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## Article

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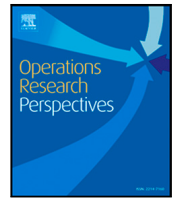
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# A systematic literature review about dimensioning safety stock under uncertainties and risks in the procurement process

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## ABSTRACT

This paper analyses literature contributions in the search for safety stock problem under uncertainties and risks in the procurement process, focusing on the dimensioning problem (determination of the safety stock level). We perform a systematic literature review (SLR) from 1995 to 2019 in relevant journals, covering 193 selected articles. These selected articles were classified into three safety stock main issues: safety stock dimensioning, safety stock management, and safety stock positioning, allocation or placement. The SLR analysis allowed the identification of literature gaps and research opportunities, thus providing a road map to guide future research on this topic.

## 1. Introduction

The supply chain is a complex and unique network that integrates different business processes involved in fulfilling the customer needs, which includes planning, procurement, production, distribution and customer interface [3,4]. All these are involved in the entire product life cycle, from procurement to manufacturing, distribution and customer service [5]. The importance of the supply chain management in business strategy, in attracting and retaining customers and markets, in the effectiveness of operation management and the profitability of companies results becomes a valuable way to ensure the competitive advantage and improving the organizational performance [5–7]. Logistics plays an essential role in supply chain management and it is one of the crucial factors of the supply chain success. The logistics planning management processes aims at establishing the right product, in the right quantity, in the right condition, to the right place, at the right time, and at the right cost (i.e., minimal cost).

The supply chain management deals with a significant number of uncertainty factors that affect its performance. These uncertainty factors introduce a large number of random factors and events, affecting all dimensions of the supply chain activities, and also make the risk and vulnerability a major challenge for organizations [8]. Risks and uncertainty factors have a direct influence on both customer satisfaction levels and supply chain related costs. To deal with some of these factors, buffering techniques such as safety stock is included

as the way for aiding the operational planning of manufacturing stages to cover both demand and supply uncertainties so that to provide the promised service level to the customers [9,10]. Although a higher safety stock level represents a higher service level, it must be optimized in order to not increase the total costs of the supply chain [10].

Several authors have studied the safety stock research problem and proposed their inventory models considering different types of uncertainty and risks, using different approaches. The research problems related to safety stock involve typically issues such as dimensioning, management, and positioning, placement or allocation [11]. Safety stock dimensioning consists of setting the appropriate safety stock level for each item. Safety stock management involves setting of both the safety stock levels and the time for replenishments. And, safety stock allocation, positioning or placement consists on setting safety stock levels and determine where to allocate them on supply chain structure. There are several terminologies in the literature for the same problem of safety stock placement. Safety stock placement, safety stock allocation and safety stock positioning represent the same problem [12–14]. In this Systematic Literature Review (SLR)<sup>1</sup> we adopt the terminology safety stock placement to portray this problem.

Although the scope of this research is on safety stock dimensioning strategies, we extend it and consider all safety stock dimensions (this is, dimensioning, management and placement), since the dimensioning issue is present in each of these dimensions. Schmidt et al. [15] argued

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<sup>1</sup> Systematic Literature Review (SLR) is the main method of synthesis that aimed for identifying, evaluating and interpreting the best quality research studies on a specific topic, research question or phenomenon of interest [1,2].

that is very difficult to survey scientific publication related to safety stock dimensioning. Within our knowledge, there are only three surveys/reviews that cover totally or partially the safety stock problem. Caridi and Cigolini [11] analysed and classified safety stock damping methods for manufacturing systems by considering uncertainty factors. Schmidt et al. [15] analysed mathematical methods for safety stock dimensioning and perform a simulation study to compare these methods regarding service and safety stock level. Finally, Eruguz et al. [16] focused only on safety stock placement issue, more specifically on the guaranteed-service modelling approach.

A comprehensive SLR was made by analysing research papers from 1995 to 2019 of safety stock research efforts by considering uncertainty factors or risks, or even both, in the procurement process. The selected papers were filtered manually and reduced to 193 papers in this review and classified into three dimensions of safety stock problem: safety stock dimensioning, safety stock management, and safety stock placement, allocation or positioning. Furthermore, literature gaps were identified, allowing to disclose future research opportunities.

This paper is organized as follows. Firstly, Section 2 provides an overview of the main concepts related to procurement, supply chain risk and uncertainty, sources of uncertainty and risk in procurement processes and some traditional safety stock dimension strategies. Section 3 presents the review methodology followed for analysing the literature contributions. Section 4, we present a descriptive and co-occurrence analysis of selected papers. Then, in Section 5, the selected papers are categorized according to the research problem. Section 6 presents the literature gaps and research opportunities. Finally, we conclude this paper in Section 7.

## 2. Theoretical background

### 2.1. Procurement: sourcing and purchasing

The terms purchasing and procurement are often used as the same concept, although they differ in scope. Purchasing is related to the actual buying of materials and the buying process activities. On the other hand, procurement has a broader scope comparing with purchasing [17,18]. It includes purchasing, warehousing, and all activities of receiving inbound materials [17]. Purchasing is the first step in procurement within a process-based supply chain.

Chopra and Meindl [3] defined Procurement as “the process of obtaining goods and services within a supply chain”. Also, the [19] provides a definition for Procurement: “the activities associated with acquiring products or services. The range of activities can vary widely between organization to include all of the parts of the functions of Procurement planning, purchasing, inventory control, traffic, receiving, incoming inspection, and salvage operations”.

Procurement represents one of the key processes in the supply chain and can influence the success of the entire organization. It ensure the sufficient supplies of raw materials at the right price, of the required quantity, in the right place and at the right time [20].

The procurement process includes activities such as the “make or buy” decision process, purchasing and appraisal of both supplier and contractor. Fig. 1 represents the procurement cycle in a resumed way.

#### 2.1.1. Sourcing

Sourcing, also known as strategic procurement consists of a set of business processes that are required to purchase goods and services [3, 21]. It includes processes such as formalize specification, selecting suppliers and contracting process [6,21].

- **Formalizing specifications** — in this process are defined the requirements of purchasing, as well as the “make or buy” decision (decision to make goods or provide a service rather than buying this goods/service) [6,20]. The first step of this process consists to define functional and technical specifications of items to be purchased [6];

- **Selecting suppliers** — this process consists of searching and identifying suppliers in the market [6,21]. Important decisions, such as the method of subcontracting to be adopted (e.g., partial or total subcontracting, payment in fixed-price or in refundable cost), the criteria for the preliminary qualification of potentials suppliers, the requisition and analysis of received proposals and selection of suppliers are necessary to be taken [6,20];
- **Contracting** — in this process are defined the terms of the contract (e.g., delivery conditions and price, payments conditions, penalty clauses, and warranty conditions) and afterwards the signing of the contract [6].

#### 2.1.2. Purchasing

Purchasing or operational procurement consists of the processes of buying goods and services [21]. For efficient purchasing is necessary to know the on-hand stock quantity so that to order the correct amount. An efficient purchasing requires inventory control management. Hence, safety stock as an extra inventory held to deal with uncertainties in demand and supply is used to plan future purchase quantities.

Purchasing includes processes such as the ordering of material and services, monitoring and evaluation [6].

- **Ordering** — this process consists to submit the purchasing order, but firstly is necessary to guarantee the definition of the contracting terms and consequently the signature of the contract;
- **Monitoring** — this process involves a set of different tasks related to the monitoring of submitted orders, such as visits to suppliers facilities, as well as negotiations related to changes regarding technical specifications, requisition of production plans and expected delivery date, verification of concordance of the delivered products with the agreed specifications, and lastly, the exchange of the commercial correspondences with customers;
- **Evaluation** — this process consists basically of the execution of complaints, activation of penalty clauses (when is applicable), and organization of documentation related to the project and supplier.

### 2.2. Supply chain risk and uncertainty

Often-times, the risk is confused with uncertainty, but these two terms are not the same [22,23]. Knight [24] differentiate risk from uncertainty arguing that risk is something measurable while uncertainty is not quantifiable and unpredictable (with unknown outcomes). Manuj and Mentzer [25] argues that risk is an expected outcome of an uncertain event, and Rao and Goldsby [26] view risk as an event and uncertainty as possible outcomes.

There are several definitions in the literature regarding the risk in the supply chain context. But, do not exists a universal definition, although there have been several attempts [27,28]. Tables 1 and 2 presents some of the key definition of risks and Supply Chain Risks (SCR).

#### 2.3. Uncertainty factors and risks in the procurement process

There are a variety of uncertainty factors and risks associated to the procurement process, such as uncertain lead time, demand fluctuations, variations of prices, uncertain yield, supplier delays and order crossover, as follows described.

- **Lead time uncertainty** — supply lead time represents the average of time between when the order is placed and when the product arrives [3,38]. The uncertainty in supply lead time must be controlled properly in order to not increase the total cost and reduce customer service level [39]. Besides that, the high variation of supply lead-time increases the difficulty in procurement planning [40], more properly to perform the Material Requirement Planning (MRP) process. For an efficient production is

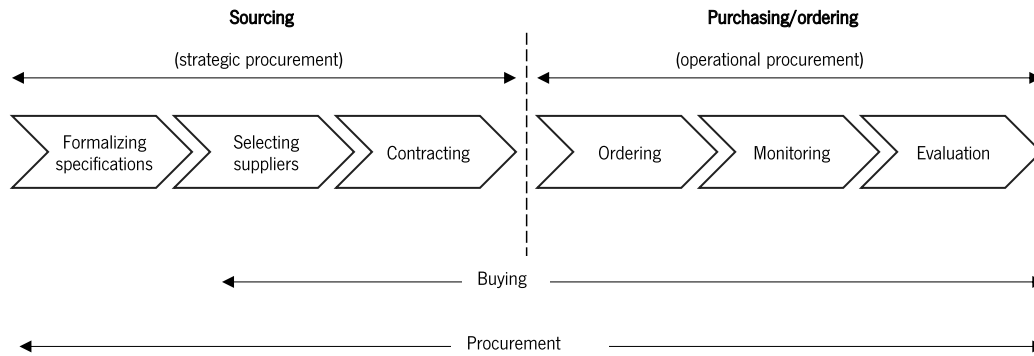


Fig. 1. Steps of Procurement process adapted from [6].

Table 1

Risk definitions.

References	Definitions
[29]	"the variation in the distribution of possible SC outcomes, their likelihoods, and their subjective values."
[30]	"The probability that a particular adverse event occurs during a stated period of time, or results from a particular challenge. As a probability in the sense of statistical theory, risk obeys all the formal laws of combining probabilities."
[31]	"the probability of loss and the significance of that loss to the organization or individual."
[32]	"a chance of danger, damage, loss, injury or any other undesired consequences."

Table 2

SCR definitions.

Reference	Definitions
[33]	"the identification of potential sources of risk and implementation of appropriate strategies through a coordinated approach among supply chain members, to reduce supply chain vulnerability."
[34]	"any risks for the information, material and product flows from original supplier to the delivery of the final product for the end user."
[35]	"supply chain risk is the potential occurrence of an inbound supply incident, which leads to the inability to meet customer demand."
[36]	"anything that (disrupts or impedes) the information, material or product flows from original suppliers to the delivery of the final product to the ultimate end-user."
[37]	"the management of supply chain risks through coordination or collaboration among the supply chain partners so as to ensure profitability and continuity."
[28]	"the likelihood and impact of unexpected macro and/or micro-level events or conditions that adversely influence any part of a supply chain, leading to operational, tactical or strategic level failures or irregularities."

necessary to estimate properly the procurement lead time and on-time delivery in order to prevent delays on deliveries that can lead to a shortage of inventory and consequently manufacturing disruption, increasing the total cost and revenue losses. Several strategies are used to cope with this type of uncertainty, such as safety stock, safety lead time and supplier backups. Safety stock is the most used strategy to increase the supply chain flexibility under both demand and supply uncertainty [39,41];

- **Demand uncertainty** — demand uncertainty includes factors such as errors in demand forecast, changes in customer orders and uncertainty about the product specification that the customers will order [41]. Demand forecast consists to estimate the future Stock Keeping Units (SKUs) in order to meet customer demands. The demand forecast is a complex task [17,40] and when demand is not estimated accurately (forecast error) can lead to inventory short supply or surplus, low service level, rush orders, inefficient utilization of resources and bullwhip effect propagation along the supply chain [3,40,42]. This type of uncertainty assumes an important role in the dimensioning of production lines, dimensioning of transportation modes, line assembly, distribution centres and cross-docking platforms [6] and also plays an important role as input for procurement planning [42]. Component

commonality, risk pooling, safety stock, safety lead time, flexible supply contracts, subcontracting/outsourcing and postponement are examples of strategies to cope with demand uncertainty [39,41];

- **Price uncertainty** — represents the fluctuations in the suppliers selling price of materials or raw materials due to the constant price fluctuation in the market or discount campaigns [39]. Pricing must be considered as an important factor in the procurement process because it influences the logistics total cost, as well as the operational decisions [43]. Flexible contract and price risk hedging are examples of strategies that can be used to deal with price uncertainty [39,41];
- **Yield uncertainty** — limited capability or defective products (quality issues) represent possible causes for yield uncertainty. There are two main approaches used to mitigate this type of uncertainty: supplier diversification (select multiples suppliers for unreliable supplier) and collaboration with suppliers [39]. Another approach/strategy to cope with this uncertainty is capacity buffer [39,41];
- **Supplier delay** — on-time delivery is a standard objective of procurement and when is not properly estimate can lead to a shortage of inventory and consequently manufacturing disruption. Sometimes suppliers delays are caused by their quote

delivery dates that cannot be achieved [44]. Strategies such as supplier backups are the common strategies used to cope with this type of uncertainty [39,41];

- **Supplier constraints** — supplier constraints, also known as supply disruptions consist of situations that sometimes are unusual which can affect the supplier performance or even lead to a partial and complete failure of supply [15,45]. These constraints are important to be considered, so that to be mitigated (the negative effect) when they occur. Supplier constraints can be caused by factors such as earthquakes, power failures, terrorist attacks, snowstorms, customs delays, fires, slow shipments or workers strikes that can lead to shutdowns or temporary closures or causing lead-time delays due to loss of production/or transportation capability [15, 46]. Supplier backups are the most common strategies to deal with this risk [39,41];
- **Order crossover** — order crossover happens when orders are received in a different sequence from the one that they are placed [47–50]. It can occur due to two components of the replenishment lead time: the required time interval for the supplier to produce the order (which includes the actual production time, delays before production and order transmission time to the supplier) and the required time interval for the order transportation (caused by geographic location, the variability of transportation time and multiple transportation modes) [47,48,50]. Several strategies are used to cope with this type of uncertainty, such as safety stock [39,41].

## 2.4. Dimensioning of safety stock (traditional strategies)

Strategies such as safety stock and safety lead-time are typically used in inventory management to cope with both demand and supply uncertainties [9,51]. Safety stock also known as buffer stock, consists of an extra inventory held to deal with both demand and supply uncertainties so that to prevent stock-outs [17,20,21,41,51,52]. The safety stock of finished goods is used to attend unexpected demand, and safety stock of raw material is used to protect against supply problems and production stoppages [17,20,21]. There are multiples traditional methods for dimensioning of safety stock (See Table 3). Those methods are characterized as mathematical stochastic methods [15]. The standard formula for calculating safety stock (Method 1) consists to multiply the safety factor (depends on the service level based on normally distributed demand) with the deviation of the demand during the replenishment time, this is, determine the safety stock as the function of service level. With the extension of this method considering the replenishment time (supplier lead time) originate the Method 2. Then, [53] proposed a new method (Method 3) whose purpose is to determine the safety stock as the function of service level using the forecasting error for the demand during the replenishment time (determined using historical data from the mean squared deviation of the forecasted demand from the actual demand). Later, [54] propose Method 4 as the extension of Method 3, in which the objective was to determine the safety stock oriented to the demand through the ‘undershoot’. Method 5 resulted from the extension of Method 4 and [54] extend it in order to determine Method 6, considering the ‘undershoot’. Gudehus [55] applied to Method 5 an adaptive service level factor, resulting in Method 7. For this, was considered that only disruption during the replenishment cycle can conduct to the absence of delivery capacity. Later on, [55] extends this last method to determine Method 8 by considering the dynamics of the parameters (parameters determined by means of simple exponential smoothing). The traditional Methods 1–8 (excluding Method 3) described above are based on normal distributed parameters. Lastly, Method 9 was proposed with a purpose of calculating the safety stock for a target service level of 100%, considering extreme values, mean and standard deviation [15].

The main methods for safety stock dimensioning described in Table 3 consider different approaches for estimating demand variability,

which is a key parameter for establishing adequate safety stock levels. When assessing the applicability of the different safety stock methods in real-world supply chain contexts, we note that formulations based on the standard deviation of demand during lead time might hardly be applied (with effectiveness) in practice. This is due to the fact that demand patterns and dynamics are typically unknown and should be forecasted by a suitable forecasting approach over a given time horizon. For instance, Method 5 is widely used in seminal inventory management textbooks [56] and it considers stochastic demand and supply patterns. However, it does not take into consideration the variation of forecasting errors over the lead time. It is well-known that normal distribution may not be an appropriate representation of demand during the lead time because it is often skewed [57–59]. Yet, we observed that several research studies have been assumed Gaussian demands in their safety stock formulations (see, for instance, [11,58,60,61] and [62]). Clark [57] argues that the deviation of normal distribution demand during lead time can be characterized completely by the skewness. Ruiz-Torres and Mahmoodi [58] state that “traditional models to determine the appropriate safety stock level may result in more safety stocks at sub-assembly and finished goods levels than necessary and thus lead to higher inventory carrying costs than desired. Such models generally incorrectly assume that the demand during the lead time follows a normal distribution”. Disney et al. [59] state also that, despite this is a popular approach to determine safety stock levels, it results in errors even for simple systems. An alternative is the use of Method 3, which considers the standard deviation of forecast error during replenishment lead time (here presented as deterministic and known). However, it should be used ideally considering the time replenishment (TPR) as stochastic rather than deterministic, to cope with real-world supply chain needs. The main challenge inherent to their application relates to the estimation of  $\sigma_F$ . At this point, there are two approaches that can be followed: theoretical and empirical. The theoretical approach consists of first providing an estimation of  $\sigma_1$  (one-step-ahead standard deviation of the forecast error) and then employing an analytic expression that relates  $\sigma_L$  and  $\sigma_1$ . On the other hand, the empirical approach estimates  $\sigma_L$  (the standard deviation of the forecast error for a certain lead time  $L$ ) directly from the lead-time forecast error [61].

It is common knowledge that service levels represents a crucial input parameter for determining safety stocks. Following the described methods, the safety factor depends on the service level (SL). There are several ways to measure the SL, although the most discussed in the literature and therefore most common are the Cycle Service Level (CLS —  $\alpha$ ) and Fill Rate (FR —  $\beta$ ) [3,58,63–65]. The CLS, also known as Type I Service Level, is defined as the probability of no stockout per replenishment cycle (i.e., portion of time between placing an order and the corresponding replenishment). The FR, also known as Volume Fill Rate (to distinguish from the Order Fill Rate) or Type II Service Level, is defined as the proportion of demand that is completely fulfilled from the available stock [3,63,65–67]. Most studies in the literature, including supply chain books, discusses the CSL measure, although, supply chain practitioners prefer the FR measure [61,65]. Both measures have advantages and disadvantages. For instance, CLS is much easier to optimize mathematically than the FR. For computing the CLS is only necessary to consider the stock level during an order cycle, while to properly determine the FR is necessary to record the excess of demand. On the other hand, CLS does not determines the expected backorder or lost sales during a cycle. Chopra and Meindl [3] and Vandeput [65] argues that FR is more relevant when compared with CLS, especially when the order cycles are long. The FR is impacted by both cycle stock and safety stock, whereas the CSL is only impacted by the safety stock.

## 3. Review methodology

This review methodology represents a set of processes for selecting relevant scientific publications for this SLR. It is divided into three phases as represented in Fig. 2:



**Table 3**  
Traditional methods for safety stock dimensioning [15,52].

Method	Formula
1	$SSL = SF(SL) * \sigma_D$
2	$SSL = SF(SL) * \sigma_D * \sqrt{TRP}$
3	$SSL = SF(SL) * \sigma_F * \sqrt{TRP}$
4	$SSL = SF(SL) * \sqrt{Var(U) + TRP * \sigma_D^2}$
5	$SSL = SF(SL) * \sqrt{TRP * \sigma_D^2 + D^2 * \sigma_{TRP}^2}$
6	$SSL = SF(SL) * \sqrt{Var(U) + TRP * \sigma_D^2 + D^2 * \sigma_{TRP}^2}$
7	$SSL = SF(1 - \frac{(1-SL)*QRP}{TRP*D}) * \sqrt{TRP * \sigma_N^2 + D^2 * \sigma_{TRP}^2}, \forall QRP > TRP * D$
8	$SSL = SF(1 - \frac{(1-a)*QRP}{TRP(t)*D(t)}) * \sqrt{TRP * \sigma_N(t)^2 + D(t)^2 * \sigma_{TRP(t)}^2}, \forall QRP > TRP * D$
9	$SSL = LSL_0(SL^2 - 1) + SSL_{100\%} * \sqrt{1 - (1 - SL)^C}$ $LSL_0 = \frac{QRP}{2}$ $SSL_{100\%} = \sqrt{(DV_{d,max}^+ * D)^2 + ((D_{max} - D) * TRP)^2 + (DV_{QRP,max}^-)^2}$
Legend	<p>SSL — Safety Stock Level [units];  SF — Safety factor (depends on the service level);  SL — Service Level;  <math>\sigma_D</math> — Standard deviation on-demand [units/SCD];  SCD — Shop Calendar Day;  TRP — Time Replenishment [SCD];  <math>\sigma_F</math> — the standard deviation of the forecast error for the demand during TRP [units/SCD];  Var(U) — Variance of the undershoot [units<sup>2</sup>/SCD<sup>2</sup>];  D — mean demand per period [units/SCD];  <math>\sigma_{TRP}</math> — the standard deviation of replenishment time [SCD];  QRP — replenishment quantity [units];  TRP(t) — replenishment time forecasted for period t [SCD];  N(t) — mean demand per period forecasted for period t [units/SCD];  <math>\sigma_N(t)</math> — the std. deviation of demand during replenishment time forecasted for period t [units/SCD];  <math>\sigma_{TRP(t)}</math> — the standard deviation of replenishment time forecasted for period t [SCD];  LSL<sub>0</sub> — lot stock level [units];  C — C-Norm parameter;  <math>DV_{d,max}^+</math> — max. positive Deviation from the due date [SCD];  <math>DV_{max}^-</math> — maximum demand per period [units/SCD];  <math>DV_{max}^- - DV_{QRP,max}^-</math> — max. negative Deviation in replenishment quality [units];</p>

- The first phase (Searching phase) involves the definition of the research query and searching for scientific publication in both Web of Science and Scopus databases;
- The second phase (Selecting phase) aims to exclude scientific publications that did not meet the defined criteria or did not address safety stock research problems;
- Lastly, the third phase (Analysing phase) consists to select relevant articles for conducting this study.

### 3.1. Searching phase

The majority of scientific publications are published in peer-reviewed scientific journals and the more relevant ones are indexed in two of the major online databases: Thomson Reuters' Web of Science (WoS) and Elsevier Scopus. The coverage of journals in WoS is approximately 13.600 journals and in Scopus is 20.346 journals [68]. For this first phase of review methodology, all scientific publications are searched in both Web of Science and Scopus databases using the query described in Table 4. The search query considers keywords such as “safety stock” and “safety inventory” so that to capture in broader way topics related to safety stock problem. Keywords related to factors of uncertainty and supply chain risks in the sourcing process, such as *demand, price, lead-time, yield, order crossover, suppliers delay, variability, variation, fluctuation, uncertain and uncertainty* are also considered. Lastly, the query excludes all deterministic terms, aiming to focus only on uncertainty factors.

After performing this searching in the Scopus database resulted in a sample of 937 bibliographic references and 649 bibliographic references in the Web of Science database. All these resultant bibliographic references (from both databases) are merged and all duplicated references are removed. After that, a total of 1149 references are selected for the next phase of this review methodology.

### 3.2. Selecting phase

For the selecting phase are defined three screening criteria levels in order to exclude bibliographic references that did not meet the defined criteria. For the first level of screening criteria, the choice of the consulted references was based on the following criteria:

- The bibliographic references searched included only articles from the peer-reviewed journals;
- Research articles published from 1995 to 2019, a period of 24 years;
- Publications written in English language.

In the second level of screening criteria, the SCImago Journal Rank (SJR) indicator and the subsequent journal Quartile was defined as the main selection criteria of articles for the next phase (Analysing phase). In this level of screening criteria, only articles published in journals ranked as Q1 and Q2 (Quartiles) in SJR were selected. The main objective is to consider/select relevant articles for this Systematic Literature Review (SLR) and exclude articles that did not meet the defined criteria.

The third level of screening criteria involves the reading of the abstract of selected articles, thereby excluding articles that did not address the safety stock research problem considering at least one of risks or uncertainty factors described previously. After this phase, a total of 193 references are selected for the next phase (Analysing phase).

The co-occurrence analysis was performed in order to validate the filtering process and selection criteria of research papers (see, Section 4.2).

**Table 4**

Query for searching of bibliographic references (Literature analysis).

Research query (Literature analysis)	((“safety stock” OR “safety inventory”) AND (demand OR price OR “lead time” OR yield OR “order crossover” OR “supplier delay” OR variability OR variation OR fluctuation OR uncertain OR uncertainty)) *AND NOT deterministic
Results in Scopus	937
Results in Web of Science	649
Results (bibliographic references merged and duplicates removed)	1149

\*AND operator is not necessary to search for bibliographic references on the WoS database.

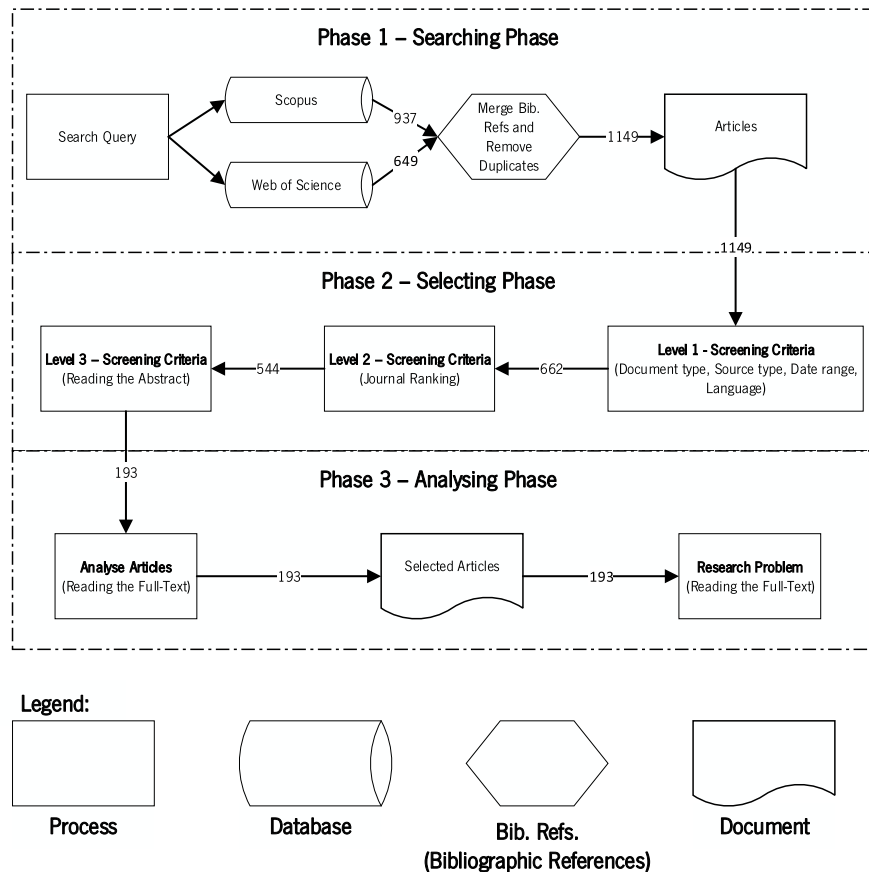


Fig. 2. Adopted review methodology.

### 3.3. Analysing phase

This last phase aims to read the whole text of the article and select the more relevant ones and those that meet the purpose of this investigation. After a final manual inspection of the obtained references, a total of 193 articles was selected as the primary bibliographic reference for this Systematic Literature Review (SLR).

After that, all articles were classified following the safety stock research problem present in [11], therefore classified into three safety stock research problems: safety stock dimensioning, safety stock management, or safety stock positioning (allocation or placement). This classification was made by reading each article and identifying the focus of it. Some of the articles contain explicitly the research focus (research problem), but in the majority of selected articles, this classification was made exclusively through our perception where the article fits regarding the safety stock research problem.

## 4. Descriptive and co-occurrence analysis

### 4.1. Descriptive analysis

The descriptive analysis was performed using the **BibExcel** tool. This tool allowed to execute the initial bibliometric and statistical analysis, which included data from the Web of Science and Scopus databases [69]. Then, the tool output was exported to the Excel tool, allowing to execute other graphical statistical analyses. The selected articles were analysed according to the number or the frequency of publications over the years, the venue of publication (name of the journal where the article is published), the research problem studied in the article, the author's influence and affiliations, and the approach adopted for modelling the problem.

#### 4.1.1. Year of publication

Fig. 3 illustrates the number of scientific publications published (annually) in the period from 1995 to 2019. The safety stock research problem has been gained attention from researchers especially since 2007 until now. Only 10.88% of articles were published from a period of 1995 to 1999, and 9.33% were published in the period from 2000

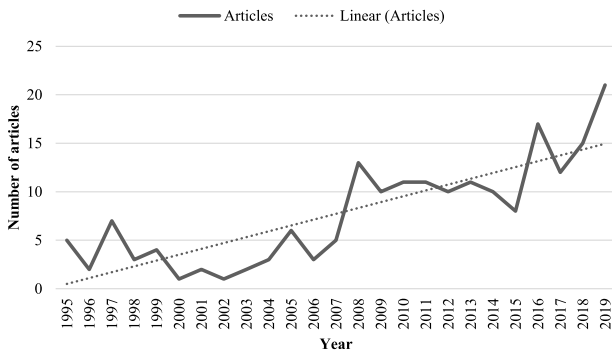


Fig. 3. Distribution of scientific publication over the years.

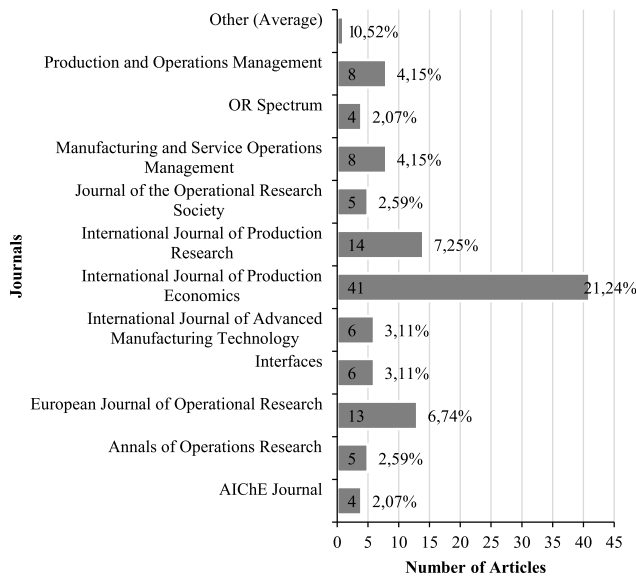


Fig. 4. Distribution of publication and their percentage per journal.

to 2006. From 2007 to 2019, 79.79% of articles were published, representing the increase of importance or attention of this research topic by researchers and practitioners.

#### 4.1.2. Venue of publication

Regarding the journals where the articles were published, Fig. 4 shows the distribution of publications and their percentage per journal. There are 62 different journals where the reviewed articles were published. Fig. 4 explicitly represents the considered journals that have at least three articles selected within this SLR.

International Journal of Production Economics, International Journal of Production Research and European Journal of Operational Research represent the top 3 journals that mostly contributed with published articles. The first journal contributed with 41 articles that represents 21.24% of a total of reviewed articles. The second journal contributed with 14 published articles, that represents 7.25% of the reviewed articles. Finally, the third journals contributed with 13 published articles, representing 6.74% of the reviewed articles.

#### 4.1.3. Research problem

The reviewed articles involve different safety stock research problem as shown in Fig. 5. The problem of safety stock dimensioning is the most studied problem in the reviewed articles (a total of 79 articles, that corresponds 40.93% of safety stock research problems covered all articles). Figs. 6 and 7 illustrate the distribution of the articles for each safety stock problem in the period from 1995 to 2019.

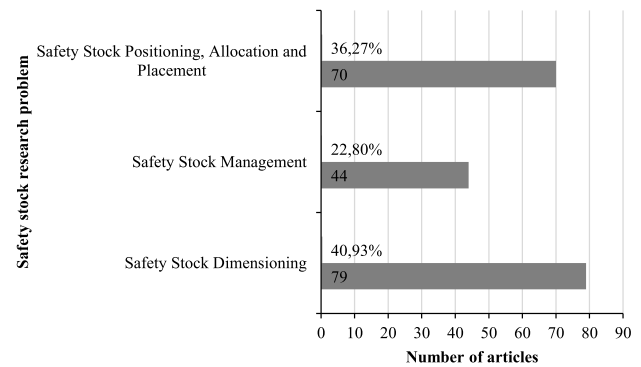


Fig. 5. Distribution of publications for each safety stock research problem.

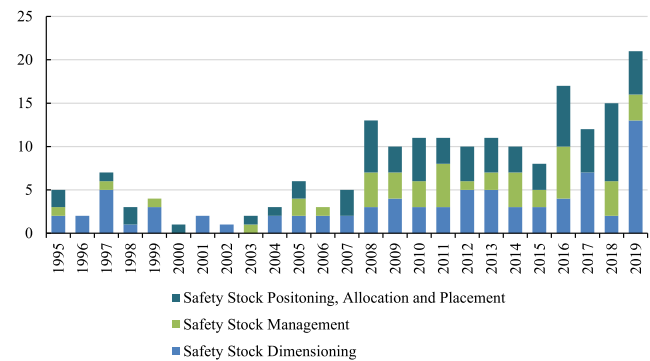


Fig. 6. Distribution of publications for each safety stock research problem over the years.

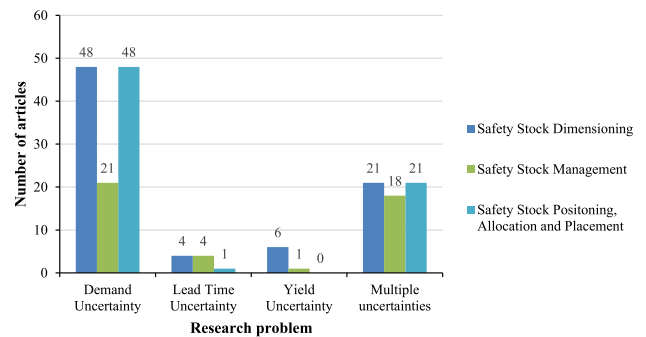


Fig. 7. Distribution of publication for each safety stock problem under different uncertainty factors and risks.

#### 4.1.4. Authors influence and affiliations

Table 5 describes the main authors who the most contribute with articles within the 193 articles selected. Only 26 per cent of all authors have contributed with more than one article, and the remaining 74 per cent of authors contributed with just only one research article.

The affiliation of the authors is illustrated geographically in Fig. 8. Both the city and country of the author's affiliation were extracted, allowing to perform their graphical visualization using the website [gpsvisualizer.com](https://gpsvisualizer.com). The size of the red circle represents the occurrence of this affiliation, this is, the greater is the red cycle, more occurrence this affiliation have. Table 6 summarizes the number of articles published by the top contributing affiliations.

#### 4.1.5. Approach followed

In terms of the approach adopted to tackle safety stock research problems, four main approaches were used in the reviewed articles,





Fig. 8. Geographical locations of authors' affiliations (using [gpsvisualizer.com](https://gpsvisualizer.com)).

Table 5

Key contributing authors (first author).

Authors	Nr. of articles
Grubbström R.	4
Inderfurth K.	4
You F.	4
Braglia M.	3
Kumar K.	3
Moncayo-Martínez L.	3
Avci M.	2
Boulaksil Y.	2
Graves S.	2
Kim J.	2
Klosterhalfen S.	2
Kristianto Y.	2
Louly M.	2
Manary M.	2
Monthatipkul C.	2
Prak D.	2
Puga M.	2
Taleizadeh A.	2
Trapero J.	2
Woener S.	2

Table 6

Top contributing affiliations.

Affiliation	Country	Nr. of articles
Carnegie Mellon University	United States	5
Ghent University	Belgium	5
Linköping Inst. of Technology	Sweden	5
Massachusetts Institute of Technology	United States	4
Otto-von-Guericke-Universität Magdeburg	Germany	4
Pennsylvania State University	United States	3
Purdue University	United States	3
Università di Pisa	Italy	3

as shown in Fig. 9. Moreover, Table 7 specifies the most used techniques in the reviewed articles. In terms of the Mathematical modelling approach, the Inventory theory is the most used technique, followed by the Markov chain, Laplace transformation, Probability theory and Input-output analysis. Regarding the Optimization approach, the Heuristics technique is the most used in the reviewed articles, followed by Dynamic programming, Mixed-integer nonlinear programming, Nonlinear programming, Linear programming and Genetic algorithms (meta-heuristic). The top used Simulation techniques include Monte Carlo simulation, followed by the Discrete event simulation,

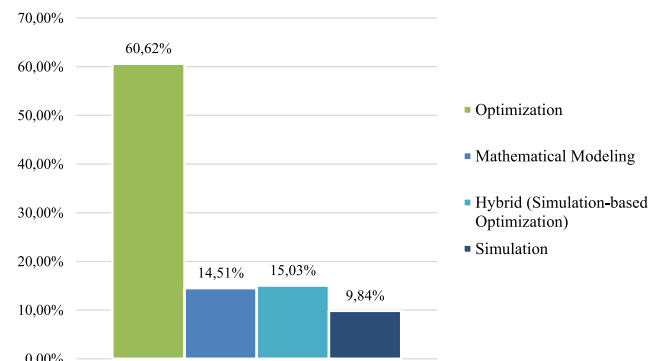


Fig. 9. Distribution of adopted approaches.

Table 7

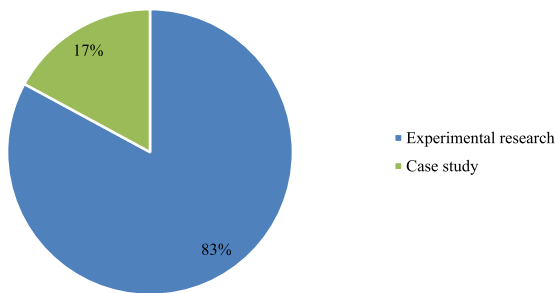
Top adopted techniques.

Method	Technique	Nr. of articles
Mathematical Modelling	Inventory theory	16
	Markov chain	3
	Laplace transformation	2
	Probability theory	2
	Input-output analysis	2
Optimization	Heuristics	25
	Dynamic programming	25
	Mixed-integer nonlinear programming	16
	Nonlinear programming	11
	Linear programming	9
	Genetic algorithm (meta-heuristics)	6
Simulation	Monte Carlo simulation	11
	Discrete event simulation	8
	Infinitesimal perturbation analysis	3
	Event-driven simulation	1
	Continuous simulation	1

Infinitesimal perturbation analysis, Event-driven simulation and Continuous simulation.

#### 4.1.6. Research method

The results show that the large majority of reviewed articles (83%) used experimental research methods as the research method (see Fig. 10). The case study was used in 17% of the reviewed articles.



**Fig. 10.** Distribution of research methods.

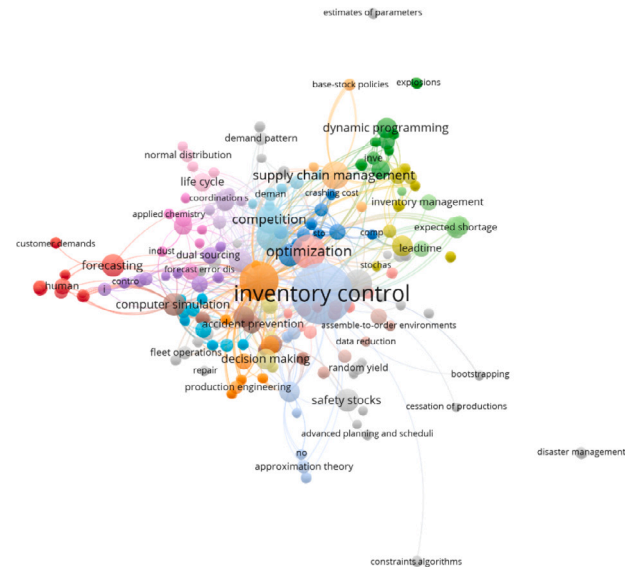
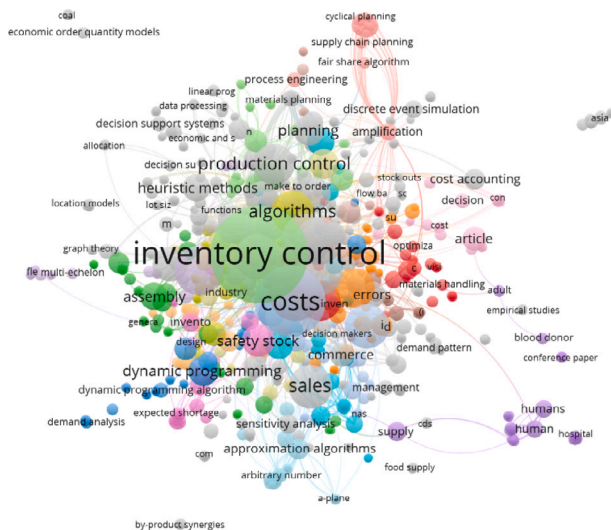


Fig. 12. Co-occurrence map (Level 3).



**Fig. 11.** Co-occurrence map (Level 1).

The experimental research includes methods such as simulated experiment, computational simulation or demonstration/exemplification test.

#### 4.2. Co-occurrence analysis

The software **VOSviewer** was used for performing this co-occurrence analysis. This tool allows the construction and visualization of bibliometric networks [70]. Both of Figs. 11 and 12 represent the keywords co-occurrence map of the reviewed articles. Fig. 11 (left) shows the co-occurrence map of keyword after the Level 1 Screening Criteria and Fig. 12 (right) illustrates the co-occurrence map after the Level 3 Screening Criteria process. Both Screening Criteria are an integral part of phase 2 of the review methodology. The bigger circles illustrate the more occurrence of keywords in reviewed articles. The keywords with more occurrence are: “*inventory control*”, “*costs*”, “*production control*”, “*optimization*” and “*safety stock*”.

## 5. Literature analysis (scientific contributions)

The safety stock research problem involves typically problems of dimensioning, management and positioning, placement or allocation. Based on both safety stock research problems and the uncertainty considered in the study (multiple uncertainties or just one uncertainty factor), all the selected articles were discussed, as follows in the next sub-sections.

### 5.1. Safety stock dimensioning

Caridi and Cigolini [11] defined safety stock dimensioning as “the dimensioning issue deals with finding the appropriate value of safety stocks for each item.”. In this subsection are analysed several contributions related to the safety stock dimensioning strategies under different risks and types of uncertainty.

### 5.1.1. Considering demand uncertainty

Material Requirements Planning (MRP) is one of the most used systems for production planning and control in the manufacturing industries, helping to reduce inventory, increase operating efficiency and improve customer service. In this sense, several research studies in the literature focus on dimensioning of safety stock issue in MRP context, by considering several uncertainties/risks. Therefore, [71] proposed one-level and simplest two-level serial system models to determine the optimal safety stock level using Laplace transformation and considering the traditional average cost (sum of the expected average cost of set-ups, inventory holding and backlog) as the main performance criterion. Then, three more extensions of this study were proposed. Firstly, Grubbström [72] focused only on the one-level model, considering the Net Present Value (NPV) based criterion (the annuity streams) as the main criterion, instead of the traditional average cost approach used previously. Afterwards, Grubbström et al. [73] generalized the models using Laplace transformations and input–output analysis, by considering demand uncertainty as Gama-distributed. Finally, Grubbström [74] extended it for the multi-level system.

Still, in MRP environments, Zhao et al. [75] studied and evaluated alternative methods to determine the safety stock level in multi-level MRP systems under demand uncertainty (forecast error). Others relevant studies in MRP environments can be found in [76]. Furthermore, different studies that focus on safety stock dimensioning in Assemble-to-Order (ATO) and Make-to-Order (MTO) environments can also be found in [77] and [78]. Hsu and Wang [77] proposed a possibilistic linear programming model to manage production planning problems, such as the regulation of dealers forecast demand, determination of the appropriate safety stock and the number of key machines while minimizing of the sum of the product stockout costs, the material inventory holding costs, and idle capacity penalty costs. Jodlbauer and Reitner [78] developed analytical formulas to describe the relationship between cycle time, safety stock and service level. Furthermore, they

presented algorithms to find the pair cycle time and safety stock which minimize the relevant costs.

Several real-world case studies in worldwide companies have been reported (see, e.g., [79–85] and [86]). For instance, Caridi and Cigolini [79] proposed and implemented a new methodology for both dimensioning and managing safety stock in an Italian leader company in the electromechanical components brand industry by considering demand forecast error as an uncertain factor. Persona et al. [80] focused on safety stock dimensioning on both MTO and ATO environments. This study proposed models to determine optimal safety stocks for pre-assembled modules (ATO production systems) and manufacturing components (MTO production systems) used in final products. These models were applied in two Italian companies that operate in different sectors. However, Kanyalkar and Adil [81] considered a trade-off among the plan change costs, safety stock violation penalty and inventory carrying costs for a capacitated multi-item production system in their proposed linear programming model. This model aimed at determining the optimal level of safety stock in rolling horizon. Boulaksil et al. [82] focus on dimensioning of safety stock in multi-item multi-stage inventory system. The author proposed an approach and then implemented on a worldwide biopharmaceutical company, so-called Organon. Using the simulation based-optimization approach, Chen et al. [83] proposed a framework to determine the appropriate level of pooled safety stock levels by considering demand forecast. This framework was applied to a clinical trial company. On the other hand, Prawira et al. [86] based on inventory control theory to proposed their model. This model focusing on determine the most reasonable amount of safety stock in the Indonesian oil and gas service companies.

Concerning the Economic Lot Scheduling problem (ELSP) with safety stock, Brander and Forsberg [87] presented a model to determine the safety stock for the problem of scheduling the production of multiple items on a single facility, both with and without the existence of the idle time. Without the presence of idle time in the system, the safety stock level is calculated from the service level considering the demand variation during lead time. On the other hand, for dealing with idle time a control model is presented. In the control model, the safety stock level is calculated for time to safety stock or TSS (time to reach the safety stock level).

Dey [88] focused on safety stock dimensioning in single-vendor single-buyer supply chain context. This study proposed an integrated production–inventory model and also a methodology for determining the optimal values of the number of shipments from the vendor to the buyer, the safety stock, the buyer's order quantity and the probability of the production process goes “out-of-control”. This methodology aimed to minimize the crisp equivalent of the total cost of the integrated system. Before this research of [88], other studies have been conducted in this context. For instance, Glock [89] studied a single-vendor single-buyer integrated model with stochastic demand and lot-size dependent lead time under different methods for lead time reduction (and their impact on expected total costs and safety stock). This model aimed to find the approximate optimal solution. Afterwards, Mou et al. [90] proposed an extension of the integrated model, by considering transportation time as the main performance criteria and assuming two different safety stocks. However, is important to underline that nowadays is rarely to a supply chain operate in an environment with only one vendor and buyer.

Over times, analytical approaches have been explored to establish safety stock. For instance, Krupp [91] proposed approaches for determining safety stock based on classic statistical theory. Wang et al. [56] developed formulas to determine the reorder point and safety stock when lead time and demand are correlated. Moeeni et al. [92] based on the basic traditional inventory models to proposed three models (for different scenarios) for determining safety stock and reorder point. Prak et al. [93] derive closed-form expressions for the correct reorder level under uncertainty of both the mean and the variance of the

demand. Moreover, both optimization and hybrid (e.g., simulation-based optimization) approaches have been also used. Hoque and Goyal [94] developed a heuristic solution procedure to determine safety stock in an integrated inventory system under controllable lead-time between a vendor and a buyer. Srivastav and Agrawal [95] used the multi-objective particle swarm optimization (MOPSO) algorithm to solve their multi-objective hybrid backorder inventory model and generate Pareto curves. Huang et al. [96] developed an optimization model to determine the optimal combination of reactive capacity and safety stock to cope with random demand, in order to minimize the total costs related to the minimum service-level constraint. Beutel and Minner [97] developed two data-driven frameworks to determine safety stock when demand depends on external factors (e.g., prices fluctuations and weather condition).

Zhou and Viswanathan [98] proposed a new method for determining the safety stock under intermittent demand so-called bootstrapping method. The authors compared this new method through computational experiments with the parametric method. They concluded that the bootstrapping method works better with a large amount of randomly generated data. However, the parametric method works better with data generated in a real industry environment.

Recently, Trapero et al. [61] and Trapero et al. [62] based on empirical methods to deal with safety stock dimensioning issue. Trapero et al. [61] proposed empirical methods based on kernel density estimation (non-parametric) and Generalized Autoregressive Conditional Heteroscedastic (GARCH (1,1)) models (parametric) for calculating the safety stock levels under standard deviation of the lead time forecast error. On the other hand, Trapero et al. [62] proposed an optimal combination of the alternative empirical methods for calculating the safety stock levels, so that to minimize the piecewise linear loss function (tick loss).

Concerning of safety stock dimensioning in a production system with limited/constrained capacity, Altendorfer [99] proposed a model for optimizing planning parameters (lot size, safety stock and planned lead time) for a multi-item single-stage production system with limited capacity. On the other hand, Helber et al. [66], besides coping with this environment (capacity constrained production system), they also concerned with Stochastic Capacitated lot-sizing Problem (SCLSP). They proposed two different approximation models and used a fix-and-optimize algorithm to solve them, in order to determine production quantities and safety stock.

Other research studies of setting safety stock regarding just-in-time (JIT) production system [100]; joint optimization of responsive supply chain design with inventory and safety stock [105]; inventory management decision problem with service constraints [106]; serial inventory system [108]; periodic review inventory system with lost sales [109] demand-driven materials requirement planning (DDMRP) replenishment context [113]; supply chain reliability requirements [111]; remanufacturing system with production smoothing [112]; cyclic production schedules [114] have been also conducted.

This section encompasses the problem of safety stock dimensioning under demand uncertainty and comprises 48 articles (24.87% of the total sample) as described in Table 8.

#### 5.1.2. Considering lead time uncertainty

Abdel-Malek et al. [115], Louly and Dolgui [116], Digiesi et al. [117] and [118] are four studies that address the problem of safety stock dimensioning incorporating the lead time as the uncertainty factor (see Table 9). These four studies represent 2.07% of the total sample considered in this SLR. Abdel-Malek et al. [115] proposed a framework based on Markovian modelling and queueing theory (tandem queues and sojourn times) that estimates the safety stock for outsourcing strategies in the multi-layered supply chain, considering lead time uncertainty. The authors highlight that in some case, long-term partnership applies better than competitive bidding/E-bidding

**Table 8**  
Chronological scientific contributions on safety stock dimensioning under demand uncertainty.

Reference	AF <sup>a</sup>	T <sup>b</sup>	SLM <sup>c</sup>	Main criteria
[100]	O	G	–	Min. the expected average cost per period
[101]	MM	ST	FR	Service level
[71]	O	G	–	Traditional average cost (set-ups, holding and backlog costs)
[91]	MM	IT	ND	Safety stock carrying cost; recouped profit
[102]	O	G	CSL	Min. expected annual total cost
[103]	O	H	–	–
[72]	O	G	–	Max. of the annuity stream
[73]	MM	LT, IOA	–	Min. the average costs or max. of the net present value of production
[74]	MM	LT, IOA	–	Net present value (the annuity stream)
[77]	O	PLP, ZFP	FR	Min. of costs
[75]	S	G	CSL	Total cost, schedule instability and SL
[79]	S	G	ND	Nr. of stock-outs, stock-out quantity and nr. of replenishments for safety buffers
[94]	O	H	–	Min. of the total cost, inventory holding and lead-time crashing
[87]	S	ND	CSL	Min. of the total costs
[80]	O	ND	CSL	Min. of the total cost
[104]	S	MCS	ND	Service level
[105]	O	MINLP	FR	Max. the net present value and min. the expected lead time
[81]	O	LP	CSL	Min. the overall cost
[82]	S	ND	FR	Min. total costs (holding & backorder cost)
[56]	MM	IT, PT	–	–
[106]	O	LP	–	Lost sales; probability stock-out during LT
[98]	S	ND	CSL	Total inventory-related cost, average inventory level, fill rate and stock out rate
[107]	SO	SP, IPA	FR	Min. total inventory holding and shortage costs
[78]	O	G	FR	Min. the total relevant cost
[97]	O	LP	CSL, FR	Min. the service level and costs
[89]	SO	G	–	Min. the expected total costs
[92]	MM	IT	ND	Service level
[108]	O	H	–	Min. the total cost
[109]	MM	IT	FR	Fill rate
[83]	SO	DES, MILP	CSL	Min. the operational cost
[66]	O	MILP, PLA	P	Min. the expected costs
[84]	O	MILP	CSL	Min. the total direct rail car cost and the number of rail car types
[76]	O	ND	–	Min. the long-run expected costs
[110]	SO	DES, VNS, RSM, OQ	FR	Service level
[95]	O	MOPSO, MOGA	FR	Min. the total cost, stockout units and the frequency of stockouts
[96]	O	ND	CSL	Min. long-run average cost
[93]	O	ND	CSL	–
[90]	O	ND	–	Min. the expected cost
[111]	MM	PT	–	Total cost
[112]	O	NLP	–	Min. the expected total cost
[85]	SO	DES	CSL	Min. the inventory holding and rush ordering costs
[99]	O	H	ND	Min. inventory and backorder costs
[86]	O	ND	ND	Min. the costs (storage and inventory ordering costs)
[113]	MM	IT	CSL	Average inventory level and shortage rate
[61]	S	ND	CSL	–
[62]	O	MCS	CSL	Min. the tick loss function
[88]	MM	FRV	–	Min. the crisp equivalent of the expected annual integrated total cost
[114]	S	MCS	ND	Min. the safety stock and holding costs, and improving the service level

<sup>a</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization, S — Simulation, SO — Simulation-based optimization.

<sup>b</sup>Technique (T): DES — Discrete event simulation, FRV — Fuzzy random variable, G — Generic procedure, H — Heuristics, IOA — Input-output analysis, IPA — Infinitesimal perturbation analysis, IT — Inventory theory, LP — Linear programming, LT — Laplace transformation, MCS — Monte Carlo simulation, MILP — Mixed-integer linear programming, MINLP — Mixed-integer nonlinear programming, MOGA — Multi-objective genetic algorithm, MOPSO — Multi-objective particle swarm optimization, NLP — Nonlinear programming, OQ — OptQuest, PLA — Piecewise linear approximation, PLP — Possibility linear programming, PT — Probability theory, RSM — Response surface methodology, SP — Stochastic programming, ST — Statistical Theory, VNS — Variable neighbourhood search, ZFP — Zimmermann's fuzzy programming.

<sup>c</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed, P — Proposed service level measure.

strategies, inasmuch as the gains achieved in competitive bidding/E-bidding strategies related to the lower price and higher flexibility is dissipated by the increase of the safety stock level, and consequently the increase of inventory costs. In the context of single-level just-in-time (JIT) assembly systems, Louly and Dolgui [116] developed a novel approach based on original lower bound and dominance properties, and a branch and bound algorithm that focus only in determining the optimal safety stock of components under lead time uncertainty.

Regarding a real-world case study, Digiesi et al. [117] proposed an extension of Sustainable Order Quantity (SOQ) model by considering lead time uncertainty and external cost of freight transport in order to identify optimal order quantity, reorder level and safety stock. A procedure was also developed to solve this model and applied to a spare parts inventory from the automotive industry.

Last but not least, Sellitto [118] developed a method to calculate the lead-time, inventory and safety stock in a make-to-order (MTO) job-shop manufacturing context.

### 5.1.3. Considering yield uncertainty

This section describes the scientific research regarding the problem of safety stock dimensioning under yield uncertainty. In this subject, there are only 6 articles (3.11% of the total sample considered) which proposed their models, approaches or frameworks following different approaches for solving this problem of safety stock dimensioning (see Table 10). In the research study of [120], a framework of production policy was developed to determine the required quantity (this is, the optimal value) of safety stock, production rate and production lot size to minimize the total expected system costs, considering machine breakdown as an uncertainty factor.



Table 9

Chronological scientific contributions on safety stock dimensioning under lead time uncertainty.

Reference	AF <sup>a</sup>	T <sup>b</sup>	SLM <sup>c</sup>	Main criteria
[115]	S	ND	ND	Annual cost
[116]	O	BB	ND	Min. the average holding cost
[117]	O	G	ND	Logistics cost
[118]	SO	ND	–	–

<sup>a</sup>Approach followed (AF): O — Optimization, SO — Simulation-based optimization.<sup>b</sup>Technique (T): BB — Branch and bound algorithm, G — Generic procedure, ND — Non-disclosed.<sup>c</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

Table 10

Chronological scientific contributions on safety stock dimensioning under yield uncertainty.

Reference	AF <sup>a</sup>	T <sup>b</sup>	SLM <sup>c</sup>	Main criteria
[119]	MM	MC	–	Min. of the average demand loss/backlog cost
[120]	MM	MC	–	Min. the total expected system cost
[121]	O	RO, DP	ND	Max. the profits
[122]	O	ND	–	Min. the total costs
[123]	O	ND	–	Min. the costs
[124]	SO	MIP, MCS	CSL	Max. the total production amount

<sup>a</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization, SO — Simulation-based optimization.<sup>b</sup>Technique (T): DP — Dynamic programming, MC — Markov chain, MCS — Monte Carlo simulation, MIP — Mixed-integer programming, ND — Non-disclosed, RO — Real options technique.<sup>c</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

In the context of the manufacturing environment with imperfect/defective products, Taleizadeh et al. [122] proposed an integrated inventory model for determining the optimal lot size and production uptime under random machine breakdown. The safety stock was used in the proposed model to prevent shortages in the case of machine breakdown. Recently, a similar study on manufacturing environment with defective production was conducted by [123]. The study was conducted to obtain the optimal safety stock level, optimal controllable production rate and the optimal amount of production quality during the random machine breakdown under optimum energy consumption within the framework of smart production management. A real-world case study from the mining sector could be found in [121]. In this study, the authors proposed a new real options method (modified real options method) for determining the safety stock of ore for mining production from Kittilä mine. By comparing both this new method and the conventional Economic Order Quantity (EOQ) methods, they highlight that the real options method provides higher accuracy, better profits and robust performance when procurement costs are changed. Other relevant scientific contributions on safety stock dimensioning in the manufacturing context or contribution that consider the safety stock dimensioning as one of the multiple features for solving production/manufacturing problems, can be found in [119] and [124].

#### 5.1.4. Considering multiple uncertainties and risks

Several types of research studies have been investigating the issue of safety stock dimensioning in the MRP system. In [125], a simulation-based optimization study was proposed to jointly optimize lot-sizes, safety stock and safety lead times considering both demand and lead-time uncertainty. The author performed a comparison between safety stock and safety lead time in order to determine the best method. He highlights that both lead time and demand variability influences the level of optimal safety lead time and optimal safety stock. Furthermore, he also highlights that safety stock method is the best choice in the case of a low level of stockout/inventory holding cost ratio, high level of demand variability and low level of lead time variability. On the other hand, the safety lead time is the best choice in the case of a high level of stockout/inventory holding cost ratio and high level of demand variability. Still, Guide and Srivastava [126] studied the dimensioning of safety stock in the MRP system modified for use in a re-manufacturing environment under random demand and lead time.

Besides MRP contexts, studies in the literature focusing on dimensioning safety stock in Master Production Scheduling (MPS) and

Available-To-Promise (ATP) environments can be found in [127] and [128]. Therefore, Campbell [127] proposed a new method so-called “optimal safety stock” from two most known methods (constant cycle service level and constant safety stock) for establishing the safety stock in MPS environment under demand and lead time uncertainties. On the other hand, Hung and Chang [128] considered the lead time and yield uncertainties on their proposed method for ATP environment.

Real-world case studies have been already reported by [129,134,138,141,142] and [143] regarding this issue of safety stock dimensioning by considering multiples uncertainties/risks. Thereupon, Taluri et al. [129] applied their model for managing the made-to-stock inventories in a multinational pharmaceutical company. They considering both demand and lead time uncertainty. As a result of comparing this model with existing models, costs benefits were achieved with the proposed model. Kanet et al. [134] proposed a software system for production planning so-called Dynamic Planned Safety Stock (DPSS) for planning a time-phased set of safety stock over a planning horizon. As a result of applying this in industry, significant savings were achieved. Another real case study was reported by [138], which aimed to apply optimal safety stocks in nursing workforce management. Recently, Avci and Selim [141] proposed multi-objective framework for supply chain inventory optimization and then developed a decomposition-based multi-objective differential evolution algorithm (MODE/D) for this framework. This aimed to determine supplier flexibility and safety stock levels in a real-world multi-national automotive supply chain. Lastly, Saad et al. [142] developed a mechanism and integrated with SAP to determine adequate safety stock under the required service level. After testing the mechanism at Wavim company, the authors highlight that the mechanism should be considered as a new development for the manufacturing industry.

Inderfurth and Vogelgesang [135] proposed an approach for determining dynamic safety stock by considering different yield uncertainties and random demand. Besides that, they presented ways to convert these dynamic safety stocks into static one, in order to be applied easily in practice. Keskin et al. [136] proposed a mathematical programming model (MILP) to optimize simultaneously production, inventory and backorder quantities for multi-product, multi-period real-life problem by considering demand and yield uncertainties.

Kumar and Evers [137] proposed an alternative approach to the random sums approach (traditional approach for determining safety stock). This alternative approach, so-called multiplication approach,



**Table 11**

Chronological scientific contributions on safety stock dimensioning under multiple uncertainties and risks.

Reference	UR <sup>a</sup>	AF <sup>b</sup>	T <sup>c</sup>	SLM <sup>d</sup>	Main criteria
[127]	D, LT	MM	IT	CSL	Total cost
[126]	D, LT	S	ND	CSL	Stock-out percentage; SS level
[125]	D, LT	SO	SA	ND	Total cost
[128]	Y, LT	S	LP	ND	–
[129]	D, LT	MM	IT	CSL	Min. costs and efficiency improvement
[130]	D, LT	O	NLP	ND	Min. total cost
[131]	D, LT	O	G	CSL, FR	Min. expected inventory costs; max. the expected profit
[132]	D, LT	MM	IT	ND	Total logistics costs
[133]	D, Y	MM	IT	CSL	Production, holding and shortage costs
[134]	D, LT	O	LP, G	FR	Min. total inventory and average annual fill rate
[135]	D, Y	S	ND	FR	Min. the backlog and holding costs
[136]	D, Y	O	MILP, GrA, GA	–	Min. the total cost of the production plan; lot sizes
[137]	D, LT	S	ND	–	Min. the total supply chain costs
[138]	D, LT	O	ARMA	ND	–
[139]	D, Y	MM	IT	CSL	Service and inventory level
[140]	D, Y	O	H	–	Min. the inventory costs
[141]	D, SD	SO	MODE/D, NSGA-II	–	Total holding cost; premium freight ratio
[142]	D, LT	O	G	ND	Customer service, inventory and operating cost
[64]	D, LT	S	EDS	FR	Fill rate
[143]	D, SC	S	SD	FR	Expected total cost
[144]	LT, OC	O	GA	–	Expected total cost

<sup>a</sup>Uncertainty or risk (UR): D — Demand, LT — Lead time, OC — Order crossover, SC — Supplier constraints, SD — Supplier delay, Y — Yield.<sup>b</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization, S — Simulation, SO — Simulation-based optimization.<sup>c</sup>Technique (T): ARMA — Autoregressive moving average, EDS — Event-driven simulations, G — Generic procedure, GA — Genetic algorithm (meta-heuristics), GrA — Greedy algorithm, H — Heuristics, IT — Inventory theory, LP — Linear programming, MODE/D — Multi-objective differential evolution algorithm, ND — Non-disclosed, NLP — Nonlinear programming, NSGA-II — Non-dominated sorting genetic algorithm II, SA — Simulated annealing, SD — System dynamics.<sup>d</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

consider data quality issues, as well as the correlation between demand and lead time (both stochastic) for setting safety stock.

Based on analysis from stochastic inventory control theory, Inderfurth [133] and Lu et al. [139] proposed their research studies for different environments. The first author, Inderfurth [133], studied the issue of safety stock dimensioning in the production control environment, more concretely in MRP control systems by taking into consideration both demand and yield uncertainty. On the other hand, Lu et al. [139] studied also this issue in construction material environment, considering non-stationary stochastic demand and random supply yield.

In the recent past, Chaturvedi and Martínez-De-Albéniz [140] proposed a modelling framework based on queueing and inventory theory that optimized simultaneously inventory (safety stock), excess capacity and diversification of supply source under yield (supply capacity) and demand uncertainties. The main objective of this framework was to minimize the inventory costs (holding and shortage costs). The authors considered an infinite-horizon periodic-review inventory model for solving this problem. Recently, Ben-Ammar et al. [144] studied the problem of multi-period supply planning. Aiming to solve this problem, a general probabilistic model under random lead-time and order crossover was proposed. Then, they developed a genetic algorithm (GA) for this model to determine planned lead-times and safety stock level, by minimizing expected total costs (sum of expected backlogging cost and expected inventory holding costs).

This section encompasses the problem of safety stock dimensioning under multiple uncertainties and risks and comprises 21 articles (10.88% of the total sample) as described in Table 11.

## 5.2. Safety stock management

Safety stock management is crucial for organizations so that aims to maintain customer service levels, as well as controlling the costs. Caridi and Cigolini [11] defined safety stock management as “the managing issue deals with finding the appropriate time for safety stocks replenishments and with setting the appropriate delivery dates for replenishments”. Indeed, the safety stock management intends to answer two main questions: “when to order? And, how to order?”. To this, there are several models

in which answer in a different way to these two questions. The most known models are continuous review, periodic review and Economic Order Quantity (EOQ) [6].

### 5.2.1. Considering demand uncertainty

This section encompasses the problem of safety stock management under demand uncertainty and comprises 21 articles (10.88% of the total sample) as described in Table 12.

The main inventory management models are applied in environments where the demand or supply is random or uncertain. Generically, the studies proposed in the literature takes advantage of this inventory management models considering the demand as a distribution function (e.g., normal, gamma, and other) or as time series forecasting. By considering continuous-review inventory control system under stochastic demand during lead time, Kim and Benton [145] studied the interrelationship between lot size and lead time and their implication on lot size and safety stock decisions (how much to order and when). The authors proposed an interactive algorithm for determining simultaneously the lot size and safety stock and then compared it with a conventional sequential approach (EOQ). As a result, they concluded that the algorithm provides better results in terms of cost savings. On the other hand, Urban [146] developed an algorithm for solving a periodic-review problem with stochastic, serially correlated and inventory level dependent demand.

Based on optimization techniques such as Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-objective electromagnetism-like optimization (MOEMO), Tsou [147] addressed the problem of multi-objective inventory control, so that to minimize the expected total cost annually under lost sales. Other optimization-based techniques, such as Mixed-integer nonlinear programming (MINLP) and Mixed-integer linear programming (MILP) was also used to optimize simultaneously the safety stock, reserve and base stock levels in tandem with the material flow in supply chain planning (see, [148]).

Overall in this topic, only two studies report a real-world case study (see, [149] and [150]). For instance, You and Grossmann [149] developed a computational framework for simultaneously optimized the tank-sizing decisions, safety stock levels and estimated vehicle routing costs. This framework consists of stochastic approximation model (MINLP problem) under random demand.

**Table 12**  
Chronological scientific contributions on safety stock management under demand uncertainty.

Reference	AF <sup>a</sup>	T <sup>b</sup>	SLM <sup>c</sup>	Main criteria
[145]	O	G	CSL	–
[151]	MM	IT	ND	–
[152]	O	G	FR	Fill rate
[153]	SO	AVM, RL	ND	Average service level
[146]	MM	IT	–	Max. the expected profit
[154]	O	NLP	ND	Min. expected cost; optimal frozen period
[155]	O	H	–	Min. the expected total cost
[147]	O	MOEMO, MOPSO	ND	Min. the expected total cost, number of stockouts and stocked item annually
[156]	O	AA	CSL	Min. total order and holding cost
[149]	O	MINLP, BR	CSL	Min. the total expected costs
[157]	MM	IT	FR	Fixed manufacturing and holding costs
[158]	O	NLP	–	Min. the total expected inventory costs
[159]	MM	DT	CSL	Min. the expected inventory costs
[150]	O	H	FR	Target fill rates
[160]	O	ABC	–	Safety stock; total inventory cost
[60]	O	SA	CSL	Total cost
[161]	SO	ND	ND	Min. inventory holding cost
[162]	O	MINLP	FR	Min. the costs
[148]	SO	MILP, MINLP	CSL	Min. transportation and inventory costs
[163]	O	H	FR	Min. total inventory costs
[164]	MM	ND	–	Min. expected cost

<sup>a</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization.

<sup>b</sup>Technique (T): AA — Approximation algorithm, ABC — Artificial Bee Colony algorithm, AVM — Action-value method, BR — Branch-and-refine algorithm, DT — Diffusion theory, G — Generic procedure, H — Heuristics, IT — Inventory theory, MILP — Mixed-integer programming, MINLP — Mixed-integer nonlinear programming, MOEMO — Multi-objective electromagnetism-like optimization, MOPSO — Multi-objective particle swarm optimization, NLP — Nonlinear programming, ND — Non-disclosed, RL — Reinforcement learning, SA — Simulated annealing.

<sup>c</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

From a different perspective of earlier studies in the literature regarding safety stock management problem, Hsueh [157] considered in his research study the product life cycle (introduction, growth, maturity and decline), inventory control and manufacturing/remanufacturing system simultaneously. The author studied inventory control policies during the Product Life Cycle (PLC) and presented closed-form formulas of optimal lot size, reorder point and safety stock during each phase of the PLC. Yue et al. [160] also considered the PLC and inventory control in their research. They proposed a method so-called Improved ABC-PF based on PLC theory. A PLC model based on cubic polynomial with two stages was developed and then was used Artificial Bee Colony — ABC (machine learning algorithm) to optimize the parameters of the two-stage PLC model. The proposed method allows also to determine the safety stock during each PLC phase and replenishments in order to prevent stockouts.

Some of the research studies dealt with inventory control problem in multi-echelon supply chain systems. The studies proposed by [153,156] and [163] are some examples. Chu and Shen [156] applied a POT (Power-of-two) policy to multi-echelon stochastic inventory model. The authors developed a polynomial-time algorithm to derive a closed-to-optimal POT policy for a given target service level. On the other hand, Kim et al. [153] proposed two adaptive inventory control model (centralized and decentralized models) under non-stationary demand for solving the issue in two-echelon supply chain system (one supplier and multiple retailers). The proposed models consider the target service level predefined for each retailer as the main performance criteria. Recently, Sakulsom and Tharmmaphornphilas [163] proposed a heuristics for determining an ordering policy in a divergent two-echelon inventory system (single warehouse and N non-identical retailers). By comparing this heuristic with MIP models, the authors concluded that the heuristic provides goods solutions as MIP models. Based on stock diffusion theory (SDT), Braglia et al. [159] proposed a dynamic model for inventory control under non-stationary demand. The authors used the Fokker Planck (FP) equations for obtaining both the time-dependent probability distribution of the stock consumption and the reorder time.

Braglia et al. [60] focused on safety stock management issue in a single-vendor single-buyer supply chain context under continuous review and Gaussian demand, adopting the PV criterion. They presented both approximated and exact algorithms for optimizing the safety stock.

Other studies used inventory management models considering demand as time series forecasting. Demand forecast has become an essential component in safety stock management. An inaccurate forecast can lead to inventory shortages or even overstocks and also to low customer service level. Lian et al. [154] dealt with this issue, considering also the frozen period. They studied the frozen period in a periodic review inventory model considering forecast demands and then developed a non-linear programme so-called order policy (OOP). By comparing the forecast order policy (FOP) model with the proposed OOP models, they concluded that both present similar and consistent results, confirming the FOP as a very good heuristic order policy and the OOP a good alternative. Other relevant studies proposed through consecutive efforts by [151,155,158,161,162] and [164].

### 5.2.2. Considering lead time and yield uncertainty

As shown in Table 13, there are few studied that address both the problem of safety stock management considering lead time uncertainty and considering yield uncertainty, regarding the sample considered in this SLR. A total of 4 articles (2.07%) address this problem under lead time uncertainty, namely. Louly et al. [165], Chandra and Grabis [166], Wang and Wang [167] and [168]. Cobb [169], is the unique study that considered the yield uncertainty in this topic (0.52% of total considered articles). For instance, Louly et al. [165], developed a model and approach of inventory control for a single-level assembly system under random component lead times. The authors highlight that this model could be used for determining safety stock or safety lead time in the MRP context for each component under lead time uncertainty. Chandra and Grabis [166] proposed a research study on integrating procurement costs and inventory models by considering the variable lead-time. Wang and Wang [167], developed a mathematical model and deviation to determine the linkage relationship between two key parameters in inventory management: lead time uncertainty and safety stock. Focusing on addressing this problem by considering yield uncertainty, Cobb [169] proposed an integrated inventory control model for the inspection, repair, and purchase of returnable transport items in a closed-looping supply chain. In this model, the safety stock is determined under uncertain return, so that to buffer the inventory of used and repairable containers.

**Table 13**

Chronological scientific contributions on safety stock management under lead time and yield uncertainties.

Reference	UR <sup>a</sup>	AF <sup>b</sup>	T <sup>d</sup>	SLM <sup>c</sup>	Main criteria
[165]	LT	O	BB	ND	Min. average holding cost
[166]	LT	O	G	–	Min. total inventory and procurement costs
[167]	LT	MM	MD	CSL	–
[168]	LT	O	H	–	Min. total cost of the supply chain
[169]	Y	MM	ND	ND	Min. expected costs

<sup>a</sup>Uncertainty or risk (UR): LT — Lead time, Y — Yield.<sup>b</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization, SO — Simulation-based optimization.<sup>c</sup>Technique (T): BB — Branch and bound algorithm, G — Generic procedure, H — Heuristics, MD — Mathematical derivation, ND — Non-disclosed.<sup>d</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

### 5.2.3. Considering multiple uncertainties and risks

In the literature, many authors addressed different problems inherent to safety stock management by considering different types of uncertainties and risks. Based on optimization approaches, Tang et al. [170] developed an algorithm using Lagrangian relation for solving the problem of raw material inventory faced by Shanghai Baoshan Iron and Steel Complex (Baosteel) company. The algorithm aims to determine the fixed order size and fixed interval of the replenishment process. On the other hand, for solving multi-buyer multi-vendor supply chain problem, Taleizadeh et al. [171] proposed a harmony search algorithm to determine the reorder points, the safety stocks, and the numbers of shipments and packets in each shipment of the products under random demand and lead time. Some of these research works have dealt with dynamic inventory control policies under non-stationary demand, such as [172]. The authors developed an approach for the inventory control system (focused on a single-stage and single-item inventory system) under non-stationary demand incurring to the use of forecasts and random lead-time. It was developed a dynamic periodic re-order point (rk, Q) control policy for controlling the system at the end of every review period. This (rk, Q) dynamic policy was evaluated in terms of performance (service level achieved) and compared to the static (r, Q) policy. The authors concluded that both policies are similar in terms of performance.

In the past few years appeared many research studies that integrated pricing and inventory models, since pricing decision has become an important issue in supply chain management. Here, Zhou and Chao [179] studied this issue in a periodic-review inventory system with dual supply modes (regular and expedited) in order to mitigate the demand uncertainty under deterministic procurement costs. On the other hand, Xiao et al. [181] focused on the effect of procurement fluctuations in the optimal pricing and sourcing policy, providing new insights related to this impact (namely to the fact that procurement cost fluctuation can alter the strategic relationship between dynamic pricing and dual sourcing, and the risk-neutral firm can achieve a higher expected profit under a more volatile spot market cost process). Other investigation that considers price sensitive (demand are auto-correlated and dependent on selling price) in their inventory model can be found in [175].

Zhang et al. [177] proposed an inventory-theory-based interval stochastic programming (IB-ISP) model for addressing the inventory problem in the electric-power generation system, considering demand uncertainty (forecast of the electricity demand) and yield uncertainty (transportation problems). The proposed model consists of planning the resources purchase patterns and electricity generation schemes of the coal-fired plants. By testing the model with real data of real environment (Beijing's electric-power generation system planning), the IB-ISP model performed better than the traditional EOQ model, since this model can provide effective measures for not-timely coal supplying pattern with reduced system-failure risk.

Recently, an real-world case study in a multi-national automotive supply chain was reported by [183] as an extension of [141]. The authors developed an approach for solving the inventory replenishment problem with premium freights using simulation-based optimization

techniques. They used the decomposition-based multi-objective differential evolution algorithm (MODE/D) for determining several parameters, such as demand forecast adjustment factor, safety stock and supplier flexibility in order to minimize the total holding cost, inbound and outbound premium freight ratios. Another real case study can be found in [176] and [174].

Some research studies have already been proposed in the literature focusing on determining the reorder point. Hayya et al. [49] discussed this issue considering demand uncertainty, lead time uncertainty and order crossover, where demand and lead time are independently and identically (iid) random variables. They developed regression equations for calculating the optimal cost, optimal order quantity and optimal reorder point. Another research study based on reorder point, but now considering just random demand and random lead time, was proposed by [58]. The authors presented an alternative reorder point model (EVR method) that aimed to determine the safety stock and possible outcomes of the replenishment cycle (how much and when to replenish the inventory) without considered any distributional assumptions.

Other relevant studies proposed through consecutive efforts by [59,173,178,180,182] and [48]. This section encompasses the problem of safety stock management under multiple uncertainties and risks and comprises 18 articles (9.33% of the total sample) as described in Table 14.

### 5.3. Safety stock allocation, positioning or placement

In the literature, there are several terminologies for the same problem of safety stock placement. Safety stock placement, safety stock allocation and safety stock positioning represent the same problem [12–14]. In this SLR is adopted the terminology safety stock placement to portray this problem. The problem of safety stock placement is concerned with the question of where to position the safety stock and how much is needed [12]. Caridi and Cigolini [11] defined safety stock placement as “the positioning issue deals with finding the appropriate items in the bills of materials where safety stocks are to be placed”.

The problem of safety stock placement is divided into two main research streams widely studied: safety stock placement for multi-stage or multi-echelon supply chain and supply chain network design with safety stock placement [184]. The complexity of these safety stock problems is directly related to the structure of the supply chain. There are three main structures, as depicted in Fig. 13: serial network, spanning tree and general acyclic network [14,185]. The assembly (convergent) network and distribution (divergent) network represents two special cases of spanning tree structure. The divergent network is represented with a single and central stage and several successors, and the convergent network consists of a one-end stage with several predecessors.

The serial network consists of sequential dependencies among supply chain stage, this is, each stage of the supply chain has a single predecessor and successor [14,185]. The general acyclic network is a combination of the previous structures [185]. There are two modelling approaches in multi-stage or multi-echelon safety stock placement: stochastic-service model and guaranteed-service model. The difference between these two approaches lies in the way that the replenishment mechanism between stages in the supply chain is modelled [186].

**Table 14**  
Chronological scientific contributions on safety stock management under multiple uncertainties and risks.

Reference	UR <sup>a</sup>	AF <sup>b</sup>	T <sup>c</sup>	SLM <sup>d</sup>	Main criteria
[173]	D, LT	O	G	FR	Min. annual total logistics costs
[170]	D, Y	O	LR, H	–	Min. total cost
[49]	D, LT, OC	SO	G	–	Min. costs
[172]	D, LT	S	G	CSL	Total inventory costs; service level
[58]	D, LT	S	ND	CSL	Holding cost; Service level
[174]	D, LT	O	MIP	ND	Min. total supply chain costs
[171]	D, LT	O	HS, GA	CSL	Min. total cost
[175]	D, P	O	G	–	Max. profit
[176]	D, SC	MM	PVB	–	Min. total cost
[177]	D, Y	O	SP, SVR	–	Min. system cost
[178]	D, LT	MM	G	ND	Min. stockholding and SS costs
[179]	D, P	O	DP	–	Max. expected discounted profit
[180]	D, LT	O	DP	–	Min. expected ordering, inventory holding and shortage penalty costs.
[181]	D, P	O	DP	–	Max. expected discounted profit
[59]	LT, OC	MM	IT	–	Min. inventory costs
[182]	D, LT, OC	MM	MA, MC	FR	Min. safety stock level and fill rate
[183]	D, SD	SO	MODE/D, NSGA-II	–	Min. total holding cost; inbound & outbound premium freight ratios
[48]	D, LT, OC	SO	DES, CS	CSL	Min. costs

<sup>a</sup>Uncertainty or risk (UR): D — Demand, LT — Lead time, OC — Order crossover, P — Price, SC — Supplier constraints, SD — Supplier delay, Y — Yield.

<sup>b</sup>Approach followed (AF): MM — Mathematical modelling, O — Optimization, S — Simulation, SO — Simulation-based optimization.

<sup>c</sup>Technique (T): CS — Continuous simulation, DES — Discrete event simulation, DP — Dynamic programming, G — Generic procedure, GA — Genetic algorithm (meta-heuristics), H — Heuristics, HS — Harmony search, IT — Inventory theory, LR — Lagrangian relaxation, MA — Matrix analytic method, MC — Markov chain, MIP — Mixed-integer programming, MODE/D — Multi-objective differential evolution algorithm, ND — Non-disclosed, NSGA-II — Non dominated sorting genetic algorithm II, PVB — Prékopa-Vizvari-Badics algorithm, SP — Stochastic programming, SVR — Support vector regression.

<sup>d</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

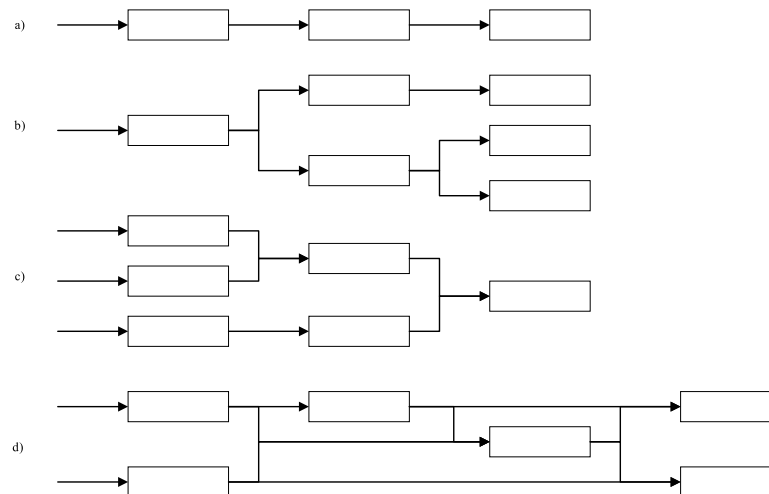


Fig. 13. Supply chain structure: (a) Serial network, (b) Divergent network, (c) Convergent network, (d) General acyclic network adapted from [14].

### 5.3.1. Considering demand and lead time uncertainty

There is a set of studies in the literature regarding the problem of safety stock placement, allocation or positioning in the multi-stage or multi-echelon system and supply chain network design with safety stock placement under demand uncertainty. A total of 48 articles (24.87%) of the total sample (193 articles) address these problems. Regarding the problem of safety stock placement in the multi-echelon supply chain, several authors discussed this problem in their studies. For instance, Simpson [187] was the first author that proposed a guaranteed-service model for supply chain structured as a serial network, so that for satisfying the demand of downstream stages at minimum inventory costs. Since then, the guaranteed service approach has been extended into several directions for solving this problem for supply chain networks modelled as assembly, distribution, spanning tree or general acyclic networks [184]. Inderfurth [188] proposed a model for multi-stage supply chain structured as serial and divergent network, where demands are correlated both between products and time. The author highlight that ignoring the correlation of demand

can lead to a high deviation in the optimal buffer policy. Inderfurth and Minner [189] and [190] are an extension of Simpson's work. Both of these authors proposed a dynamic programming approaches for optimizing the safety stock in multistage inventory systems of the serial supply chain, assuming normally distributed demand and periodic review base stock control policy. Minner [190] considered both service level and cost as performance criteria and [189] assumed the service level constraints as the main performance criteria. The work proposed by [12] represents also an extension of Simpson's work. Graves and Willems [191], Schoenmeyr and Graves [192], Grahl et al. [193] and [194] proposed extensions of the modelling framework developed by [12]. Graves and Willems [191] considered non-stationary demand for finding the optimal placement of safety stock under Constant Service Time (CST) policy, while [192] considered the evolving forecast, and [184] considered due date demand. Grahl et al. [193] extended the approach to service time differentiation. Kumar and Aouam [194] proposed a model to jointly optimize production capacity, production



smoothing and service times in a multi-stage supply chain structured as spanning tree network.

Several of these research studies were applied in real-world contexts by world-wide recognized companies, such as Intel [195,196], Microsoft and Case New Holland [197], CIFUNSA [198] and Tera-dyne, Inc. Schoenmeyr and Graves [192]. Other examples of real-world applications in companies operating in the automotive industry can be found in [199–201] and [202] is also an example of a real-world implementation at an industrial electronics industry.

Manary and Willems [195] developed adjustment procedures for determining the appropriate inventory target under demand uncertainty (forecast bias) for solving the problem faced by Intel in their multi-echelon inventory optimization model so-called “MEIO” regarding the presence of bias in the sales forecast data. Manary et al. [196] extended the adjustment procedures developed in [195] considering forecast bias, non-normal forecast errors and forecast error heterogeneity.

Neale and Willems [197] and Schoenmeyr and Graves [192] proposed extensions of [12] for incorporating the non-stationary demand and evolving forecast. Moncayo-Martínez and Zhang [198] proposed an extension of the [186] using meta-heuristics algorithms regarding the cost and lead time minimization of products in the generic bill of materials.

Both [200] and [202] proposed studies for addressing the problem of safety stock placement for the automotive industry. The first study used meta-heuristics or modern optimization algorithms (swarm intelligent algorithms: ant colony and intelligent water drop) and in the second study developed a framework.

Other relevant studies proposed through consecutive efforts by [185,203–205] are found in the literature. All these studies aim to optimize the multi-echelon inventory system under guaranteed service approach.

The problem of supply chain network design with safety stock placement represents a classical problem in operational research [184]. This consists to jointly optimize design decisions of the supply chain with safety stock placement. Studies proposed by [184,198,212,214,217] and [225] address this kind of problem. Yao et al. [214] proposed a mixed-integer nonlinear programming model to address the facility location-allocation and inventory problem. A solution procedure was developed also to solve the proposed model. You and Grossmann [212] presented a mixed-integer nonlinear programming model for determining the optimal transportation, inventory level and network structure in a multi-echelon supply chain. Liao et al. [217] in its turn, proposed a mixed-integer programming model for multi-objective optimization of the supply chain network and a multi-objective evolutionary algorithm approach. This model considers the total cost, customer service level (fill rate) and flexibility as the main performance criteria.

Funaki [184] proposed a multi-echelon safety stock placement model in supply chain design under due-date demand and an optimization procedure for this model. This multi-echelon safety stock placement model represents an extension of guaranteed-service model proposed in [12] and [189]. Moncayo-Martínez and Zhang [198] developed an approach based on the MAX-MIN ant system for solving safety stock placement problem in which to minimize the total supply chain cost and product lead time. Other relevant studies regarding the problem of supply chain network design with safety stock placement can be found in [13,219] and [232].

Lastly, [149,208,210,211,213,216,218,220,222–224,226–230] and [233] also proposed their model for solving safety stock placement problem considering demand as uncertainty factor.

Only 0.52% (1 article) address this problem of safety stock placement considering uncertain lead-time. Schneider et al. [206] proposed approximations of two-echelon periodic review inventory model under lead time uncertainty, using the power approximation. Table 15 provides an overview of all articles considered to this topic of safety stock placement under demand and lead time uncertainty. This overview includes the description of the type of uncertainty considered by the author, as well as the approach followed and the main performance criteria.

### 5.3.2. Considering multiple uncertainties and risks

Regarding the problem of safety stock placement for multi-stage or multi-echelon supply chain, Simchi-Levi and Zhao [235] proposed a framework for evaluating and coordinating inventory policies for supply chains with three network structures (serial, assembly and distribution systems) following the stochastic service model approach and considering demand and lead time uncertainties. Each stage of this structure controls its inventory with continuous base-stock policy. Osman and Demirli [236] proposed a safety stock placement models (decentralized and centralized) for determining and placing the safety amounts in a multistage supply chain under demand and lead time uncertainty. The fill rate and safety stocks at each stage of the supply chain are determined in order to minimize the safety stock placement costs through the entire supply chain. Unlike studies proposed in [237] and [238] where the guaranteed service model for general acyclic supply chain was extended considering the demand uncertainty and deterministic lead time, Humair et al. [239] extended the guaranteed service model incorporating both demand and lead time uncertainties. The guaranteed service model proposed in [205] applied the study of [240], but for two-stage serial line supply chain instead for the spanning tree network as considered by these authors. This configuration model aimed for determining the chosen option (cost and lead time pairing) and inventory stocking level at each stage of the supply chain under demand and lead time uncertainty. Graves and Schoenmeyr [241] generalized the guaranteed-service model for safety stock placement incorporating the yield (capacity constraints) and demand uncertainties. Other relevant studies regarding the problem of safety stock placement under multiple uncertainties/risks can be found in [242,243] and [244]. Sonntag and Kiesmüller [242] proposed a model of in-house multi-stage serial production systems with random yield and demand, in order to calculate the optimal safety stock and positions of quality inspections through the production stages and optimize the position of inspections. Woerner et al. [243] developed a simulation-based optimization model for determining the optimal base stock level of a multi-echelon assembly system under capacity constraints (yield uncertainty) and uncertain demand. The authors compared this model with guaranteed service model providing better results in terms of reducing costs keeping the same service level. Last but not least, De Smet et al. [244] proposed two modelling approaches (extensions of the guaranteed-service models and the stochastic service model) for multi-echelon inventory optimization problem in a distribution network under lead time and demand uncertainties.

Recently, Schuster Puga et al. [256] addressed a study related to the problem of supply chain network design with safety stock placement. They formulated a model for two-stage supply chain design for jointly integrate the safety stock placement and delivery strategy decisions considering demand and lead time uncertainties, in order to minimize the costs of transportation, facility opening, cycle inventory, ordering and safety stocks. In this work, the guaranteed-service approach was used for modelling the safety stock placement decisions.

Other relevant scientific studies regarding this topic of safety stock placement can be found in [10,207,245–253] and [254]. This topic related to the problems of safety stock placement has been widely studied by several authors, considering different types of uncertainty factors, performance criteria and following different modelling approaches, as shown in Table 16. Considering the total sample of considered articles (193) to this SLR, 21 of these articles (10.88%) addressed this problem.

## 6. Literature gaps and research opportunities

Considering the literature analysis described in Section 5, we identify in this section some research gaps. Moreover, research opportunities and a Literature Map<sup>2</sup> are also provided.

<sup>2</sup> Literature Map is a visual representation of the literature search results. It allows to identify the relationships between research work results and also to illustrate the literature gaps [257].



**Table 15**

Chronological scientific contributions on safety stock allocation, positioning and placement under demand and lead time uncertainties.

Reference	UR <sup>a</sup>	AP <sup>b</sup>	T <sup>c</sup>	SLM <sup>d</sup>	Main criteria
[188]	D	O	G	CSL	Min. expected holding costs
[206]	LT	SO	G	CSL	Min. overall costs
[190]	D	O	DP	CSL	Min. average holding costs
[189]	D	O	NLP	CSL	Min. of costs, service level
[207]	D	O	NLP	CSL	Min. the total cost
[208]	D	O	H	–	Min. the total expected units short
[209]	D	O	LP	FR	Min. of the total cost
[199]	D	O	DP	CSL	Min. inventory levels
[195]	D	O	G	CSL	Units of product
[210]	D	O	LR	CSL	Min. the sum of facility location, transportation, inventory costs
[185]	D	S	MCS	ND	Service level
[191]	D	O	DP	–	Min. safety stock holding costs
[211]	D	O	H	ND	Min. of costs
[196]	D	O	G	ND	Min. production costs, lost-sales costs and deviation cost
[197]	D	O	ND	CSL	Min. safety stock holding cost
[192]	D	O	DP	ND	Min. inventory holding costs
[212]	D	O	MINLP	CSL	Min. total supply chain design cost
[213]	D	O	NLP	CSL	Total cost
[214]	D	O	MINLP	CSL	Min. expected total cost
[215]	D	SO	H	–	Min. lost sales
[149]	D	O	MINLP	CSL	Min. the annualized cost and the maximum GS* times of the markets
[216]	D	O	LP	ND	Max. profits and min. safety stock costs
[217]	D	O	MINLP, NSGAII	FR	Min. total cost, Max. fill rates, responsive level
[184]	D	O	DP	CSL	Min. total costs
[218]	D	O	MINLP	CSL	Min. the total cost over
[198]	D	O	ACO, IWD	ND	Min. total supply chain cost and product lead time
[200]	D	O	DP	–	Min. safety stock cost
[203]	D	O	H	ND	Min. long-run average expected inventory and backorder costs
[201]	D	O	DP	CSL	Min. total safety stock holding cost
[219]	D	O	MINLP	CSL	Min. cost of the supply chain
[204]	D	O	DP	CSL	Minimization of the average total cost
[220]	D	SO	G	FR	Min. transportation and holding costs
[193]	D	O	GA	CSL	Min. total holding costs
[202]	D	O	ACO, IWD	–	Min. inventory cost and lead time
[221]	D	O	ND	–	Min. total safety stock cost
[222]	D	S	G	–	Min. holding and backorder cost
[223]	D	O	MINLP, H	CSL	Min. the total annual cost
[224]	D	O	CQMIP, H	CSL	Min. the location, transportation and inventory costs
[225]	D	O	MINLP	CSL	Min. the total cost
[226]	D	O	H	CSL	Min. the total holding cost
[227]	D	O	MINLP	CSL	Min. the facility location, transportation and inventory cost
[228]	D	O	PSO, STA	ND	Min. the overall cost of the SC
[229]	D	O	MINLP	ND	Max. total net profit
[230]	D	SO	G	FR	Min. overall holding costs
[13]	D	SO	DP	ND	Min. system-wide production and inventory costs subject
[231]	D	O	DP	ND	Min. WIP and holding costs; setup time reduction investment
[232]	D	O	ND	–	Min. total costs
[233]	D	O	DP	–	Min. expected total cost
[234]	D	O	DP	CSL	Min. expected total cost

<sup>a</sup>Uncertainty or risk: D — Demand, LT — Lead time.<sup>b</sup>Approach followed: O — Optimization, S — Simulation, SO — Simulation-based optimization.<sup>c</sup>Technique: ACO — Ant colony optimization (meta-heuristics), CQMIP — Conic quadratic mixed-integer programming, DP — Dynamic programming, G — Generic procedure, GA — Genetic algorithm (meta-heuristics), H — Heuristics, IWD — Intelligent water drop algorithm (meta-heuristics), LP — Linear programming, LR — Lagrangian relaxation, MCS — Monte Carlo simulation, ND — Non-disclosed, MINLP — Mixed-integer nonlinear programming, NLP — Nonlinear programming, NSGA-II — Non-dominated sorting genetic algorithm II, PSO — Particle swarm optimization algorithm (meta-heuristics), STA — Spanning tree-based algorithm.<sup>d</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.

\* GS — Guaranteed service.

Fig. 15 illustrates the Literature Map resulted from this SLR, providing an overview of distinct proposed formulations of the safety stock problem in the literature. The Literature Map consists of four levels of iterations. The first level shows the literature gaps identified in the literature. The second level describes the safety stock problems, namely Safety stock dimensioning, Safety stock management and Safety stock placement (allocation or positioning). The third level describes several uncertainties factors and risks associated with the procurement process and therefore considered as input to address safety stock related problems, namely Demand uncertainty, Lead-time Uncertainty, Yield uncertainty and Multiple uncertainties and risks. The last level represents different approaches followed, as well as scientific contributions that use these same approaches to solve safety stock related problems.

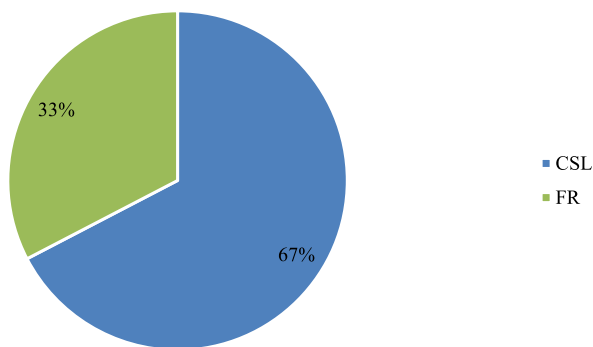
Analysing Fig. 15 we highlight that:

- In general, the Optimization approach is the most used to address safety stock problem and techniques such as heuristics, dynamic programming and mixed-integer nonlinear programming are the most used techniques related to the Optimization approach (as described in Table 7).
- Demand uncertainty is the most common uncertainty factor in the proposed inventory models. On the other hand, there is a lack of studies that considered the lead time uncertainty, as well as the yield uncertainty.
- Recent data-driven approaches, such as Business Analytics (BA) and Big Data Analytics (BDA), are producing a strong impact in diverse research fields, including supply chain management. However, BA and BDA has not yet been explored to solve safety stock related problems.

**Table 16**

Chronological scientific contributions on safety stock allocation, positioning and placement under multiple uncertainties and risks.

Reference	UR <sup>a</sup>	AF <sup>b</sup>	T <sup>c</sup>	SLM <sup>d</sup>	Main criteria
[245]	D, Y	O	SP	–	Min. sum of stockout and holding costs
[246]	D, LT, SD	O	NLP	CSL	Min. total inventory capital
[247]	D, LT, Y	SO	H, MCS	CSL	Min. costs
[235]	D, LT	SO	DP, MCS	FR	Min. inventory cost
[248]	D, LT	O	ND	ND	Total safety stock cost
[10]	D, Y	SO	LP, DES	ND	Min. total expected inventory
[249]	D, LT	SO	DES	FR	Min. components fill rate
[250]	D, Y	O	G	ND	Min. global empty container costs
[236]	D, LT	O	BD	FR	Min. safety stock costs
[251]	D, LT	SO	GA, MCS	ND	Backorders and inventory level
[252]	D, LT	O	H	ND	Nr. of backorders, safety stock level and lead time variability
[239]	D, LT	O	NLP	ND	Min. inventory costs
[253]	D, LT, SD	O	DP	–	Min. total safety stock and project cost
[205]	D, LT	O	ND	–	Min. total supply chain costs
[241]	D, Y	O	DP, H	–	Min. holding cost
[242]	D, Y	O	H	CSL	Min. overall costs
[243]	D, Y	SO	CLM, IPA	FR	Min. holding costs
[254]	D, LT	S	SysD	CSL	Min. inventory costs
[255]	D, LT	O	G	ND	Min. total cost
[256]	D, LT	O	CQMIP	CSL	Min. overall costs
[244]	D, LT	O	G	FR, CSL	Min. holding, fixed order and operating flexibility costs

<sup>a</sup>Uncertainty or risk (UR): D — Demand, LT — Lead time, SD — Supplier delay, Y — Yield.<sup>b</sup>Approach followed (AF): O — Optimization, S — Simulation, SO — Simulation-based optimization.<sup>c</sup>Technique: BD — Benders decomposition, CLM — Constrained level method, CQMIP — Conic quadratic mixed-integer programming, DES — Discrete event simulation, DP — Dynamic programming, G — Generic procedure, GA — Genetic algorithm (meta-heuristics), H — Heuristics, IPA — Infinitesimal perturbation analysis, LP — Linear programming, MCS — Monte Carlo simulation, MINLP — Mixed-integer nonlinear programming, ND — Non-disclosed, NLP — Nonlinear Programming, NLP — Nonlinear programming, SP — Stochastic programming, SysD — System Dynamics.<sup>d</sup>Service level measure (SLM): CSL — Cycle service level, FR — Fill rate, ND — Non-disclosed.**Fig. 14.** Distribution of Service level measure adopted.

After conducting a critical literature analyses, described in Section 5, some research gaps are identified and discussed herein, as well as the research opportunities:

- Several studies in the literature and leading supply chain books, as well as inventory management software tools, assume that the demand during the lead time follows a normal distribution. Yet, several authors have already warned that such assumption may be flawed because lead time demand is often skewed (see, [58,106,113]). This statistical assumption can lead to higher service level than desired, resulting an overestimation of safety stock and consequently higher inventory costs [58]. Hence, in practice, future demands must be forecasted based on historical observations.
- The majority of peer-reviewed articles focus on determining safety stock/inventory based on statistical parameters (e.g., standard deviation or mean of demand) and simplifications (e.g., distribution of statistical parameters, parameters are known) [15]. There is a lack of articles that focus on providing dynamic models that consider the knowledge of future volatility of parameters for determining safety stock. More research is needed to explore not

only the application of more realistic safety stock closed-form stochastic approaches considering the variation of forecasting errors rather than the variation of demand, especially in multi-product multi-echelon inventory management settings, but also to study the benefits of such safety stock methods in case studies with practical interest. Moreover, empirical non-parametric approaches for estimating the variability of forecast errors (see, [61, 62,258]) could be further exploited using for example business analytics techniques. Note that BA and BDA techniques allow the use of predictive analytics for applying machine learning techniques on real data in order to learn or obtain knowledge from data and predict future supply chain demand based on historical and current data. In this context, the prediction capabilities could be also optimized using metaheuristics.

- Several methods for calculating safety stock can be found in the literature based on two main service level measures, namely cycle service level and fill rate. Although the cycle service level has been criticized for not being relevant from a customer perspective and also not recommended for inventory control practice [64,67], it remains the most used in the literature, as illustrated in Fig. 14. Several studies and supply chain books considered the CSL measure because, unlike the FR measure, it is of easy computation. Chopra and Meindl [3], Vandeput [65], Tyworth [259] argued the necessity of transition from CLS to FR because fill rate is a more relevant measure.
- The inventory control problem under lead-time uncertainty is not sufficiently studied, particularly in assembly networks [165]. Demand uncertainty is the most considered factor in the literature (see Figs. 7 and 15). Several studies considered constant lead time, which is not realistic for major of supply chain environments due to the unexpected events that can occur causing random delays. These delays may require to incurring the special/premium freight so that to avoid stockouts and consequently an extra cost for organizations. Moreover, there are few studies that address the safety stock problems on MRP environment considering the lead time uncertainty. Herein, empirical

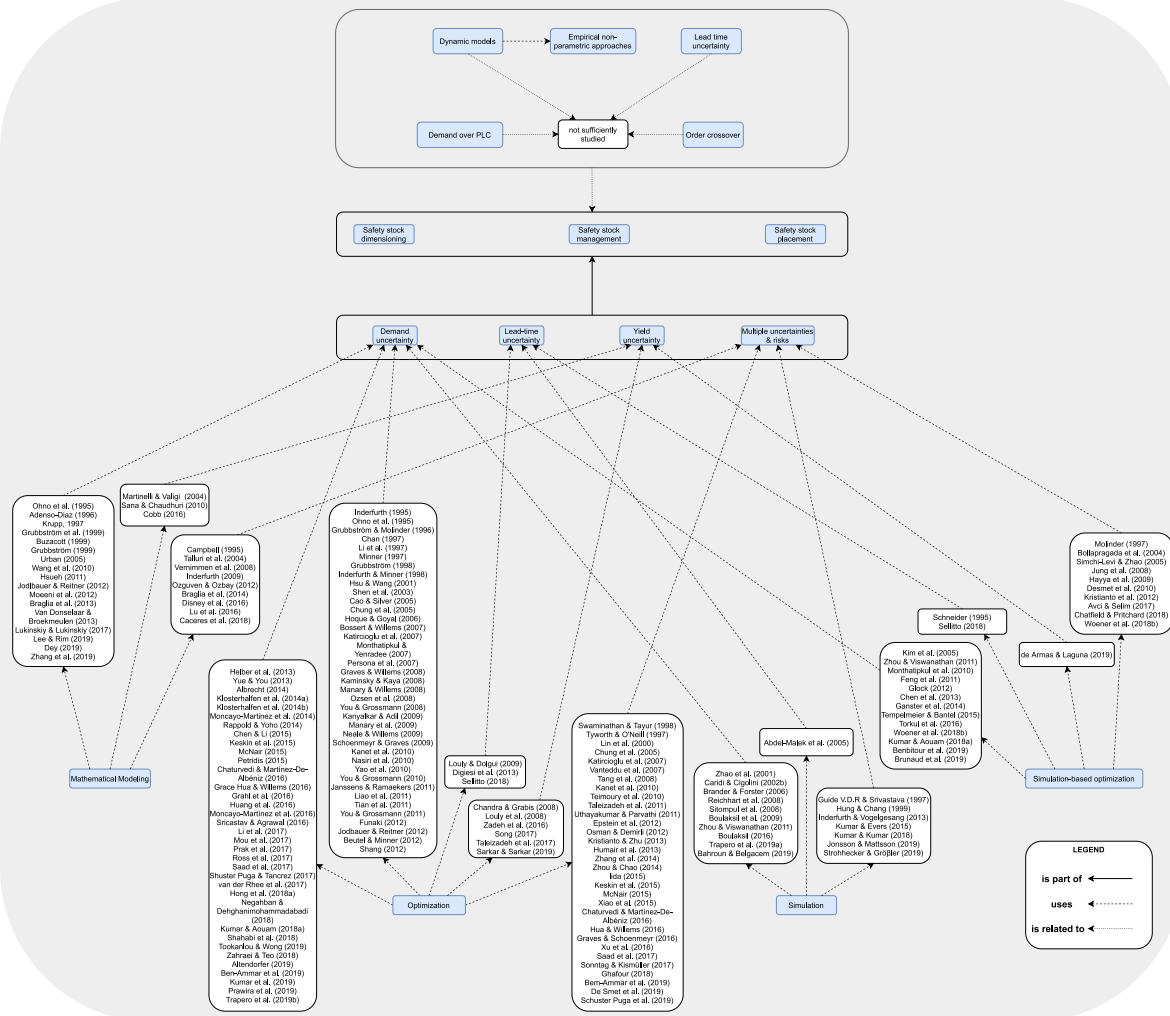


Fig. 15. Literature Map.

non-parametric approaches could also be exploited to address lead-time uncertainty.

- The impact of order crossover in determining safety stock is under-researched. Recent studies in the literature demonstrated not considering order crossover can be translated to larger inventory costs [48]. Riezebos [260] argued that the modern supply chain needs to address the issues concerning expected order crossovers, generally neglected in inventory control literature. Modern supply chains facing the growing occurrence of order crossover, as well as with the increasing importance of service performance [48]. Chatfield and Pritchard [48] stated that “classical inventory modelling methods should be re-examined and perhaps reformulated in order to accommodate the possibility of order crossover”.
- There is a lack of research studies that address the safety stock problem by considering the variation of demand over the Product Life Cycle (PLC) and seasonality [143]. In this review, the only works addressing this issue are [157] and [160]. The PLC is becoming smaller due to technological advances as happens for instance in the mobile phone and electronics components industries. During the PLC, the product demand may increase rapidly at the ramp-up stage, then it stabilizes and starts decreasing at the decline stage. Several traditional inventory models considered that this increase of product demand as stationary, instead of a change in demand in a certain stage of the product life cycle. An accurate demand forecasting is crucial for real-world application

(directly effects the safety stock level, as well as the total inventory costs) and sometimes is very difficult to be estimated under short product life cycle (for instance, fashion products such as shoes and clothing). Techniques such as BA and BDA could be helpful to cope with this issue. For instance, [96] highlight that companies can take advantage of big data for coping with demand surges. In effect, BDA is producing a great impact in various research fields including SCM, providing tools for supporting and enabling strategic and operational decision-making.

## 7. Conclusions

In this paper, we review the topic of safety stock dimensioning strategies under uncertainty factors in procurement process. Safety stocks are important at all stages of the supply chain and due to this makes it an attractive field for researches and practitioners. This topic has been gaining increasing attention over time and this trend is confirmed with the increasing number of publications (see Fig. 3). The systematic literature review was performed following a review methodology which represents a set of processes for selecting relevant scientific publications. It starts with the definition of the “search query” that is applied in both Web of Science (WoS) and Scopus databases (major online databases where the relevant peer-reviewed scientific journals are indexed). After this first stage, the scientific publications are filtered and finally grouped into three main safety stock research domains: safety stock dimensioning, safety stock management and

safety stock allocation or positioning or placement. As a result, a set of 193 scientific publications was selected from 1995 to 2019. A co-occurrence analysis is performed in order to identify research concepts related to the safety stock problem. This review might have limitations, even with a large number of scientific publications analysed (is not devoid of limitations). Two main limitations are pointed out. Firstly, some of the relevant publication could be non-identified due to the “search query” developed in the review methodology. Secondly, we only considered publications that meet the defined criteria in three “screening criteria” of our review methodology (e.g., only considered peer-reviewed publications while excluding the conference proceedings and only considers publication written in English). The current research gaps and research opportunities are identified and discussed so that to provides a road map to guide future research agenda on this topic.

Considering the presented literature review, we highlight several relevant insights regarding different contexts:

- For the MRP context under both demand and lead time uncertainty, the safety stock is the best technique in case of the low level of stockout/inventory holding cost, and also in case of a high level of demand variability and low level of lead time variability. On the other hand, safety lead time is the best technique in case of a high level of stockout/inventory holding cost ratio and in case of a high level of demand and lead time variability [125];
- For the manufacturing/remanufacturing context under stochastic demand, should be adopted different inventory control policies for different PLC phases (introduction, growth, maturity and decline); Moreover, the inventory control policy is not sensitive to the phase length and the demand changing rate [157];
- Demand uncertainty is the most considered factor for determining safety stock in different contexts, in contrast, lead-time uncertainty is not sufficiently studied, especially in the MRP environment [165]. Fig. 7 reinforces this statement, showing that demand uncertainty is the most considered uncertainty factor in proposed studies in the literature;
- There are several factors/parameters that should be considered, such as the PLC, demand uncertainty (demand forecast and forecast errors), lead time uncertainty, price fluctuations (e.g., price fluctuation in the market, discount campaigns, promotions), seasonality (sales pattern) and supplier constraints or supply disruptions. Considering only basic parameters (e.g., lead time, actual demand, forecast demand and forecast errors) for calculating safety stock is insufficient. The ERP systems widely used by companies consider values of these parameters from past data to calculate the safety stock using statistical formulas.

In conclusion, the safety stock problem is still an interesting topic for researches and practitioners, since, with the emergence of the industry 4.0 new challenges have been arisen in all processes of the supply chain. Although the safety stock is used in inventory management to deal with demand and supply uncertainties, it does not solve all problems related to this domain. Other techniques or strategies, such as buffering (reactive) and redesigning (proactive) can also be used for solving or mitigating inventory management problems, such as safety time or capacity buffer. The use of these techniques depends on the specific case study and the context.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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