Advanced Structured Materials manuscript No.
(will be inserted by the editor)

Demand forecasting, production planning, and control: a systematic literature review

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Received: date / Accepted: date

Abstract The study of demand is fundamental for organizations in all three sectors. In particular, it marks the Production Planning and Control (PPC) of goods and services, which are fundamental steps for the sustainable development of any business. Thus, there is much research on demand forecasting as well as on PPC. In this sense, the use of more or less sophisticated mathematical models dedicated to the theme of time series is indispensable. However, some authors warn about these practices' decline by production managers for two reasons: the shortcomings of the simpler models and the complexity of the best models. Thus, there is no consensus or even intense discussion about the best formalism of demand time series modeling to adopt in PPC. This paper presents a systematic review of recent literature on demand forecasting for PPC and the underlying time series formalisms from this proposition. We found 60 articles on the topic, from 2014 to 2019, based on Scopus, ScienceDirect, IEEE, EBSCOhost, Emeraldinsight, Jstor, Taylor & Francis Online, CAPES Journal Portal, and InderScienceOnline. The synthesis of the review was performed from a lexical analysis. As the main findings, the research reveals the literature imbalance, which raises the difficulties of better results in PPC. It should also be noted that few works dedicated to the PPC have resorted to the combination of predictors, one of the most successful time series modeling and forecasting classes, either for its simplicity or the quality of its results.

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Keywords Demand Forecasting · Time series · Production Planning and Control · Systematic review · `IRaMuTeQ` software · Lexical Analysis · Quality control · Stochastic Process · Management

1 Introduction

The need for a sustainable development model has challenged organizations and governments. For example, to remain competitive in the market, manufacturers need to produce high quality under low cost, short-term customization, maintain sufficient flexibility, and meet rapidly changing customers' demands [1]. Further, respecting the characteristics of the natural environment has been paramount. In recent years, various methods, following different theories and approaches, have been proposed to analyze the complexity of production [2]. This scenario has led engineers, production managers, and business managers to use tools capable of mathematically modeling, designing, and analyzing production systems. These tools facilitate the incorporation of robust policies in the presence of disturbances and mitigate the negative impacts of turbulence on the production environment [3].

Thus, Production Planning and Control (PPC) has become an essential task of the production system [4]. In particular, demand planning is critical once it is based on predictions of future demands [5]. The big challenge is to identify the best modeling strategy to promote statistically accurate and efficient predictors. Indeed, it is expected that no single forecasting method (i.e., that is based on only one modeling formalism) surpasses all other methods for all-time series cases [6]. The probability of poor results under individual modeling is high [7].

This paper investigates, from a systematic literature review, the scope under which the PPC and tools of time series analysis of demand interact. Specifically, the paper seeks to map scientific production regarding demand time-series analyses applied to the PPC: the models, methods, techniques, and practices used by the manufacturing and remanufacturing industries to study their demands. Text mining tools drive the methodological route, making it easier to navigate a more significant number of documents.

The article is structured in six sections. Section 2 presents the general context for demand forecasting and PPC. Section 3 highlights introductory concepts about lexical analysis. Section 4 summarizes the methodological course adopted in the paper. Section 5 summarizes the results and discussion, and finally, Section 6 shows the paper's conclusions.

2 General Context

The PPC deals with the determination and solution of the tasks related to production, considering the main productive factors (resources, operations, conditions, and objectives) and controlling the execution of decisions [8, 9]. This

interpretation includes the planning and implementation of production [10]. According to [1], PPC has a fundamental role in the operation of a company. It allows the manufacturer to gain visibility and control over all manufacturing activities [11]. [10] point out that one of the fundamental problems of the PPC is that readiness for delivery, inventory, and utilization of production resources are complex variables that cannot be managed independently of each other, mainly when disturbances and/or uncertainties occur during the execution of the processes. Successful production planning depends on the modeling quality of numerous problem-related aspects, including production lead times, capacity, and demand uncertainty. The value of demand forecasting information has been the subject of many kinds of research in the inventory literature, but with limited application in production planning [12]. Demand forecasting becomes a fundamental component within a production planning system [13]. Forecasts are revised as new information becomes available over time [12, 14].

The primary source of information for forecasting is a time series. A time series is a sequence of observations collected at regular periods about the same phenomenon [15]. Therefore, it is known when a new registration occurs, although the outcome of the phenomenon to be registered is uncertain. Its modeling facilitates system synthesis, control, and intervention actions, while its prediction favors planning actions. The prediction problem of these series arises naturally in several areas [16]. In this sense, research and statistical modeling have been very useful [17]. As an example, we highlight not only the demand series forecast for the PPC [7, 18–20] but also applications in the remanufacturing industry [18], in production planning integrated with inventory management [12], in inventory control itself, for spare parts [21], intermittent demand processes [22] and spare parts [23, 24], in fault-prone production systems [25], and in the food manufacturing industry [20]. There is the problem of uncertainty in common, being considered one of the most critical planning issues [26].

Given the importance of anticipations for the PPC, several researchers worked on approaches to contribute to the forecasting system [27]. Research describes more accurate and efficient statistical forecasting models that minimize total costs, improve inventory levels and production planning. Among a large number of published methods, some of the most cited are summarized in Table 1.

3 Lexical Analysis

The lexical analysis appears as a promising method for understanding the structure and trends of literature in general. Once a set of texts, or textual corpus, has been constructed, reflecting the literature on a given theme, one can use lexical analysis to facilitate content analysis. This text mining involves ranging from frequency distributions of terms to figures and association tests that summarize the main ideas behind the documents. Accurately, studies of

Table 1 List of published works with approaches to demand forecasting for the PPC

Approach	Features	Authors
PPC in remanufacturing	They examined the effectiveness of remanufacturing demand or remanufacturing by time series analysis, considering two characteristics that complicate PPC in remanufacturing: uncertainty in terms of time and quantity of products returned and the need to balance returns with demands.	[18, 26, 28]
Production planning based on demand forecasting	The proposition of a method for the automatic selection and configuration of a prediction model appropriate for customer demand time series. The method incorporates correlations between 26time series characteristics and predictive accuracy of six distinct methods.	[7]
Manufacturing industry production planning based on demand forecasting	They developed a framework based on time series-driven forecasting methods to select reordering strategies for the independent demand of a product for small manufacturing companies.	[19]
Single-item single-level production planning issue with dynamic and uncertain demand	They optimized production planning by integrating the forecast update procedure, specifically performed on a single system of single level with non-stationary and random demand, where production lead time is reduced for a period, and backlogs are allowed. The optimal production quantities were calculated in a specific case where linear regression is the forecasting method used, and the production lead time is equal to one period.	[29]
Robust production planning under demand uncertainty via conditional value at risk.	He proposed a mathematical model for robust production planning to optimize decisions regarding cost objectives and minimum production delays. This model considers the stochastic nature of customer demand and generates a production plan that indicates the quantities of each product to be produced, the start of production of each product, and the facility in which the products are to be produced.	[30]
Modeling, simulation, performance evaluation, and production forecasting.	Application of Petri net-based methodology to model, simulate, evaluate performance, and predict the production of a tannery industry. By applying the exponential smoothing method to predict the overall demand for each product type.	[31]
Comparison between forecasting models for production schedule planning.	Comparing the performances of the Trend Analysis, Decomposition, and Holt-Winters models for predicting a time series of food industry product demands to predict the timing of production schedule planning demands to meet customer needs customers on time.	[32]
Synchronized Demand Production Forecast.	Accurately predict fluctuating demand within several days of delivery and thus have the ability to predict production volume. The method for forecasting production volumes, based on data analysis of past order and the determination of their similarity by Fourier analysis.	[33]
Supply Chain Spare Parts Forecasting.	Improve the predicted quality of estimated machine breakdowns to improve spare parts supply chain planning.	[34]
Demand for spare parts.	Forecasting method for irregular demand, typical of spare parts dedicated to mining companies. The method combines information criteria, regression modeling, and artificial neural networks.	[23]
Grey forecast model for short-term manufacturing demand.	Applying an adaptive grey model to predict short-term manufacturing demand to solve forecasting problems related to a small data set with varying demands makes it challenging to keep up with product development trends.	[35]
Production planning in a supply chain.	Proposes a classification of forecasting methods for production planning in a supply chain. Based on the process of analytical hierarchy, it has proven useful in multicriteria decision-making in many industrial and real-world applications.	[36]
Demand forecasting by approaching system dynamics.	Capacity expansion planning from Malaysia auto industry demand forecast using systems dynamics approach.	[37]
Integrated mixing model of local experts.	Construction of an integrated mix of local experts to forecast demand using a lagged Gross Domestic Product (GDP) indicator as an independent variable. The model is employed to deal with rapidly changing situations and improve forecasting performance, providing a way to account for short-term fluctuations in demand due to changes in economic activity growth within an easy-to-use forecasting method.	[38]

group specificities, hierarchical classification, similarity analysis, word cloud, and statistical association tests can be performed [39, 40].

Concerning the word cloud graphic, for example, the grouping and graphic organization of words according to the frequency with which they appear in the analyzed corpus, allow quick identification of the most commonly used keywords [40]. The Zipf Law, also known as the empirical law, developed by George Kingsley Zipf [41], analyzes the distribution of the repetition frequency of the words of the corpus. Thus, it is possible to represent the relationship between the order of frequency of use and the frequency itself, through graphs involving the rank of occurrence of words [42]. This distribution has been used to model scientific productivity [43].

In turn, cluster analysis or classification is a group of multivariate techniques for computing significant subgroups of individuals or objects [44]. According to some predetermined criteria, its main objective is to aggregate objects based on their similarities [45, 46]. One of the main ways to illustrate these groups is through dendrograms. This diagram presents the division of the textual material used in the research into final groupings. Groups are organized into several classes from content partitions. As for dissimilarities, they can be assessed from distance measurements, such as Euclidean, and association tests, such as Pearson's chi-square [47].

The Descending Hierarchical Classification (CHD) method proposed by Reinert (1990), for example, classifies text segments according to their respective vocabularies, and their set is divided based on the frequency of the reduced forms (words already lemmatized) [48]. This analysis aims to obtain classes that, at the same time, present similar vocabulary to each other and different vocabulary from the other classes [49]. For each class is computed a list of words generated from Pearson's chi-square test [48–50].

Already the Correspondence Factor Analysis (CFA) is a multivariate technique that statistically groups words in axes, depending on the co-occurrences of words in segments [47, 51]. The analysis looks for patterns in a set of variables, clearly demonstrating the proximity and distance between the words themselves and the word clouds [52, 53]. The method determines the main factors in a dataset by defining how variables are weighted in the factors [54]. The first factor holds the most information about the association between the variables; the second retains the second-largest amount, and so on [55, 56].

The proximity analysis of words in the segments and the recurrence of this proximity indicate a conceptual field existence. Moreover, the closer two words appear in segments, the stronger the indication of the existence of an underlying conceptual field [57, 58].

Although two concepts may belong to different lexical fields, a high frequency of occurrence in the same segment indicates a conceptual field containing both [59]. This method is called the similarity analysis [60].

All of these tools can be found in software like `IRaMuTeQ`. `IRaMuTeQ` (Interface for Multidimensional Analysis of Text and Questionnaires) is a free tool created by Pierre Ratinaud (2009) with open and collaborative technology. It was developed under the open-source logic and is anchored in the R statistical

environment [61] and the Python language [50, 60]. Thus, the program enables mapping literature through lexical approaches, facilitating content analysis [62].

Although lexical analysis is incipient in the PPC approach, other areas have explored its ability to conceptualize themes that emerge from a textual corpus. As an example, [63] explored, among nursing mothers, positive and negative experiences in performing exclusive breastfeeding practice. [64] analyzed discourses in the field of ecological economics in a substantial corpus of abstracts. [65] have examined the definitions of marketing throughout the history of this management science. [66] used the method in data collected on congenital malformation, aiming to unveil the feelings experienced by mothers of babies with microcephaly. [67] applied in focus group transcripts to understand cultural differences in definition and innovation concerning traditional food products. [68] used to extract factors that motivate land-use policies in southern France from a corpus of interviews. Finally, [69] employed lexical analysis as part of the systematic literature review process for entrepreneurship.

4 Methodological Path

For the systematic review of the literature, the research problem was defined as "How do PPC and tools of time series analysis of demand interact?", aiming to establish the articles included in the study. Then, we sought a representative sample of the scientific literature that could answer the research question, using keywords such as "Demand Forecasting, Time Series, Planning and Production Control (PPC)". Finally, this literature was synthesized, and the content of the included articles was analyzed using the `IRaMuTeQ` software.

Considering the objective of mapping the scientific production on the descriptors, the construction of the textual corpus [48, 70] was performed by crossing the descriptors as well as their correlates. The research had an exploratory and descriptive character since it aimed to provide a broad understanding about the theme of Demand Forecasting, Time Series, and their interaction with Production Planning and Control (PCP), allowing to identify prominent aspects in the field and potentials research trails and gaps [71]. The research was also inferential, seeking to identify associations between terms representing the literature under a statistical study.

Scopus, ScienceDirect, IEEE, EBSCOhost, Emeraldinsight, Jstor, Taylor & Francis Online, CAPES Journals Portal, and InderScienceOnline were consulted to identify publications due to their easy access to journals, documents and by providing peer-reviewed abstracts, titles, keywords, and citations, in addition to being considered by the research community the largest databases of academic and scientific papers.

The databases also have a significant repertoire of tools that facilitate bibliometric evaluations [72]. Some of these keep several articles available to researchers and stakeholders, allowing one to export documents in various formats. After searching the databases, a Google Scholar search was performed

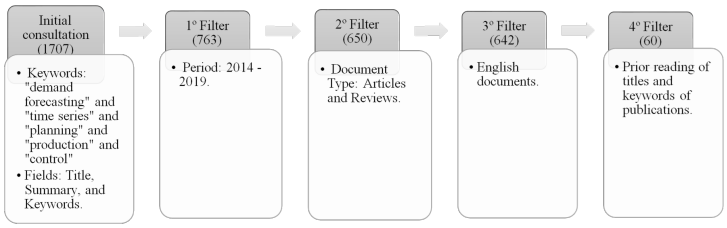

Fig. 1 Constitution of the research sample to the databases consulted about the literature involving demand forecasting, time series, and PPC

for documents not indexed in the searched databases. Figure 1 summarizes the methodology adopted for document selection.

Initially, the database indexed titles were consulted, based on the previously defined criteria for the systematic search of the documents to be analyzed, resulting in a total of 1,707 containing the search expressions in the "title," "summary," or "keywords", considering records from the entire knowledgebase period to the date of extraction - November 2019.

The first filter searched to select documents published in the period "2014 to 2019", with 763 found. The second filter applied limited the search to the categories "articles" and "reviews," leaving 650. The last filter included the restriction to documents in the English language, resulting in 642; it is considered a preview of the established sample for the research. Based on this sample, two types of analyses were performed. The first was dedicated to a previous reading of the title of the documents and keywords to identify and evaluate the characteristics of the documents related to the research theme, and 60 were selected for this purpose using `Microsoft Excel` support. Once the corpus was built, its lexical analysis began, supported by the `IRaMuTeQ` software, version 0.7 alpha 2. For this, the keywords, abstracts, introduction, and conclusion of the articles were identified and explored by the "analysis" tool text, presented through illustrations and word groupings, and allowed inferences about textual data systematically and quantitatively [73]. For the lexical analysis of the textual corpus, each article corresponded to a document. In turn, each text segment (ST) of this article corresponded to a text fragment.

5 Results and discussion

The search for articles in the databases provided insight into what is being researched and scientifically published on time series analysis for demand forecasting and PPC. We obtained 60 articles on the topic, from 2014 to 2019, a record of a significant amount of documents, showing the researchers' concern with the PPC from the demand forecast. The corpus was then composed of 60 documents, which resulted in 1,914 text segments (TSs), with about 90% utilization. From these, 60,021 occurrences (words, forms, or vocables) emerged, covering 5,391 different words (numbers of forms) and 2,123 with a

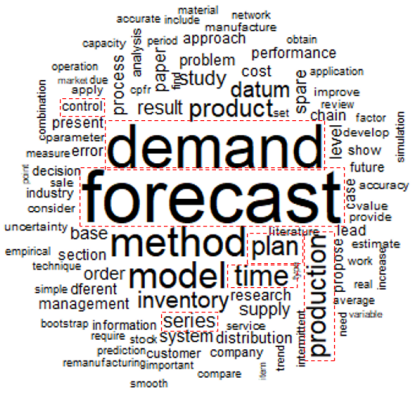

Fig. 2 Word cloud of the textual corpus about the international literature involving demand forecasting, time series, and production planning and control

single occurrence (hapax) throughout the corpus, being considered 39.38% of forms and 3.08% of occurrences.

Figure 2 highlights the 100 most frequent words in the corpus, with a minimum of 60 mentions. Therefore, the contents of the abstract, keywords, introduction, and conclusion of the selected articles were considered. From the figure, it is possible to infer the importance of the terms “forecast,” “demand,” “time,” “planning,” and “production,” with a frequency of 1340, 1094, 443, 401, and 393 repetitions respectively in the transcription of the term textual corpus. This is evidence that the analyzed documents present substantial contributions to t the topics addressed in the research. However, it is noteworthy that modeling is put in the background, with a frequency of 585 times, and the uncertainty appears 97. Besides, also in smaller quantities, it is observed the presence of the terms “series” and “control” with a frequency of 241 and 128, in that order.

Complementarily, from the Zipf distribution display in Figure 3, `IRaMuTeQ` provided the behavior of the word frequency log in the evaluated corpus. On the vertical axis, the logarithm of the number of times a form or word appears, while on the horizontal axis, the logarithm of the rank. As a result, many repeatable forms are observed, and a low number repeats many times. Note also a reasonable distance between the frequencies of the first and second most cited terms forecast (1340) and demand (1094). On the other hand, the lower the frequency of citations, the closer the ranks involved, suggesting an imbalance in the use of the main terms. Ideally, the points in the figure would suggest a linear behavior.

A Descending Hierarchical Classification (DHC) was performed to identify the main groups of relationships in the corpus in detail, leading to the dendrogram of Figure 4. Three classes were formed from the associated texts, according to Pearson’s chi-squared test. In each class, the words with the most emphasis were the most frequent, allowing to infer their main topic. Class 1,

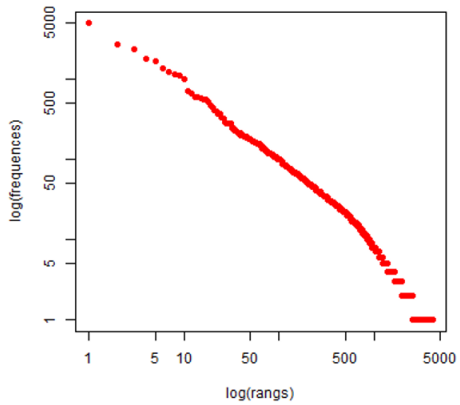

Fig. 3 Zipf diagram of active word frequency in the general textual corpus about International literature involving demand forecasting, time series, and production planning and control

here named **"Contexts and Application"**, with 793 TSs, represents 46% of the texts. In turn, Class 2, named **"Statistical Rationale"** with 650 TSs, identifies 37.7% of text segments and is dedicated to the foundations for Class 3. Class 3 is dedicated to **"Modeling and Prediction"**, with 281 TSs; it characterizes 16.3% of the complete texts. It is argued here that the high percentage of terms representing "Applications" (Class 1), relative to "Statistical Rationale" (Class 3) and even "Modeling and Forecasting" (Class 2) reveals unbalanced literature and raises the difficulties of better results in the area of PPC.

From the analyzed textual corpus, Class 2 presents the smallest number of text segments indicating a low exploration of the formative terms of the conceptual field "Modeling and Forecasting" in the PPC. This observation may reflect a departure from the formalisms dedicated to demand (considered the most crucial variable of a production system, especially for the functions developed by the PPC) concerning the other areas of the organization.

Particularly, Class 1 consists of articles that prioritize studies and concepts on PPC, Production Planning, Supply Chain, and Industry [12,20,23,25,30, 31,36,37,74–87].

Class 2 (Figure 4), on the other hand, groups concepts regarding parameters, variance, error, measurement, and estimator focused on statistical inference. It can be seen that, in addition to the concepts found, a significant relationship between the terms bootstrapping, simulation, lead time, forecast error, forecast accuracy, forecast quality, demand distributions, model parameters, and parameter estimation [21,22,26,38,88–93].

Class 3 is dedicated to the inference of demand phenomena, from formalisms such as artificial neural networks, autoregressive integrated moving average (ARIMA), exponential smoothing, and average models. In other words, it deals with concepts related to modeling and demand forecasting,

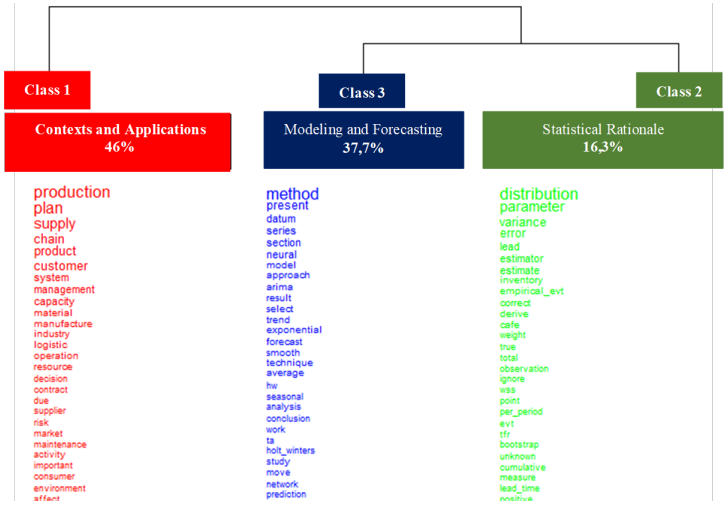

Fig. 4 Representative dendrogram of class and word breakdowns of international literature involving demand forecasting, time series, and production planning and control

involving the performance of linear and nonlinear models, combinations, and incorporation of methods [7, 13, 24, 28, 32, 35, 38, 88, 94–102].

According to Pearson's chi-squared statistic, table 2 provides a list of the main words statistically associated with these classes. In this case, the p-values for association were always less than 0.0001. The chi-square column of the table shows the dependency statistics between word and class; the higher the value, the higher the probability of dependence.

Table 2 Test of association between words and classes about the international literature involving demand forecasting, time series, and production planning and control

Class 1: Contexts and Applications			Class 2: Statistical Rationale			Class 3: Modeling and Forecasting		
Word	Chi square	% of citations	Word	Chi square	% of citations	Word	Chi square	% of citations
Production	161,57	81,3	Distribuition	225,83	69,6	Method	206,83	65,1
Planning	142,07	77,6	Parameter	159,72	64,8	Present	89,01	75,2
Supply	125,67	86,6	Variance	126,22	83,8	Data	80,22	64,5
Chain	91,79	85,3	Error	97,02	48,3	Series	75,91	67,2
Product	91,72	74,6	Lead	96,14	49,6	Section	64,37	78,8
Customer	89,05	90,5	Estimator	91,87	95	Neural	62,48	100
System	65,49	77,1	Estimate	82,8	54,8	Model	52,66	53,3
Management	65	80,3	Inventory	65,22	33,5	Approach	52,31	66,7
Capacity	54,3	96,2	Empirical	62,05	100	Arima	48,7	94,3
Material	47,77	94	Correct	59,91	83,3	Result	47,12	59,5

Also, `IRaMuTeQ` enables AFC. The analysis was applied to the text data, considering the three classes presented above and the metadata underlying the articles, in terms of year of publication, author's country, and indexed base. Thus, it was possible to synthesize the information from the proximity of the vocabularies and documents in the classes. The tool was able to model all the variability of terms citation frequencies throughout the articles visited from two factors. It is, thus, an analysis of outstanding quality [50, 55].

Figure 5 highlights, for example, the most dissimilar documents in each class among the 60 articles studied. Thus, the document labeled "$^*doc_{65}$" focused on the statistical basis (Class 2) more dissimilar or more uncommitted to contexts and applications (Class 1) and modeling and forecasting (Class 3). The paper is concerned about the effects of forecast errors and the estimation of unknown demand parameters. It proposes a framework for modeling forecast error distributions to model the uncertainty associated with estimation and include it in inventory decision-making. Besides, it uses a numerical study to show the cost of ignoring parameter uncertainty. The research is focused on inventory decision-making by forecasting uncertainty and uses the Bayes rule in parameter modeling. It contrasts the documents from the "Contexts and Applications" class, whose approaches are more related to solving production planning problems, and those in the "Modeling and forecasting" class where the significant commitment is to the development, improvement, and accuracy of forecasting methods.

The "$^*doc_{43}$" of contexts and applications (Class 1) near the center of Figure 5 appears to be the most harmonious or most committed to the three classes. It is dedicated to irregular demand forecasting in mining companies, characteristic of the class itself. It combines information criteria, regression modeling, and neural networks in the formulation of a hybrid model. The method's efficiency is verified by comparing with other traditional and artificial intelligence-based forecasting methods, properties of the modeling, and forecasting class.

The most dissimilar of the modeling and forecasting category was "$^*doc_{15}$", which shows a renewed interest in Holt-Winter (HW) forecasting technique, placing exponential smoothing procedures on solid theoretical bases, identifying and examining the models underlying statistics. It presents an improvement in the HW method to forecast noisy demand and shows that a reduction in forecast error (MSE) can be achieved. The document expresses a strong commitment to model improvement and accuracy and a distancing from class contexts, applications, and statistical foundation. This category has researchers spread across all continents. In turn, the category devoted to "Statistical Rationale" appears to be much smaller, with more excellent representation from European researchers.

The dissimilarity in the field of contexts and applications was highlighted by "$^*doc_{37}$", which demonstrates a concern with developing and constructing flexible production systems to manufacture various products while maintaining high efficiency. The system seeks to estimate the fluctuation of demand over a period accurately and thus can predict production volume, in contrast to "$^*doc_{15}$", whose commitment is to improve the forecasting method. This category has a higher concentration of research by Asian scholars.

From the graphical representation of Figures 6a and 6b, it is observed that there was a semantic range of most frequent words in the corpus: forecast, demand, method, model, and time, grouped in central and peripheral zones.

The similarity analysis performed (Figure 6a) provides a representation centered on the word forecast and on groups of concepts such as demand,

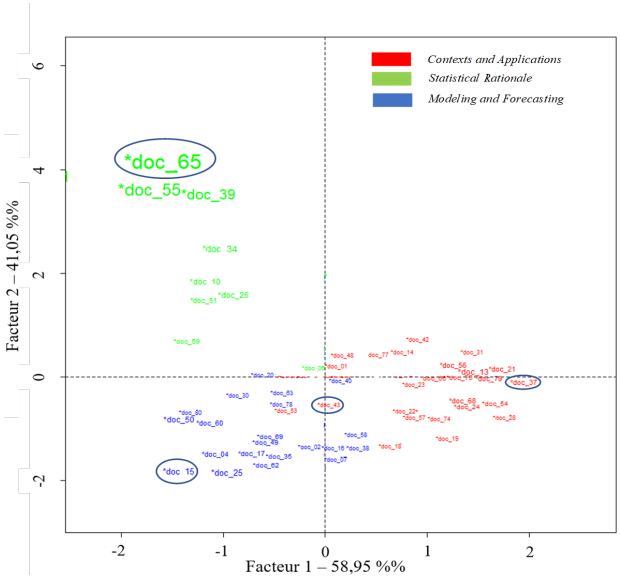

Fig. 5 Representation of metadata (Doc) about the international literature involving demand forecasting, time series, and production planning and control

plan, model, and method that are interconnected but independent. These can be considered equally important in the literature for the PPC. Thus, there is evidence that previous research considers specific study subfields applied to the PPC, such as production planning, inventory control, inventory performance, resource planning, decision-making, supply chains, etc. Still, in Figure 6a, there is a certain deficiency of research in which the demand planning for the PPC occurs from applied models (formalisms) to time series. The methods applied in these cases are considered simple and can present high forecast errors. The second lexical similarity analysis was performed considering the subset of the most commonly used words (i.e., demand, time, method, plan, and model) and without the central concept of forecasting. This analysis allows a more in-depth look into the underlying conceptual fields (Figure 6b).

Figure 6b shows the existence of some related concepts that appear in a new mapping. However, we note the low relationship between the concepts plan (green group) and demand (red group), which presents a low volume of research that uses demand as a form of production planning.

It is evident from the relationships between the subset of the active words in the dendrogram that the prediction process presupposes a rationale and practical application. This process is the starting point for making decisions related to Production Planning and Control. The words referring to the elements associated with the PCP appear independently of the terms pertinent to the forecast. This tends to show that concepts are not yet well connected in the literature. Unlike concepts such as forecasting-related *model, planning, method*, and *supply chain*, which are more clearly connected.

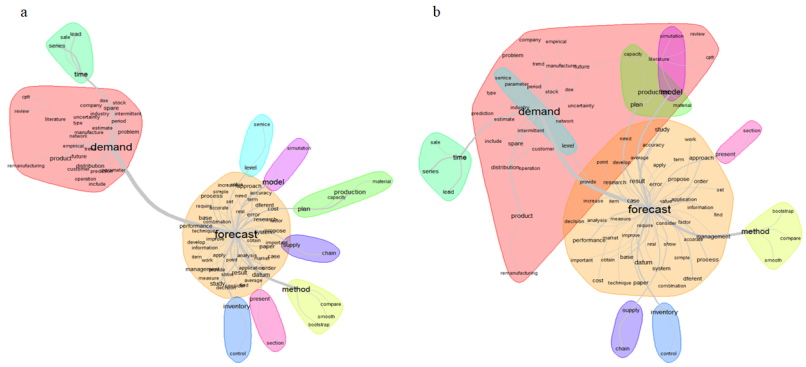

Fig. 6 Similarity Analysis (a) between corpus words about international literature involving demand forecasting, time series, and production planning and control and (b) centered on the subset of the most commonly used words about international literature involving demand forecasting, time series, and production planning and control.

The forecasting models, methods, and techniques identified in the documents analyzed are fundamental to demand planning and essential to subsequent planning and effective production control steps. Authors suggest that the quality of predictions can improve significantly by appropriately combining different methods [28,103], especially compared to individual models. For example, [23] used the combination in forecasting irregular demand, typical of spare parts. [104] established a demand prediction model for production activities, combining the forecasting mechanisms of exponential smoothing and artificial neural network methods. [88] empirically explored the efficiency of combinations in predicting intermittent demand produced by parametric methods.

Despite the use of different forecasting formalisms, from the 60 documents analyzed, there is a little exploration of robust individual methods, still less of the combination of models, and the use of different incorporation techniques in the forecasting of demand from time series and also exploitation in the footwear manufacturing industry or cleaning products.

6 Conclusion

PPC has appeared in the literature many years ago and has been a popular topic for research ever since. There is no consensus on the performance of a specific method in forecasting demand for production planning. Thus, this study has a double contribution: first, a systematic review of the literature on the interaction between demand forecasts as a powerful tool of the PCP and time series formalisms and, second, a lexicometric analysis of the literature on the selected documents, facilitating content analysis.

The analysis of the textual statistics performed by `IRaMuTeQ` revealed the contribution manifestation of the themes approached in the research and the

interaction between the demand forecast for PPC and time series formalisms. With the hierarchical study of terms representative of the literature, three classes were identified, *"Contexts and Applications", "Statistical Rationale",* and *"Modeling and Prediction",* where it was possible to infer the themes addressed in each and the relationship between them. Note that each class represents a conceptual field. However, there was a significant distance between these classes. These features reveal an imbalance in the literature that, in turn, may be contributing to an increase in the difficulty of improvement in the area of PPC. Moreover, from the percentages of the textual corpus associated with each conceptual field, it was possible to notice a higher concentration of research related to the *"Contexts and Applications",* showing a greater interest of the researchers in the subject and facilitating content analysis.

The research also reveals that the words of one class do not present a certain degree of proximity to those of another, reinforcing the existence of different conceptual fields. This finding may be due to the proximity of words within the class and possibly the relationships outside it. Thus, understanding and approaching these conceptual fields becomes a challenge for future research. The development of works that seek this approach (integration) is an alternative to be researched, explored, and developed.

The analysis of this lexometric literature review documents allowed us to identify different models and methods of demand forecasting, following different theories and approaches. Despite the use of different forecasting formalisms, we observed little exploration of robust individual methods, the combination of models, and different incorporation techniques to forecast demand from time series. Thus, identifying a path of opportunity for process improvements and forecasting performance. Consequently, it is an advance in demand and production planning.

Among the main limitations of the approach adopted in the article, it is noteworthy that it was limited to documents only identified by using the keywords *"demand forecasting", "time series",* and *"planning and control production",* indexed to databases, in English and from 2014 to 2019. Thus, documents with other terms, before this period and in another important language, may have been overlooked. Secondly, lexicometric analysis provides a means of quantifying the connectivity of concepts, but this method cannot reveal more abstract aspects, for example, stories or argument structures. Future work will be devoted to these themes.

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