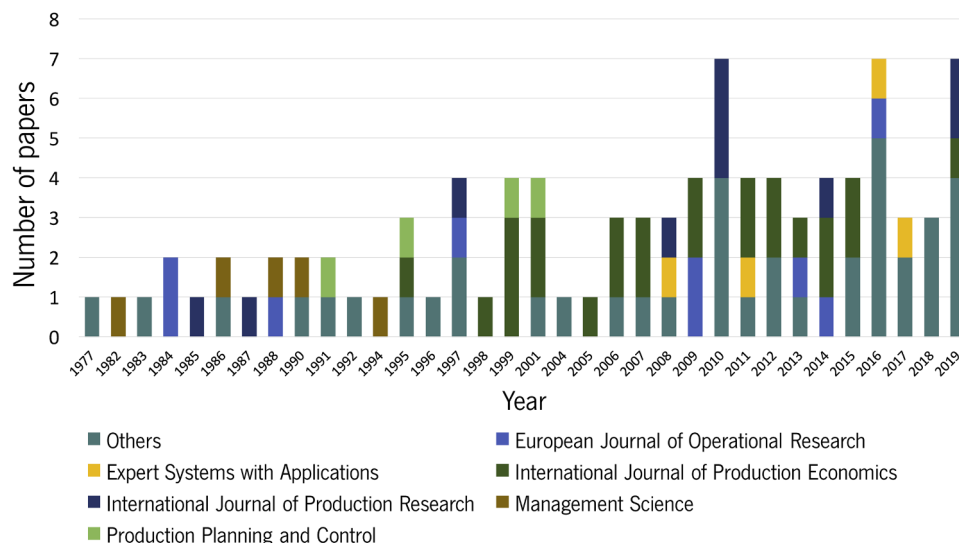

Fig. 2. Papers distribution by peer-reviewed international journal from 1977 to 2019.

Table 2
The 10 most cited papers in the safety stock dimensioning literature.

R	Title	Author(s)	TC	Journal/Year
1	Aggregate safety stock levels and component commonality	Collier, D.	171	Management Science (1982)
2	Production batching with machine breakdowns and safety stocks	Groenevelt, H., Pintelon, L., Seidmann, A.	113	Operations Research (1992)
3	Joint determination of preventive maintenance and safety stocks in an unreliable production environment	Cheung, K., Hausman W.	104	Naval Research Logistics (1997)
4	Determining safety stock in the presence of stochastic lead time and demand	Eppen, G., Martin, R.	100*	Management Science (1988)
5	Scheduling the production of several items with random demands in a single facility	Gallego, G.	76	Management Science (1990)
6	Safety stock reduction by order splitting	Kelle, P., Silver, E.	69	Naval Research Logistics (1990)
7	Possibilistic programming in production planning of assemble-to-order environments	Hsu, H., Wang, W.	69	Fuzzy Sets and Systems (2001)
8	Joint optimization of lot-sizes, safety stocks and safety lead times in an MRP system	Molinder, A.	67	International Journal of Production Research (1997)
9	Multi-objective inventory planning using MOPSO and TOPSIS	Tsou, C.	63	Expert Systems with Applications (2008)
10	Multiple-buyer multiple-vendor multi-product multi-constraint supply chain problem with stochastic demand and variable lead-time: A harmony search algorithm	Taleizadeh, A., Niaki S., Barzinpour F.,	62	Applied Mathematics and Computation (2011)

Nomenclature: R= Rank; TC = total citations; * TC according to *WoS* database.

"Other models designed for dimensioning safety stocks".

5.1. Considering the variation of normally distributed demands

Great part of the sampled papers (35%) considers the dimensioning of safety stocks based on demand variation. This section focuses on papers that, in the light of the central limit theorem, have assumed normally distributed demands in the proposed models.

One of the overriding goals of SCM is to maintain customer service levels. Considering safety stocks as a tool to meet this purpose, several studies have been including service level as main performance criterion. Kelle [28] discussed an exact solution method and an approximate formula for dimensioning safety stocks in contexts with random delivery and demand processes. Later, Kelle and Silver [29] studied a safety stock reduction strategy by exploring order splitting. The authors acknowledge that decisions on order splitting can be complicated, often requiring the assessment of nonquantitative factors (e.g., organizational considerations, vendor contracts). Dar-El and Malmborg [30] developed a service level-based model that considers rescheduling of replenishment during the inventory cycle. Placing orders earlier within the cycle time to face stock-outs constitutes the basis of that research. The proposed model allowed a reduction in the inventory carrying costs without compromising service level. Vargas and Metters [31] proposed a cost-effective optimization strategy based on a dual buffer methodology in which the former is able to provide safety stocks for time-varying demand. Alternatively, simulation models have also proved efficient in setting safety stocks under target service levels. In a multi-product environment with random demands, Gallego [32] takes advantage of a Monte Carlo simulation-based method to derive safety stocks, given a control policy and cyclic schedule. Similarly, a Monte Carlo approach was adopted by Bahroun and Belgacem [33] but to determine dynamic safety levels for cyclic production schedules under nonstationary demand patterns. Their results have shown service level and cost improvements over the traditional constant safety stock approaches. Nonetheless, we recall a study conducted by Benton [34] to emphasize that, in certain situations, little improvements of service levels generally imply a high investment in safety stocks. In such a setting, the adoption of a safety time margin when replenishing stock-on-hand should be properly tested as an alternative to the safety stocks approach [see 35].

In spite of real-world studies have already proven the benefits, in terms of service level and costs, of implementing safety stock strategies [36,37], focusing on service level alone may increase holding costs excessively, especially when uncertainty about market demand is high. As articulated in Jodlbauer and Reitner [38], setting more safety stock increases the holding costs regardless the cycle time considered. In contrast, lower safety stock levels could lead to stock-outs when demands are volatile. This central trade-off between holding and stock-out costs is investigated by Badinelli [39], who introduces an optimization procedure to determine safety stock levels under stochastic demand patterns. In a continuous-review inventory framework, the proposed approach involves the estimation of a disvalue function (via quadratic programming), an optimization method to derive stock-out performance, as well as the determination of bounds on the optimal solution. Braglia et al. [40] formulated a new model for safety stock optimization in a single-vendor single-buyer SC framework, in which the lead time is assumed to be controllable and shortages are not permitted. In that work, the service level is considered to be a function of number of admissible stock-outs and order quantity. Safety stock decisions in a similar SC framework can also be found in the work of Wangsa and Wee [41]. Nevertheless, we highlight that complex SCs rarely operate in environments with just a single vendor or buyer.

As noticed previously, in Section 2, safety stock formulations also depend on a safety factor established according to a target service level. Many authors have often combined safety stocks decisions, via safety factor, with batch size in multi-objective optimization problems. Agrell
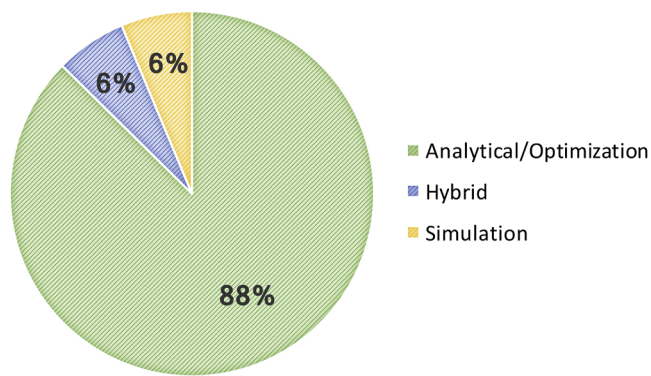
Fig. 3. Papers distribution by modeling approach.

[42], for instance, proposed a multicriteria decision-making (MCDM) model that considers batch size and safety stock factor as decision variables. The model was treated as a convex nonlinear optimization problem in which the purpose is threefold: minimize the expected annual total cost, the expected annual number of stock-out occasions, and the expected annual number of items stocked out. This problem was solved by using the interactive decision exploration method (IDEM). Very similar objective functions are further addressed in the literature by taking advantage of techniques such as multi-objective electro-magnetism-like optimization (MOEMO), multi-objective particle swarm optimization (MOPSO), technique for order of preference by similarity to ideal solution (TOPSIS) or even multi-objective genetic algorithms (MOGA) [see [43–48]]. In addition, regression-based methods have

been as well exploited to compute the safety factor. Alstrom [49] determined it as a function of the economic order, while Hayya et al. [50] have considered its calculation in order crossover environments in which demand and lead time are i.i.d. random variables.

Safety stock determination can be particularly challenging in the presence of uncertainty factors [52]. Disney et al. [53] study the effect of stochastic lead times with order crossover on dimensioning safety stocks. The authors derive a method to determine the exact safety levels for a linear generalization of the order-up-to inventory control policy. To cope with uncertainties that are caused by stochastic demand and different types of yield randomness, Inderfurth and Vogelgesang [54] proposed closed-form approaches to determine dynamic safety stocks, and discussed ways to convert these dynamic levels into static ones, easier to be applied in practical contexts. Interestingly, in the context of MRP control systems with demand and supply uncertainty, Inderfurth [55] showed that safety stock levels should not necessarily increase in a linear way with respect to yield risk. Similar uncertainty factors were investigated by Lu et al. [56], who developed a general safety stock method that accounts for nonstationary stochastic demand and random supply yield. The proposed method can be described in three main phases. First, base-stock is expressed by considering the supply yield rate as random variable in order to formulate an inventory balance equation. Secondly, stock material inbound and outbound flows are modeled by a coverage random variable. Lastly, the safety stock is calculated via fixed-point iteration method under a given non-stockout probability. At this point, a further observation we made is that despite the evident influence of uncertainty factors in inventory management, very little attention has been given to the applicability of safety stock strategies throughout the different life-cycle stages of a product

Table 3
A literature overview of modeling approaches for dimensioning safety stocks based on the variation of demand.

References	OR method/Modeling technique(s)	Main performance criteria
Agrell [42]	Decision analysis/Convex NLP	1. Holding costs; 2. Shortage freq.; 3. Stock-outs
Alstrom [49]	Statistics/Regression; Heuristic	1. Holding and ordering costs; 2. Shortage freq.
Badinelli [39]	Optimization/Quadratic programming	1. Holding, ordering and stock-out costs
Bahroun and Belgacem [33]	Simulation/Monte Carlo	1. Service level; 2. Holding costs
Benton [34]	Simulation	1. Service level
Braglia et al. [40]	Optimization/PV; Exact & Approximated minimization algorithms	1. Total costs (inc. ordering, setup, transportation and holding costs)
Brander and Forsberg [51]	Analytic/Inventory theory; Basic period approach	1. Holding and setup costs
Charnes et al. [58]	Analytic/Inventory theory	1. Stock-out probability
Cheng et al. [46]	Optimization/MOPSO	1. Holding and ordering costs; 2. Shortage freq.
Dar-El and Malmborg [30]	Analytic/Inventory theory	1. Service level; 2. Holding costs
Disney et al. [53]	Analytic/Inventory theory	1. Holding and backlog costs; 2. Availability
Gallego [32]	Optimization/Control theory; Simulation-based search method	1. Holding, backorder and setup costs
Hayya et al. [50]	Statistics/Regression	1. Holding, ordering and shortage costs
Hsueh [57]	Analytic/Closed-form expressions	1. Holding and manufacturing orders costs
Inderfurth [55]	Analytic/Inventory theory; Control theory	1. Holding, shortage and production costs
Inderfurth and Vogelgesang [54]	Analytic/Inventory theory; Control theory	1. Holding and backlog costs
Jodlbauer and Reitner [38]	Optimization/2D-Newton method	1. Service level; 2. Holding, setup and backorder costs
Jonsson and Mattsson [35]	Simulation/DES	1. Service level; 2. Ordering costs
Kelle [28]	Analytic/Inventory theory	1. Service level
Kelle and Silver [29]	Analytic/Inventory theory	1. Service level
Kumar and Evers [59]	Analytic/Inventory theory	1. (Estimated/simulated) variance
Lu et al. [56]	Analytic/Inventory theory; Fixed-point iteration method	1. Service level; 2. Inventory levels
Man-Yi and Xiao-Wo [52]	Statistics/Credibility and Fuzzy theory	1. Fill rate
Mertins and Lewandrowski [62]	Analytic/Inventory theory	1. Inventory costs
Ozbay and Ozguven [36,37]	Optimization/PVB; pLEPs	1. Total costs (inc. storage, surplus, shortage and adjustment costs)
Srivastav and Agrawal [47]	Optimization/MOGA and MOPSO	1. Ordering, holding and backorder costs; 2. Shortage freq.; 3. Stock-outs;
Srivastav and Agrawal [48], Tsou [44]	Optimization/MOPSO	1. Ordering/holding costs; 2. Shortage freq.; 3. Stock-outs
Tsou [45]	Optimization/MOEMO and MOPSO	1. Ordering/holding costs; 2. Shortage freq.; 3. Stock-outs
Tsou and Kao [43]	Optimization/MOEMO	1. Ordering/holding costs; 2. Shortage freq.; 3. Stock-outs
Wangsa and Wee [41]	Optimization/Heuristic	1. Total costs (inc. ordering, holding, shortage, setup and freight/transportation costs)
Vargas and Metters [31]	Optimization/DEA; Inventory theory	1. Fill rate; 2. Holding and setup costs

Nomenclature: NLP: Nonlinear programming; PV: Present Value; DES: Discrete Event Simulation; MOPSO: Multi-Objective Particle Swarm Optimization; PVB: Prékopa-Vizvari-Badics algorithm; pLEPs: *p*-level efficient points method; MOGA: Multi-Objective Genetic Algorithm; MOEMO: Multi-Objective ElectroMagnetism-like Optimization; DEA: Data Envelopment Analysis.

(introduction, growth, maturity, and decline), which are naturally subject to different levels of uncertainty. An exception is the work of Hsueh [57], who studies inventory control policies and closed-form expressions for the optimal safety stock across all the product life-cycle stages. Another very important aspect is that accurate safety stock estimations must account for autocorrelated demands [58] and data quality issues. Concerning the latter, the work of Kumar and Evers [59] is, to the best of our knowledge, one of the few works covering such topic by proposing a computationally efficient method that accounts for data quality and the correlation between demand and lead time in order to compute the variance of lead time demand more accurately. By softening the effect of outlier samples, the proposed method reveals to be helpful in volatile markets.

Overall, our findings showed that the problem of dimensioning safety stocks under normally distributed product demands have been intensively explored, using several types of OR models, modeling techniques and performance criteria, as summarized in Table 3. We further acknowledge that total cost is the most widely used performance criterion. However, we note that realistic SC costs, in particular shortage and holding costs, are very difficult to be measured in practice [35]. Moreover, we emphasize that the use of the Gaussian distribution for modeling demand can be fundamentally flawed in real-world SC contexts [10,60,61]. Further research into this subject is called for.

5.2. Considering the variation of the forecasting errors

Another approach for dimensioning safety stocks is based on the assumption that they are proportional to the forecasting errors. As safety stocks serve as a buffer strategy against forecast inaccuracies, if demand is properly forecasted the required safety stocks are lower, as are the levels of uncertainty. Yet, achieving accurate estimations of the standard deviation of the forecasting errors remains a challenge.

A seminal work on this topic was proposed by Eppen and Martin [60], who used the variance of the forecasting errors during lead time demand to set safety stocks, by taking into consideration exponential smoothing techniques and probability theory. The authors have shown that the general practice of assuming normal distributions for lead time demand can be misleading in safety stock decisions. Here, the use of non-parametric kernel density approaches seem to be promising to avoid the so common assumption of normal and i.i.d. forecasting errors [see 21,63]. We additionally found that many authors have assumed normally distributed lead times which, in certain cases, also bears no relation to reality. A notable exception is the work of Fotopoulos et al. [64], who proposed a novel method to derive a safety stock upper bound when demands are autocorrelated and lead times do not follow a Gaussian distribution, but an arbitrary one. For that, Chebychev's inequalities and theory of moments are explored. The authors have also emphasized that demand autocorrelation should not be overlooked in safety stock decisions, as pointed out in other studies [58,65].

As dimensioning safety stocks is typically a problem involving the optimization of a cost function, a number of different mathematical optimization models have been proposed. Purposing to minimize the total cost of the system, Buffa [66] formulated a goal programming problem, in combination with a demand forecasting model, to determine safety stocks in a multi-product environment, subject to constraints related to the availability of resources. Potamianos et al. [67] used dynamic programming to introduce a new interactive safety stock method that accounts for the accuracy of the demand forecasts. The proposed approach was designed to be added to a modified Wagner-Whitin algorithm, and well as to set safety stocks via interactions by management. Reichhart et al. [68] developed a novel and accurate safety stock formula for multi-variant products and responsive systems, by means of a Monte Carlo simulation process. An adjusted term for the standard deviation of forecasting errors is included in their formulation. Hsu and Wang [69] proposed a possibility linear programming model that encompasses forecast adjustments and demand uncertainty in the

safety stocks calculation. In assemble-to-order (ATO) environments, their work presented one of the first models to deal with imprecise data in decision-making problems involving safety stock as a decision variable. Several other methods were developed for dimensioning safety stocks according to the production control environment [70–72]. We acknowledge, however, that regardless the production environment, the generation of accurate demand forecasts is especially challenging when exogenous factors are not considered in the forecasting process. An interesting study raising relevant insights on this subject was proposed by Beutel and Minner [73], who studied a data-driven framework for establishing safety stocks. In a first step, regression methods were employed to forecast demand. The estimation errors are then used to set the targeted safety stocks. In a second step, a linear programming approach is studied to minimize a cost objective function subject to a service level constraint. One of the novelties here relates to the inclusion of external factors that might have influence in demand estimation (e.g., price and weather dynamics). This inclusion is particularly relevant since it allows to overcome the drawbacks of traditional univariate time series models that disregard these factors.

From the works above, it can be concluded that constant safety stocks might not be the most suitable approach to cope with erratic demand patterns. To overcome this disadvantage, time-phased safety stocks were studied by Kanet et al. [74], who proposed a linear programming model able to minimize inventory levels for a specific set of safety stock targets. Using real-world data from the U.S. Industry as support, it was found that the adoption of time-phased safety stocks leads to significant cost savings over the traditional constant safety stock strategy. Helber et al. [75] presented a stochastic capacitated lot-sizing problem (SCLSP) where its solution serves as the basis for determining dynamic safety stocks coordinated with the production quantities. Yet, we highlight that cost-effective safety stock decisions should additionally be coordinated with the outsourcing strategies defined with suppliers. In fact, in certain situations, it may be appropriate to establish long-term agreements with costly suppliers and setting lower levels of safety stock, rather than use several low cost suppliers and high safety levels [76]. On the other hand, such decisions should also encompass the time interval over which no plan changes are allowed (also known as frozen period) [77] in order to avoid the generation of unstable production plans for both customer(s) and supplier(s).

Table 4 provides an overall characterization of the papers included in this subsection. Here, we found that only 6 of the 17 studies included in this category reported real-world case studies [see, 21,63,66,67,73,74]), suggesting that further research with empirical validations is warranted.

5.3. Considering product structure and component standardization

Very few researchers have paid attention to study the way how product structure and component standardization may affect safety stock decisions. Indeed, only 7 papers (7% of the total sample) are included in this category. Table 5 summarizes some representative approaches on this subject.

Carlson and Yano [78] proposed an heuristic upper bound solution to establish safety stocks for each component in a product structure with periodic and replanned production schedules, under stochastic demands. Numerical simulations showed that the proposed approach resulted in savings up to 20% of total costs in comparison with the costs derived from not adopting safety stock measures. Later, the same authors studied how the frequency of rescheduling affects safety stocks decisions for a single product and its product structure in MRP contexts [79]. As a result, the fixed scheduling policy revealed to be the most economical choice. Still in MRP contexts, Grubbström [80] discussed the dimensioning of optimal safety stock levels in a single-level environment, by using Laplace transformations and taking into account annuity stream as main performance criterion, in detriment of the

Table 4

A literature overview of modeling approaches for dimensioning safety stocks based on the variation of the forecasting errors.

References	OR method/Modeling technique(s)	Main performance criteria
Abdel-Malek et al. [76]	Analytic/Markov chains; Queuing theory	1. Total costs
Beutel and Minner [73]	Statistics; Optimization/Regression; LP	1. Service level; 2. Holding and shortage penalty costs
Boute et al. [65]	Analytic/Markov chains; Matrix analytic methods	1. Fill rate
Buffa [66]	Optimization/GP	1. Holding, stock-out and resources acquisition costs
Campbell [71]	Analytic/Inventory theory	1. Total costs; 2. Service level
Eppen and Martin [60]	Analytic/Inventory theory; Chebychev's inequalities	1. Stock-out probability
Fotopoulos et al. [64]	Analytic/Chebychev's inequalities; Theory of moments	N/A
Helber et al. [75]	Optimization/MILP; Piecewise linear approximations	1. Service level; 2. Holding, overtime and setup costs
Hsu and Wang [69]	Optimization/PLP; Zimmermann's fuzzy programming	1. Stock-out, holding and idle capacity penalty costs
Kanet et al. [74]	Optimization/LP	1. Shortage freq.; 2. Fill rate
Lian et al. [77]	Optimization/Heuristic	1. Holding/expedited, ordering and setup costs
Potamianos et al. [67]	Optimization/DP	1. Production, holding and setup costs
Reichhart et al. [68]	Statistics; Simulation/Regression; Monte Carlo	1. Service level; 2. Inventory, production and backordered costs
Trapero et al. [21,63]	Analytic/GARCH models; Kernel density estimation	1. Inventory costs (understocking and overstocking); 2. Service level
Wacker [70]	Statistics/Regression	1. Statistical efficiency
Zhao et al. [72]	Simulation	1. Service level; 2. Production setup, holding and stock-out costs; 3. Schedule instability

Nomenclature: LP: Linear Programming; GP: Goal Programming; MILP: Mixed Integer Linear Programming; PLP: Possibility Linear Programming; DP: Dynamic Programming; GARCH: Generalised AutoRegressive Conditional Heteroscedastic; N/A: Not Available.

average cost approach. This paper was later generalized in Grubbström [81] for multi-level product structure systems, via input-output analysis. In any case, regardless the product structure and production environment, proper safety levels should lead to low stock-out/holding cost ratios [82,83].

In extreme cases, in the presence of raw material disruptions, the manufacturing of several end-items can be compromised. This situation can be easily aggravated in the presence of product structures in which a component is common to several end-items (component commonality). Collier [26] proposed an explicit formula for the computation of safety stocks that considers an analytical metric, based on the bill of materials (BOM), to measure the commonality degree in a firm's product line. That formulation was assessed via simulation under contexts in which uncertainty phenomena prevail. The results suggested that increasing the degree of component commonality results in lower safety stocks, regardless the constant service level imposed. It is noteworthy that the findings derived from the Collier's model are particularly meaningful in practice if the minimization of holding costs is regarded as a primary concern.

5.4. Other models designed for dimensioning safety stocks

As discussed in previous sections, many OR models and methods have been proposed to set safety stocks in different production environments. However, we found other models designed for dimensioning safety stocks that do not explicitly follow neither of the three foregoing categories and, particularly, do not settle as a whole on normally distributed parameters. For ease of exposition, we group the research studies included in this category according to the nature of the OR modeling approach employed (see Table 6). These studies are reviewed as below.

5.4.1. Stochastic models

The stochastic models for dimensioning safety stocks are firmly grounded in probability and statistical theory applied to inventory management, including queueing theory and Markov chains. Van Donselaar and Broekmeulen [99] determined safety stocks in a lost sales periodic review inventory control system with stochastic discrete demands. Linear regression was employed to propose fast approximations for the fill rate. In the case of intermittent demand patterns, Zhou and Viswanathan [97] propose a bootstrapping method to generate an estimate of the time period demand variance and calculate the safety stocks required to attain target service levels. The proposed method performed better for randomly generated demand data and high data volume. However, when testing the proposed model with a real industry data set from the aerospace sector, the bootstrapping method performed worse than parametric methods.

The studies of Hayya and Harrison [96] and Caceres et al. [103] offer an interesting perspective on how to consider the effect of crossovers in the determination of safety stocks when demand and lead times are correlated. However, the former study failed to account for non-deterministic demand and the latter to operate under a multi-product inventory system. Similarly, Wang et al. [93] discussed the problem of calculating optimal safety stocks when demand and lead times are correlated but the proposed method does not consider crossovers. The authors derive robust equations for determining mean and variance of lead time demand using different distributional forms of demand and lead time. At this point, note that safety stock is, by definition, the reorder point minus the expected lead time demand. Thus, the problem of determining the reorder point can equally be understood as determining safety stock [84]. By way of example, Ruiz-Torres and Mahmoodi [61] studied an expected value reorder point method to determine safety stock levels without considering the common assumptions related to the adoption of normally distributed lead time demand. Their work highlights the need for a proactive management of safety stocks in environments characterized either by volatile or stable demands.

In some situations, demand and supply variability also induce

Table 5

A literature overview of modeling approaches for dimensioning safety stocks based on product structure and component standardization.

References	OR method/Modeling technique(s)	Main performance criteria
Collier [26]	Analytic/Chebychev's inequalities	1. Service level; 2. Holding and setup costs
Carlson and Yano [78]	Optimization/Heuristic	1. Holding and setup costs
Grubbström [80,81]	Analytic/Laplace transform; Input-output analysis	1. Annuity stream
Molinder [82]	Meta-heuristic/Simulated Annealing	1. Holding, stock-out and setup costs; 2. Stock-out level
Persona et al. [83]	Analytic/Inventory theory	1. Service level; 2. Holding and shortage costs
Yano and Carlson [79]	Simulation	1. Service level; 2. Production/order setup and holding costs

Table 6

Summary of research studies classified as *"Other models designed for dimensioning safety stocks"* based on different OR modeling approaches.

Modeling approach	Research studies
Stochastic	Van Ness and Stevenson [84]; Van der Veen [85]; Groenevelt et al. [86]; Glasserman [87]; Cheung and Hausman [88]; Hung and Chang [89]; Dohi et al. [90]; Martinelli and Valigi [91]; Gharbi et al. [92]; Wang et al. [93]; Sarkar et al. [94]; Sana and Chaudhuri [95]; Ruiz-Torres and Mahmoodi [61]; Hayya and Harrison [96]; Zhou and Viswanathan [97]; Chakraborty and Giri [98]; Van Donselaar and Broekmeulen [99]; Chaturvedi and Martínez-de-Albéniz [100]; Manzini et al. [101]; Huang et al. [102]; Caceres et al. [103]; Altendorfer [104]
Mathematical Programming	Bourland and Yano [105]; Maia and Qassim [106]; Louly and Dolgui [107]; Teimoury et al. [108]; Janssens and Ramaekers [109]; Taleizadeh et al. [110]; Rappold and Yono [111]; Keskin et al. [112]; Rafiei et al. [113]; Ben-Ammar et al. [114]
Simulation-based Optimization	Bouslah et al. [115]; Gansterer et al. [116]; Avci and Selim [117,118]; Benbitour et al. [119]
Neural Networks	Zhang et al. [120]

additional uncertainty factors within general production systems, namely related to manufacturing capacity and processes, that directly affect safety stock decisions. Unreliable manufacturing systems with machine breakdowns are likewise included in this context. Chaturvedi and Martínez-de-Albéniz [100] argued that capacity and safety stock decisions should be jointly optimized. Their results show that the manufacturer's responsiveness levels to supply uncertainty increase whenever both safety stock and capacity increase. Huang et al. [102] studied the combination between the ability to ramp up production (reactive capacity) and safety stocks to face unexpected demands while minimizing long-term costs and maintaining a proper service level. Glasserman [87] and Altendorfer [104] also addressed the problem of setting safety stocks in inventory systems with production capacity constraints. In the seminal studies of Hung and Chang [89] and Cheung and Hausman [88], early work regarding the determination of safety stocks in uncertain manufacturing environments is conducted. The former study proposed a safety stock estimation method to soften uncertain related to variability of both flow times and yield rates in available-to-promise environments. Here, safety levels are presented as a linear function of the production rate and can be determined according to a given on-time-delivery specification. In the latter study, the authors account for the trade-off between the investment in preventive maintenance plans to reduce the machine failure rate and the establishment of safety stocks to face demand in case of machine breakdowns. In short, both works have proved that safety stocks and preventive maintenance must not be treated in isolation. Later, Dohi et al. [90] extended the work Cheung and Hausman by developing a novel stochastic model with random machine breakdowns to obtain the manufacturing quantity and the required safety stocks that minimize the expected costs per unit time. Other interesting model variants for the problem of dimensioning safety stocks in unreliable manufacturing systems can further be found in [86,91,92,94,95,98].

5.4.2. Mathematical programming models

Bourland and Yano [105] explicitly introduced, for the very first time, safety stocks together with idle time and overtime in a stochastic economic lot scheduling problem. In the proposed approach, a nonlinear mathematical program is presented to determine the safety levels required to avoid, when possible, the use of overtime in production. Maia and Qassim [106] formulated a nonlinear optimization model that incorporates delivery performance of suppliers in the calculation of safety stocks, purposing to minimize the sum of inventory and opportunity costs. It was shown that safety stocks should not be considered whenever opportunity costs are low. Conversely, safety stocks revealed to be a reasonable strategy to mitigate stock-out events when opportunity costs increase. Louly and Dolgui [107] developed a novel optimization approach together with an efficient branch and bound algorithm to calculate safety levels for components under random procurement lead times. The proposed model holds whatever the discrete distribution probability and reveals to be applicable in several domains. Taleizadeh et al. [110] studied a multi-buyer multi-vendor supply chain problem under budget constraints related to the acquisition of the products by the buyer, as well as to the space limitation in

the vendor. Safety stock is formulated as a decision variable of the proposed model that, in turn, is treated as an integer nonlinear programming problem and solved using a harmony search algorithm. Janssens and Ramaekers [109] formulated a linear programming model to establish safety stocks under incomplete information regarding the demand distribution. Rappold and Yono [111] proposed a stochastic modeling approach that can be used to provide the necessary safety stocks to stabilize production cycles while protecting against demand uncertainty and minimizing holding and backorder costs.

We note, however, that although a number of mathematical programming models have been proposed and successfully applied to real-world case studies (reporting the usefulness of safety stock strategies not just in enhancing service levels [113] but also in optimizing production, inventory quantities and backorders [108,112]) optimal planned lead times might be preferable over safety stocks in certain situations [114].

5.4.3. Simulation-based optimization models

In the past, simulation and optimization were typically considered as two separate operations research approaches. Yet, the rapid developments in computational capabilities have triggered the use of these two approaches in a combined fashion [121]. Oftentimes, this fruitful combination is used for: (i) optimizing model inputs, (ii) computing model parameters, or (iii) sampling of scenarios for mathematical programming models.

Bouslah et al. [115] approximated the optimal control parameters of an integrated lot sizing model and a feedback control policy through a simulation-based experimental approach, with recourse to the response surface methodology. The proposed approach jointly determines economic production quantity, the optimal safety stock level and the economic sampling plan while minimizing the expected overall costs. Gansterer et al. [116] proposed a simulation-optimization framework for hierarchical production planning in which planned lead time, safety stock and lot size are optimized. Interestingly, the authors have shown that, under certain modeling assumptions, safety stocks do not necessarily need to be increased when demand volatility is high.

Aiming to react to supply failures, companies often resort to premium freights, or rush deliveries [119], in order to guarantee the product availability under proper service levels. In this context, Avci and Selim [117] have recently introduced a decomposition-based multi-objective differential evolution algorithm (MODE/D) for inventory optimization that operates in a simulation-based optimization fashion. Particularly, in the simulation phase, safety stocks are evaluated in terms holding cost and premium freight ratio. Then, in the optimization phase, the outputs of the simulation are used to generate new safety stock levels. This work was further generalized in Avci and Selim [118] to consider supply and demand uncertainties in convergent supply chains.

5.4.4. Neural network models

Artificial intelligence (AI) has emerged as a powerful technique that, based on computer-aided systems, allows to generalize from training examples. As a prominent AI technique, neural network models

Table 7
Details of case studies in the safety stock dimensioning literature.

References	Case study	Paper category	Model type	Type of product		Type of uncertainty			Main results(s)
				Single	Multiple	Demand	Lead time	Other	
Agrell [42]	Pharmaceutical industry	VD	A/O	✓	–	✓	–	–	Interactive decision support system for multi-criteria inventory control
Altendorfer [104]	Children's mattress manufacturing industry	O	A/O	–	–	✓	–	–	The item specific order rate has proved to be a critical factor affecting optimal safety stocks
Avci and Selim [117]	Automotive industry, Europe	O	H	✓	–	✓	✓	–	Simulation-optimization framework to determine optimal safety stocks and supplier flexibility in divergent supply chain topologies
Avci and Selim [118]	Automotive industry, Europe	O	H	✓	–	✓	✓	–	Extension of the work of [117] for convergent supply chains and outbound premium freights
Benbitour et al. [119]	Automotive industry	O	H	–	✓	✓	–	–	Implementation of the proposed model in a real-world application with cost savings up to 66%
Beutel and Minner [73]	Retail industry, Europe	VFE	A/O	✓	–	✓	–	–	Framework for safety stock planning using external factors affecting demand
Brander and Forsberg [51]	Metal stamping industry	VD	A/O	–	✓	✓	✓	–	Proposed method can be used (on single facilities) for any fixed cyclic sequence for the production of multiple items with stochastic demands
Buffa [66]	Retail merchandising industry	VFE	A/O	–	✓	✓	✓	–	Significant reduction in (holding, stock-out, acquisition) costs in multi-product firms
Cheng et al. [46]	Pharmaceutical industry	VD	A/O	–	✓	✓	–	–	Same application with [43–45] for a multi-product inventory system
Disney et al. [53]	Global supply chains for forwarders and retailers	VD	A/O	–	✓	✓	✓	–	Safety stock requirements under stochastic lead times with order crossovers
Gansterer et al. [116]	Automotive industry	O	H	–	✓	✓	✓	–	Simulation-optimization framework to find optimal planning parameters in make-to-order environments
Hung and Chang [89]	Semiconductor wafer industry	O	A/O	–	✓	–	✓	✓	Use of flow time and yield uncertainties for determining safety stocks
Jonsson and Mattsson [35]	Miscellaneous (manufacturing, distribution, wholesale industries, Europe)	VD	S	–	✓	✓	–	–	The number-of-days method seems to be more efficient when calculating safety stocks to achieve a targeted order line fill rate for a group of items than does the demand fill rate approach
Kanet et al. [74]	Automotive industry, USA	VFE	A/O	–	✓	✓	✓	–	Introduction of dynamic planned safety stocks; 14% safety stock savings compared to the solution obtained by the constant safety stock policy
Kelle [28]	Steel & textile industries, Hungary	VD	A/O	–	✓	✓	✓	–	Inventory cost reduction while maintaining high service levels
Keskin et al. [112]	Tire manufacturing industry (BRISA), Turkey	O	A/O	–	✓	✓	–	–	Implementation of a MILP safety stock model with realistic production process constraints in a large-scale industrial environment
Lu et al. [56]	Construction industry	VD	A/O	–	✓	✓	–	✓	0-7% increase in service level and 20-46% decrease of inventory levels compared to the solution obtained with the day of supply safety stock rule
Mertins and Lewandrowski [62]	Electronics industry	VD	A/O	✓	–	✓	–	–	Reduction of inventory costs of materials in process by 60%
Ozguven and Ozbay [37]	Hurricane Katrina in New Orleans, USA	VD	A/O	–	✓	✓	✓	–	Inventory control methodology for determining minimum safety stocks of emergency inventories in humanitarian operations
Persona et al. [83]	Air conditioning & catering industries, Italy	PSCS	A/O	–	✓	✓	–	–	Implementation of a safety stock method for subassemblies of components; Reduction of safety stocks while minimizing global SC costs
Potamianos et al. [67]	Electronics industry	VFE	A/O	–	✓	✓	–	–	Application of an interactive safety stock method; 26.9% inventory cost savings and 25% stock-out reduction
Rafiei et al. [113]	Wood remanufacturing industry	O	A/O	–	✓	✓	✓	–	10.7% reduction of backorder quantities
Rappold and Yono [111]	Process manufacturing industry	O	A/O	–	✓	✓	✓	–	Stochastic inventory model that can be used to estimate safety stocks to support a production policy that stabilizes cycle lengths
Ruiz-Torres and Mahmoodi [61]	Electronics industry	O	A/O	–	✓	✓	✓	–	Safety stock determination without making any distributional assumptions; 7% holding costs savings
Srivastav and Agrawal [48]	Pharmaceutical industry	VD	A/O	✓	–	✓	–	–	For the easy use of practitioners, regression equations are formulated for the objective functions and decision variables (including safety factor)
Teimoury et al. [108]	Chemical detergent industry (PAKSHOO), Iran	O	A/O	–	✓	✓	✓	–	Application of queueing techniques to develop a computationally efficient model for safety stock determination in a multi-item capacitated warehouse
Trapero et al. [63]	Fast-moving consumer goods manufacturer, UK	VFE	A/O	–	✓	✓	–	–	Parametric and non-parametric approaches for safety stock determination
Trapero et al. [21]	Fast-moving consumer goods manufacturer, UK	VFE	A/O	–	✓	✓	–	–	Quantile combination of empirical approaches for safety stock determination

Table 7 (*continued*)

Reference	Application							Description
Tsou [44,45]	Pharmaceutical industry	VD	A/O	✓	✓	–	–	Flexible multi-objective optimization methods providing suitable lot sizes and safety stocks according to decision-makers' preferences
Tsou and Kao [43]	Pharmaceutical industry	VD	A/O	✓	✓	–	–	Safety stock determination without using any surrogate measure (e.g., service level or shortage cost) and prior preference information from decision-makers
Zhang et al. [120]	International logistics group, China	O	A/O	–	✓	–	–	Back-propagation neural network to estimate safety stocks
Zhou and Viswanathan [97]	Aerospace industry	O	A/O	–	✓	–	–	Bootstrapping approach for safety stock determination of intermittent items

Abbreviations: VD = variation of demand; VFE = variation of forecasting errors; PSCS= Product Structure and Component Standardization; O = Others; A/O = Analytic/Optimization; H = Hybrid; S = Simulation.

have often been applied in decision-making problems in different SC contexts, including time series forecasting [122], supplier selection [123] and smart logistics [124], to name a few. Recently, a study proposed by Zhang et al. [120] used a back-propagation neural network to estimate safety stock levels. The authors have considered selling frequency, storage/shortage costs, demand, and purchasing quantity as model features that may have influence on dimensioning safety stocks. However, if the values of safety stock used as training instances are not optimal in the sense of minimizing inventory costs while maximizing service level, the predicted safety stocks may also not be optimal. In any case, given that AI models have the potential of finding interesting features patterns in large amount of data, numerous research opportunities might arise in this area, particularly those regarding the enhancement of SC demand forecasting.

5.5. Industrial applications and real-world case studies

In this section, we focus our attention to surveyed papers that consider real-world industrial applications in their modeling approaches. Concretely, 33 (out of 95) papers used case studies to demonstrate the practical relevance of their modeling approaches.

Table 7 provides the classification of the case study papers according to the categorization introduced in Section 5 and the type of product and uncertainties considered. The pharmaceutical and automotive sectors dominate the industrial applications. However, with the exception of Cheng et al. [46], we found that all the papers with applications to the pharmaceutical industry generally assume supply chain topologies operating with a single product, which makes it difficult to assess the scalability of the proposed models to multi-product environments. In contrast, 60% of the papers providing empirical evidences from the automotive industry consider multi-product models, which are far more realistic. As examples, Benbitour et al. [119] show that the costs savings realized using an ATO inventory control model with safety stock considerations may amount to 66%. On the other hand, Kanet et al. [74] explore the concept of time-phased safety stocks and report 14% safety stock savings compared to the solution obtained by the constant safety stock policy. Another relevant observation from the results presented in Table 7 is that few works have been carried out to fully understand the significance of safety stocks in the field of humanitarian logistics. This becomes particularly valuable at a time where natural disasters, catastrophes and pandemic viral infections are continuously rising. At this point, Ozguven and Ozbay [37] is the only surveyed paper that, by taking advantage of real information of Hurricane Katrina in New Orleans, USA, studies optimal safety stocks of emergency inventories to prevent disruptions. Further research is needed to make a better basis for the assessment of the real potential of safety stocks in this field.

6. Conclusion and directions for future research

This paper presents the results of a systematic literature review to understand the development history and trends regarding the safety stock dimensioning problem, from an operations research (OR) perspective. Descriptive analyses showed that extensive research has been conducted to understand this problem, which is far from a closed research domain. A detailed content analysis to the collected papers allowed to describe safety stock dimensioning strategies from four different perspectives. In each one of them, each paper was further characterized according to the model type, modeling technique and performance criteria employed.

As we have shown, extensive research has been conducted in the application of OR-based models and methods to safety stock determination. Yet, extracting relevant insights from the safety stock dimensioning problem and translating them into practical benefits remains a challenge. In what follows, we highlight current shortcomings and discuss potential directions and trends for future research towards

enhanced safety stock determination.

Generalizing demand modeling. Firstly, it has become apparent that inventory management heavily depends on accurate forecasted demands, but the question of how to forecast lead-time demand variance – essential for dimensioning safety stocks [51] – is far from a closed topic [11]. Our findings revealed that several research studies have been assuming normally distributed lead time demands, notwithstanding the existence of several works warning against this generalized assumption [10,60,61]. Besides, several approaches for dimensioning safety stocks consider, oftentimes, constant/stationary or even known demand rates [see, e.g., [78,88,91,92,96,98,115]], which, in general, do not reflect the reality of major supply chains with multi-product environments, typically characterized by stochastic demands with high levels of uncertainty. This shows the need to have results beyond these deterministic assumptions. A valid and interesting starting point could be the further exploitation of non-parametric approaches (e.g., neural networks or support vector regression) able to properly and accurately capture the real dynamics of SC demand over the product's life-cycle. Secondly, demand for products could be affected by external factors (e.g., weather conditions or price volatility) that are not properly assessed, or not at all, by the current dimensioning safety stock strategies. An exception to this can be found in the work of Beutel and Minner [73]. Integrating exogenous variables (if available) into multivariate demand forecasting models would be an appealing yet challenging research pathway. Finally, the application of empirical safety stock estimations, as an alternative to the theoretical approach for estimating the standard deviation of forecast errors for a given lead time, is another interesting area that merits further research. We refer an interested reader on this topic to the works of Trapero et al. [21,63].

Modeling supplier disruptions. There is a new trend towards the use of data analytics in predicting supplier disruptions. In fact, with respect to empirically based contributions, evidence for the role of predictive data analytics in anticipating and managing for future disruptions is surprisingly scarce [125]. As lead time is a critical factor affecting optimal safety stocks, future research could be devoted to the development of machine learning based decision support systems for modeling supplier delivery performance. Such systems can be built upon descriptive and predictive analytics models and include triggers/alert generation mechanisms allowing for improved decision-making. This research pathway is not just of methodological interest, in the sense that there exist no such intelligent systems in the current literature, but also of practical significance as it allows to proactively set dynamic safety stocks to buffer against supplier-related delays. Nonetheless, we acknowledge that supply disruptions are notoriously hard to predict, which makes the efficient development and coordination of these systems a promising research direction.

Improving the content of information. We consider that there is a pressing need to formulate mathematical models that take into account data quality issues in the safety stock determination. In this review, the only research works that account for this issue are the ones of [59] and [69]. From a practical standpoint, many companies experience data consistency and/or data completeness issues that make it difficult to optimize data-driven decision-making. Both issues translate into inaccurate estimations of safety stock parameters, such as lead time forecast error variance, which depend heavily on both the availability and quality of data. As an informed decision-making process is only as good as the data on which it is based, further studies may investigate safety stock modeling extensions that account for mechanisms for monitoring and controlling data quality information. At the same time, company managers should be aware of the importance of achieving and maintaining high data quality in order to determine cost-effective safety stocks. We also found a lack of reported real-world case studies applying safety stock dimensioning models to major supply chains with multiple products and, above all, with large amounts of data. In this context, the term Big Data Analytics (BDA) has emerged as a key area of SCM, by providing effective tools to enhance decision-making processes dependent upon a large volume of data. In particular, the management of safety stocks and supplier performance can significantly benefit from BDA approaches [126]. Given the need of proactive safety stock management [61], this area would also be an excellent research direction to be exploited, especially in Industry 4.0 inventory systems.

Developing multi-product empirical evaluations. We found that several research studies have been suggesting safety stocks models based on single-product inventory systems [see, e.g., [42,44,48,88,91,94,95,100,101,103]]. As the vast majority of supply chains interoperates with multiple products that, in its turn, have different characteristics, single-product models are not able to capture the real dynamics of real-world production environments, making unfeasible their application in multi-product firms. Further safety stock investigations should focus on modeling approaches, supported by real-world case studies, that encompass multi-product SC settings. Also relevant is the extraction of historical insights regarding the interactions between relevant logistics variables associated with the various products (e.g., inventory levels and costs, demand variability) and their relationships with safety stocks. Unsupervised learning might be a reasonable approach for perceiving these relations, as well as to identify inventory risk profiles among multiple products.

Improving safety stock determination at upstream SC stages. Finally yet important, if the ultimate purpose is to set safety stocks at the component level rather than at the finished product level, another interesting research avenue concerns the development of forecasting models that capture manufacturers' demand for components without having to resort to end-customer forecasts, which can be strongly distorted from erratic market information. From a modeling perspective, there are two classical approaches for forecasting manufacturers' demand for components: the first is aligned with the material requirements planning (MRP) methodology and takes advantage of the BOM to provide the component requirements for future time periods based on finished product forecasts. Yet, if a given component is used to produce a large set of finished products, it would be necessary to forecast the demands of all these products in order to further provide the component requirements via BOM explosions. In the end, this procedure would lead to both significant cumulative forecasting errors and inventory-related costs. The second approach consists of using univariate time series forecasting models directly on historical records of manufacturers' demand, but such strategy might be biased since it uses no information from the customer(s) demand behavior. Hence, the integration of relevant leading indicators of manufacturer's demand into forecasting models can be an interesting opportunity to meet this gap.

Overall, this review allows to conclude that the safety stock dimensioning problem continues to be a hot research topic that presents challenges for both academics and practitioners. It is our belief that this study could be beneficial to foster the development of new OR-based modeling approaches, as well as to guide practitioners interested in applying safety stock dimensioning models in real-world supply chain contexts. However, it is important to retain that safety stocks should not be used as a panacea to be applied in all inventory management problems with uncertainty issues. In this regard, there exists an extensive scientific literature proposing interesting strategies to increase flexibility, visibility and performance of SC management processes of which the problem of dimensioning safety stocks is part.

Declaration of Competing Interest

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