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The order fulfillment problem in the textile industry: MIP models for service-levels constraints and integrated production-distribution problems

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Abstract

In this work, we address the production planning problem by focusing on meeting orders in the textile industry and analyzing how mathematical programming can support decision-making. Aiming to characterize the textile industry in São Paulo, Brazil, we performed an exploratory survey with managers of textile industries in the state. The survey highlighted crucial factors for the competitiveness of the companies, such as customer relationship, quick response, and production scheduling. It also shows the lack of management information systems for production planning. Additionally, an extensive literature review further contextualizes these challenges within the scope of textile supply chain management, highlight areas where mathematical programming can be applied to address production planning problems in the textile sector. Based on the identified gaps, we propose two mixed integer programming models for production planning problems focusing on customer order fulfillment. The first model focuses on service-level and capacity utilization constraints within capacitated lot-sizing problems, exploring the effects of these constraints on key performance indicators such as delay times, throughput, and capacity utilization. The second model supports integrated production and distribution decisions, demonstrating its advantages over hierarchical models through a comparative analysis. We also proposed an Adaptive Large Neighborhood Search (ALNS) heuristic to solve the integrated model in lower computational times, offering insights into the operational complexities of textile manufacturing.

Keywords: mixed integer programming, order fulfillment, lot-sizing problems, integrated production and distribution, service-level constraints

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1 Introduction

1.1 Context

The textile supply chain plays a critical role in the global economy. In 2021, the international textiles and apparel trade was valued at US$ 616 billion. Furthermore, the textile industry holds significant importance for the Brazilian economy, ranking as the second-largest processing industry in the country. In the previous year, the production of textile and clothing products amounted to 2.16 million tons, generating R$ 190.3 billion (US$ 37.50 billion) in revenue. The production involved 22.5 thousand productive facilities, 1.34 million formal employees, and 8 million indirect employees, considering both indirect and income effects (ABIT, 2022).

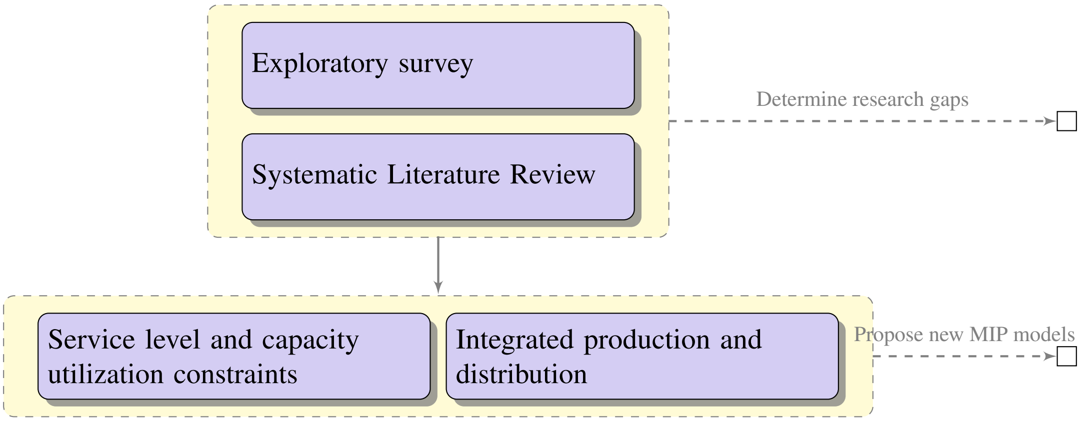
The textile industry demonstrates typical market characteristics, including a short product life cycle, high volatility, low predictability, and a high purchase level (Li et al., 2016). These challenges are presented in the Brazilian textile sector, where the state of São Paulo stands out. With a revenue of R$ 43.4 million, São Paulo leads the national ranking, accounting for 27% of Brazilian total textile revenue (CETESB, 2023). In this work, we investigate the production challenges faced in the textile sector in the state of São Paulo and how mathematical programming optimization can serve as a valuable tool for decision-making in the context of textile industries in the state of Sao Paulo.

The textile supply chain encompasses many activities, from fiber preparation, yarn manufacturing, and fabric creation to apparel production and distribution. Each production stage has unique operational challenges. This work is a multipaper thesis in which we present a comprehensive overview of production challenges in textile industries. We explore the application of mathematical programming to address production planning problems, offering insights into how these models can support the decision-making process and benefit the industry regarding sustainability, efficiency, and customer satisfaction. Based on the sector needs and literature gaps, we propose two mixed integer programming models for production planning problems focusing on order fulfillment. We also extensively discuss the results and managerial implications.

1.2 Objectives

The objective of this work is to analyze how mixed integer programming (MIP) can support decision-making in textile industries, taking into account the specific needs of the sector. Each chapter of this thesis is an independent paper contributing to the state-of-the-art and practical applications within the textile industry. To comprehensively describe the textile sector in São Paulo, we conducted an exploratory survey to identify the main production problems and the use of information systems to address those problems. A systematic literature review of mathematical programming models in the textile supply chain is conducted to identify the primary gaps in existing research. Subsequently, based on some production problems highlighted in the survey and the literature review, we proposed two MIP models to assist production planning in the textile industry at an operational level, focusing on customer order fulfillment. Figure 1 summarizes the objective of this work.

Figure 1 – Ojectives of the work.



1.3 Organization and contributions

In Chapter 2, we conduct an exploratory study on the production planning problems and management system information for textile industries in São Paulo, Brazil. Through a survey of 47 companies, the study investigates key aspects such as production processes, competitiveness factors, and the adoption of information management systems. The findings reveal critical challenges in production scheduling, inventory management, and supplier relations, alongside a notable interest in technological integration for improved operational efficiency. The survey also emphasizes the importance of customer relationships and product quality in maintaining market competitiveness. This research provides valuable insights into the production dynamics of the textile industry in the state of São Paulo, highlighting points for improvement and future research opportunities.

Mathematical programming models offer a powerful tool for modeling and optimizing the textile supply chain. In Chapter 3, we present a systematic review of models and solution approaches using mathematical programming for operations management in the textile supply chain. We organized the papers on each stage of textile manufacturing, starting from fiber production to the integrated supply chain. The systematic review results suggest that mathematical programming models can address various decision-making problems in the textile supply chain. These include blending fibers, production planning, scheduling orders, cutting patterns, transportation optimization, network design, and supplier selection. The review also highlights the potential for further research, particularly in applying optimization techniques.

The systematic review pointed out notable gaps in the literature regarding applying mathematical programming models to production problems in the textile industry. This thesis addresses two of these gaps: operational performance metrics and the integration of production and distribution planning at the operational level, focusing on fulfilling customer orders.

In Chapter 4, we investigate service-level and capacity utilization constraints within capacitated lot-sizing problems, focusing on customer orders. Service-level constraints usually are not considered in deterministic lot-sizing problems due to an assumption that there should be no delays if demand is previously known. However, backlog orders are common in textile industries due to the complexity of production. We then formulate γ service-level constraints adapted from the inventory control literature to limit backlogging orders and introduce new ones. The impact of service-level constraints is analyzed on solution structure and performance indicators such as average delay, maximum delay, throughput, lead time, work in process, and capacity utilization. Through extensive computational testing across diverse demand scenarios, we reveal that global service-level constraints enhance production planning flexibility. Finally, we compare the different service-level constraints, suggesting in which context they are best applied, and show the contrast between high-capacity utilization in a make-to-order context.

The survey and literature review identified the scheduling problem as the main production planning problem for the textile industry. The scheduling problem is addressed in the integrated decisions of scheduling, lot-sizing, distribution with cargo unitization, and order fulfillment presented in the model proposed in Chapter 5. We analyze order fulfillment, carryover setup sequence-dependent constraints, and cargo arrangement in lot-sizing and distribution decisions. A comparative analysis of the integrated model is performed with a hierarchical model. In addition, a computational study is presented to evaluate the model behavior. To solve the proposed integrated model, we developed an adaptive large neighborhood search (ALNS) as a solution method.

2 Production planning problems and information systems in the textile industry: an exploratory study

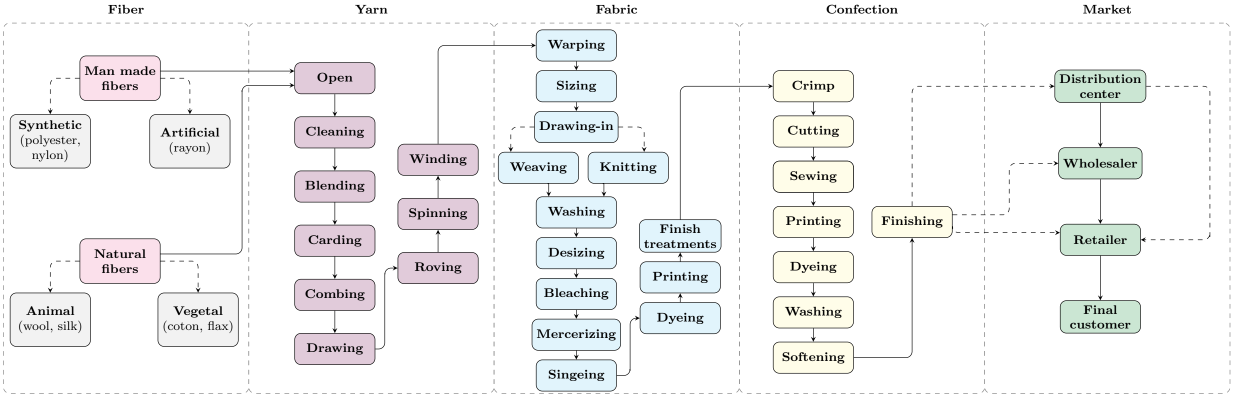
2.1 Introduction

The textile production system comprises a range of raw materials, including cotton, wool, silk, flax, and synthetic fibers, which can either be blended or remain unblended. Each material has unique processing characteristics, making it imperative to understand the complexities of the industry. To make the process easier to understand, it is divided into five steps: fiber preparation, yarn manufacturing, fabric manufacturing, apparel manufacturing, and distribution operations.

During fiber preparation, the fibers are cleaned, blended to remove impurities, and fed to the combing machine to align the different types of fibers. In the next stage, the combed fibers are twisted and strengthened on the carding machine to reduce their thickness. To prepare yarn for spinning, roving is employed to twist and strengthen it. After obtaining the desired characteristics, the yarns are wound onto bobbins using specific machines for each blend. The subsequent step involves weaving or knitting, where the yarns are interlaced to form a flat or knitted fabric. The primary distinction between these two types of fabrics is the interlacing method of yarns.

After weaving or knitting, the fabrics undergo finishing operations such as dyeing, printing, and mechanical or chemical finishing to achieve the desired colors and shapes. Finally, the fabrics are sent to confections, where they undergo further operations such as cutting and sewing to produce garments, home textiles, automotive textiles, and technical textiles. A general production process of the textile supply chain is illustrated in Figure 2.

Figure 2 – Production process of the textile industries.



Source: Adapted by CETESB (2023)

As one of the most traditional industries in the world, the textile industry is a relevant market due mainly to the different production links that the sector has in its production chain. The world textile market finds room to continue registering steady growth regarding the volume produced and its foreign trade. The textile industry plays an essential role in the Brazilian economy. In 2021, the production volume of textile and apparel products was 2.16 million tons, representing R$ 190.3 billion (US$ 37.50 billion) of revenue in Brazil. If we add the indirect and income effects, this production requires 22.5 thousand productivity facilities, 1.34 million formal employees, and 8 million indirect employees (ABIT, 2022).

The Brazilian textile and apparel sectors are globally significant, ranking as the fifth-largest textile and fourth-largest apparel industries. These industries compose the fourth most extensive and vertically integrated production chain globally, from fiber to finished garments. The state of São Paulo textile industry alone created 212,100 jobs and led the national revenue with $R$$43.4 million, accounting for 27% of the total in 2021 (CETESB, 2023). The state of São Paulo has eight textile centers, listed in Table 1 with their respective production characteristics.

Table 1 – Textile centers in the state of São Paulo.

Textile center	**Production characteristics**
Americana, Santa Bárbara d'Oeste, Nova Odessa, Sumaré, and Hortolândia	Integrated textile chain, from fibers to clothing, more focused on artificial and synthetic lines
Tietê and Cerquilho	Apparel, with a predominance of children's clothes and jeans
Sorocaba and Itapetininga	Apparel, with a predominance of jeans production and fabrics for toys production
São Paulo City	Apparel
Amparo, Itatiba, and Jundiaí	Integrated textile chain focused on beachwear
Lindoia, Serra Negra e Socorro	Knitting
São José do Rio Preto	Textile chain focused on children's apparel
Gália e Bastos	Silk production

Source: CETESB (2023)

Considering the importance of the textile sector and the key position São Paulo holds in the Brazilian textile industry, in this chapter, we present an exploratory survey to identify challenges and requirements faced by companies within this sector. The survey is part of a broader effort to map trends and identify the demands affecting textile companies in São Paulo. The research is particularly focused on uncovering the production-related issues afflicting textile manufacturers and evaluating the adoption of production management solutions within these companies. The objectives of this research are reflected in the following research questions:

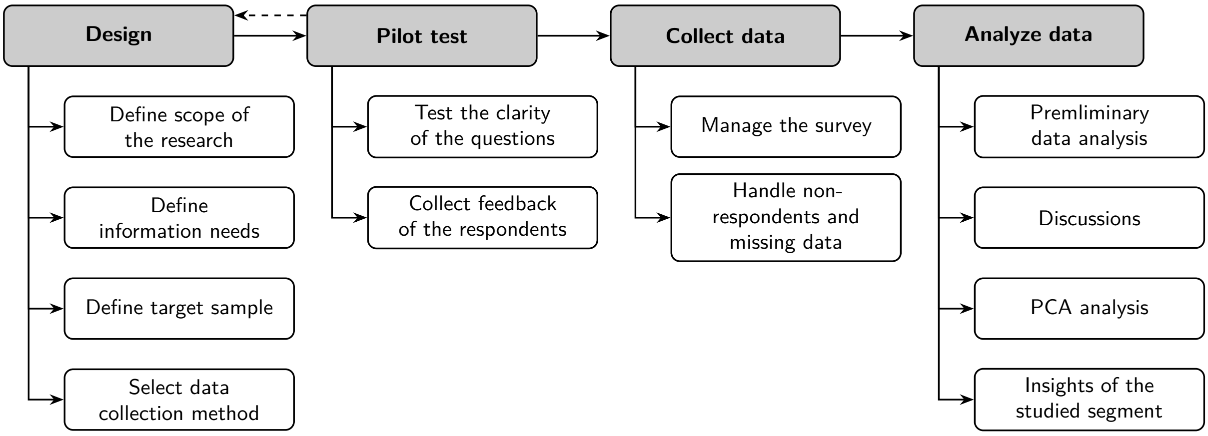
- RQ1: *What are the main production problems for the textile industries in São Paulo?*
- RQ2: *How interested are companies in using computerized tools to manage production problems?*

2.2 Methodology

Survey research is characterized by collecting information in a structured format through various means such as mail, telephone, or face-to-face interviews, where respondents may represent themselves or their affiliations. The quantitative nature of the surveys requires standardized data to analyze variables or their relationships. Using a sample from a larger population allows for generalization of findings (Malhotra and Grover, 1998). A survey is categorized into exploratory, confirmatory, and explanatory types. Exploratory research produces initial insights for identifying new aspects and relationships. Confirmatory research, or theory testing, evaluates and tests theoretical concepts and models, carefully considering potential errors. Explanatory research establishes causal relationships between variables, with hypotheses predicting the direction and nature of these relationships (Forza, 2002; Malhotra and Grover, 1998).

The methodology design is based on the framework for survey in operations management proposed by (Forza, 2002). Our study is centered on exploratory survey research, where the development of conceptual models or connections to theoretical frameworks is outside the scope of our analysis. First, we define the survey design to determine the scope of research, the information needed, the target sample, and the data collection method. Then, we ran a pilot test with a few respondents to verify the quality of the questions. We collected data using business social media and emails. After collecting the data, we conducted a descriptive and multivariate principal component analysis (PCA) to interpret the results, focusing on identifying patterns and trends. The results are discussed to provide insights into the operations of the textile industries and inform future research. The survey process of this work can be summarized in Figure 3.

Figure 3 – Survey research process.



2.2.1 Question design

Fernandes and Leite (2002) proposed an exploratory survey aiming to analyze market foundries in the interior of the state of São Paulo in automation and production management information systems. The authors investigated the main production problems faced by the companies interviewed and their interest in using automation and information systems. We adapt the questions proposed by Fernandes and Leite (2002) for the textile companies. The survey is divided into the following sections.

- **General information:** In this section, our objective is to identify the main processes of the textile industry and operating city. Additionally, we want to classify the company size based on the number of employees and revenue. Finally, we aim to determine the educational levels of the workforce and the monthly production level.
- **Products:** This section delves into the production characteristics of the product or product line that significantly contribute to the company's revenue. Topics include main production lines, product profit distribution, outsourcing strategies, competition intensity, and prevailing business trends.
- **Competitiveness factors and key performance indicators (KPIs):** Here, we aim to identify critical factors the company perceives as crucial for maintaining market competitiveness. We also want to understand how the companies measure the operation performances. Focus areas include cost management, operational flexibility, product quality, dependability, delivery speed, supplier relationships, and customer management.
- **Production planning problems:** The focus is identifying significant production management issues impacting competitiveness. We also explore the use of computational tools for production planning and the interest of the company in adopting or improving automated systems for production management. Topics include production scheduling, distribution planning, inventory management, workforce skills, order fulfillment, and supplier management.

In order to cover all the needed information, we use multiple-choice, Likert scale (South et al., 2022), and essay questions, as proposed by Fernandes and Leite (2002).

2.2.2 Target Sample

A search was carried out on public domain websites containing information on companies operating in the textile sector in Sao Paulo to determine the target sample. The taxpaying companies in São Paulo are listed on the website: `https://www.cadesp.fazenda.sp.gov.br`. The government website provided a large file (1.25 GB, with 4,677,818 rows) with the information of the companies. To handle this file, we used a script in Python language, using the Pandas library for the filtering process.

The initial criterion for selecting companies was their economic activity. We employed Portuguese equivalents such as "fiber", "yarn", "weaving", and "knitting" to identify textile businesses. This approach yielded a list of 4,554 companies. Cotton cultivation operations were omitted from our analysis as they are not part of the manufacturing phases under consideration. Our research aims to assess the use of automation and production management solutions; thus, we concentrated on medium and large enterprises. The survey scope was further narrowed by excluding small companies involved in the apparel production phase due to their high prevalence. Finally, we remove duplicate entries, companies with more than one economic activity with the same national register (*Cadastro Nacional de Pessoas Jurídicas - CNPJ)*. We have a sample with 573 textile companies at the end of the filtering process.

Given the geographical limitations of face-to-face company interactions, we have chosen an online survey as our data collection method. Wu et al. (2022) and Melnyk et al. (2012) have highlighted challenges in obtaining high response rates for online surveys, attributing this to several factors like the number of questions and the time required to answer them. For this reason, we aimed to distribute the questionnaire to as many companies as possible within our target population, leading to a sample size equivalent to the entire population.

2.2.3 Pilot test

We conducted a preliminary test with five companies randomly selected to evaluate our contact administration protocol. The goals were to assess the time required to complete the survey and ensure the clarity of the questions. At the end of the questionnaire, respondents could provide feedback, including their impressions and suggestions for improvement. Based on this feedback, we refined the number of questions, resulting in an average completion time of 8 minutes.

2.2.4 Collect data

The questionnaire was administered using the Microsoft Forms platform, and the link was sent to the managers of the textile companies by Linkedin and e-mails from August to October 2023. A personal message was sent to each potential participant. When a respondent could not complete the questionnaire, efforts were made to identify an alternative respondent within the same company. It was ensured that responses were collected from only one individual per company to maintain data integrity. This approach was implemented across three rounds of questionnaire distribution. All questions in the survey were designed to be mandatory, requiring a response before proceeding to mitigate the issue of missing data.

2.3 Results

2.3.1 Overview of the sample

The unit of analysis in this survey is a textile company based in São Paulo state. The process for determining the sample, as detailed in Section 2.2, yielded a selection of 573 companies. These companies are distributed across various cities in the state, as shown in Table 2. Notably, Americana is the city with the highest concentration of textile companies. Also, there are 55 cities that each host a single textile company.

Table 3 outlines the primary textile processes employed by the companies in this study. Most of these companies specialize in producing woven fabrics from synthetic yarns, including polypropylene fabrics, fiberglass, household textiles, and raffia bags. Additionally, some companies have their activities categorized as the "Manufacturing of other textile products not previously specified". This category contains a diverse range of textile products, such as bags made of cotton and other textile fibers, raffia tape bags, flags, and others, particularly when these are not part of an integrated weaving process. It also includes trimmings (such as gallons), elastic ribbons and fabrics, filaments, lace, and embroidered fabrics.

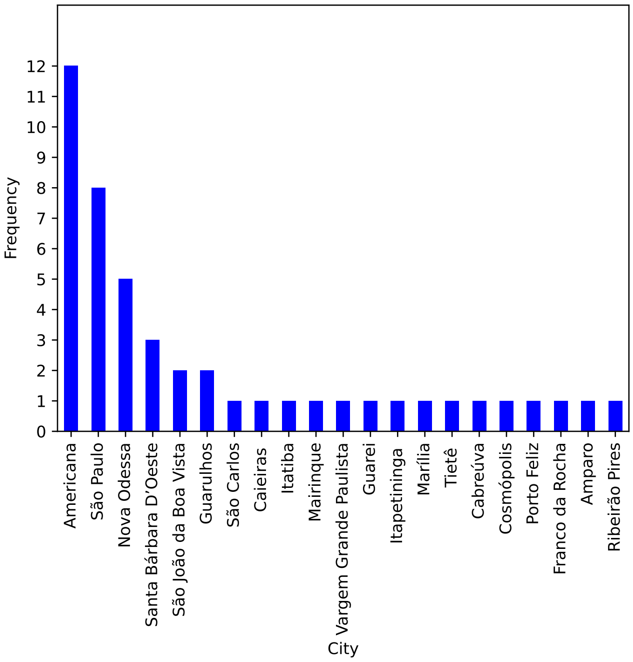
Table 2 – Number of textile industries by city.

City	**Quantity**	**City**	**Quantity**
AMERICANA	127	SÃO PAULO	97
SANTA BARBARA D'OESTE	70	NOVA ODESSA	36
SUMARE	18	GUARULHOS	15
SÃO BERNARDO DO CAMPO	9	CERQUILHO	7
SOROCABA	6	ITATIBA	6
IBITINGA	6	LARANJAL PAULISTA	6
BOM JESUS DOS PERDOES	5	CARAPICUIBA	4
JUNDIAI	4	AMPARO	4
INDAIATUBA	4	LIMEIRA	4
PIRACICABA	4	CAPIVARI	3
OSASCO	3	FRANCA	3
VINHEDO	3	SANTO ANDRE	3
VALINHOS	3	ITAPIRA	3
ITAQUAQUECETUBA	3	SÃO JOSE DOS CAMPOS	3
ARUJA	3	FERRAZ DE VASCONCELOS	3
ATIBAIA	3	COTIA	3
VOTORANTIM	3	SALTO	2
RAFARD	2	RIBEIRÃO PRETO	2
JANDIRA	2	SANTA ISABEL	2
PAULINIA	2	MORUNGABA	2
TATUI	2	ELIAS FAUSTO	2
BARUERI	2	ARARAS	2
ARACARIGUAMA	2	COSMOPOLIS	2
PORTO FELIZ	2	POA	2
SÃO CARLOS	2	DIADEMA	2
LOUVEIRA	2	PEDREIRA	2
BORBOREMA	2	SUZANO	2
ARTUR NOGUEIRA	2	OTHERS	55

Table 3 – Overview of textile manufacturing processes in the population by manufacturing stage.

Textile manufacturing process	**Quantity**
Synthetic fiber manufacturing	27
Spinning of cotton fiber	49
Spinning of natural textile fibers other than cotton	27
Spinning of synthetic fibers	46
Weaving of cotton yarn	95
Weaving of yarn from natural textile fibers other than cotton	27
Weaving of synthetic fiber yarns	250
Knitting	26
Manufacturing of other textile products not previously specified	26

Figure 4 – Frequency of respondent textile companies by city.

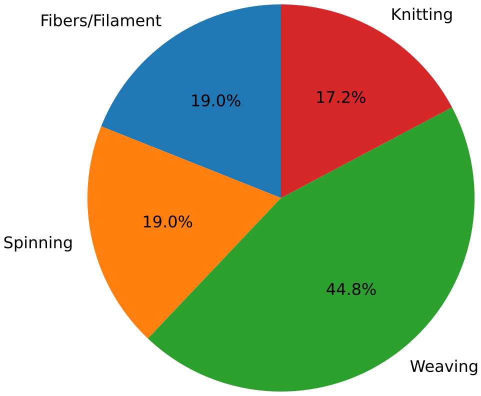


2.3.2 General information

The survey was distributed to directors, production managers, and production supervisors at the identified textile companies. We sourced the email addresses and LinkedIn contacts, selecting respondents based on their job titles as listed on LinkedIn. In total, we garnered 47 responses. Figure 4 shows the cities where the textile companies are located.

We identified the primary production stages as Fibers/Filament, Spinning, Weaving, and Knitting. Companies engaged in integrated operations across multiple stages could select more than one category. As illustrated in Figure 5, the results show that a significant proportion of those interviewed indicated that their companies were predominantly involved in the weaving sector. Following a similar proportion of the population.

Figure 5 – Textile process of the surveyed companies.

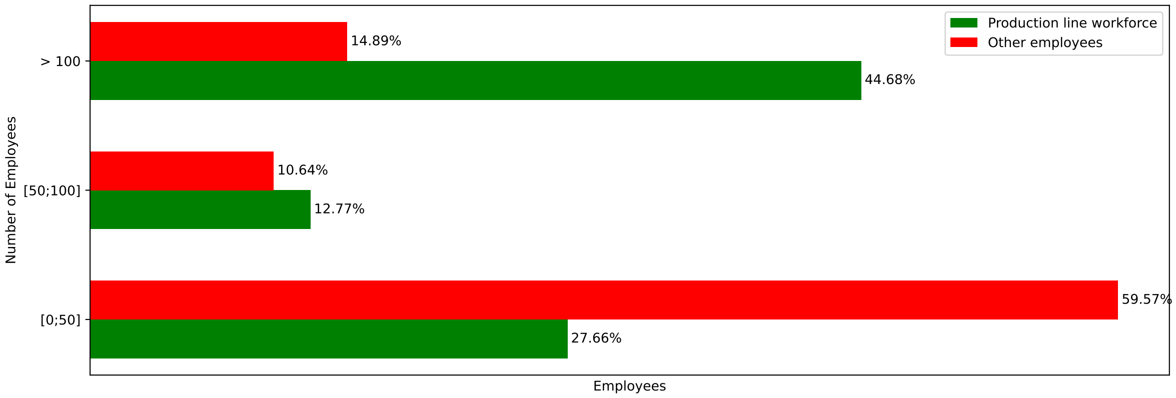


From the surveyed companies, 92.5% are Limited Liability Company, while 7.5% are publicly traded. Among these, only seven companies have multinational operations, with the remaining majority exclusively operating within the Brazilian domestic market. Concerning the company revenue, 75% of the companies presented a revenue ranging from R$4.8 million to R$300 million in 2022, .

Regarding outsourcing operations, 12.5% of surveyed companies outsource their distribution processes, while 22.5% outsource dyeing and finishing activities. A smaller portion, 7.5%, outsource their entire production process. The rest of the companies do not employ outsourcing activities.

Figure 6 exhibits the number of employees for the surveyed companies divided into production lines and other functions. Most surveyed companies have over 100 employees on the production line and less than 50 employees in other company functions. In examining the distribution of employees by education level across different textile processes, our results reveal that the most elevated education level among production line employees is high school, with some employees having incomplete elementary education. In contrast, the minimum educational level for employees in other company functions is complete elementary education; few have higher education qualifications. These results suggest that a low-skilled workforce is needed in São Paulo's textile sector. However, it is interesting to note that when asked about a difficulty present in the company, 40.42% answered that the lack of skilled labor is a problem for the industry.

Figure 6 – Number of employees for the surveyed companies.



The total production of the companies varied due to their diverse business models, with measurements in length (kilometers, meters) and weight (tons). The most productive company, with over R$300 million in 2022 revenue, produces 8 million meters of fabric monthly. For companies earning between R$4.8 million and R$300 million, the average monthly production is 504 tons, with the top producer making 1,700 tons of yarn. A linen weaving mill with revenues between R$360,000 and R$4.8 million reported monthly production of 100,000 meters of fabric per month.

2.3.3 Production characteristics

This section focuses on identifying the production characteristics of the most significant product (or family line) contributing to the revenue of the company. The frequently mentioned products include cotton, synthetic yarns (like acrylic, polyester, and nylon), and cotton, synthetic, and blended fabrics. Other notable items are tapes, sterile compresses, blankets, and propylene packaging.

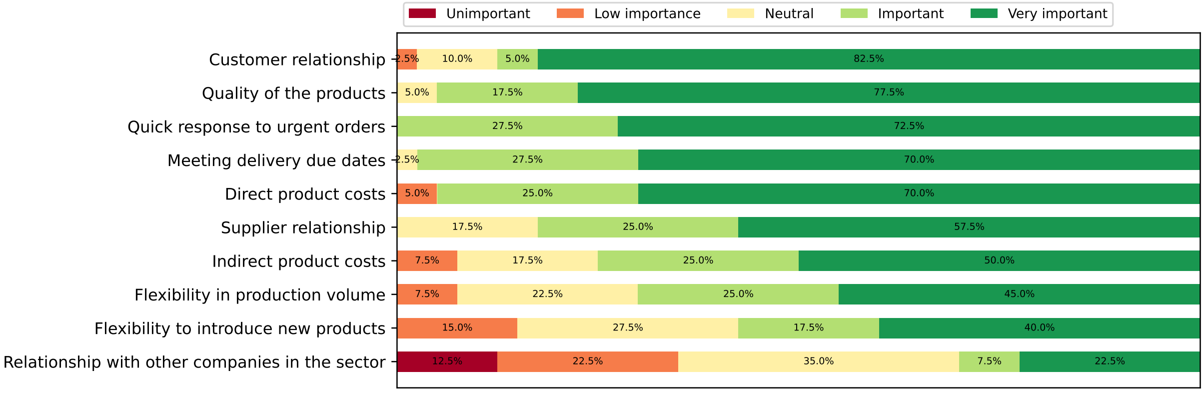
Our results show that for 52.5% of the surveyed companies, the primary production items represent over 80% of their revenue. Furthermore, 78% of respondents report high competition in the market for these products. Despite considering the importance of these items in revenue, 20% of companies say they outsource the production of these items.

Regarding product growth trends, 60% of companies report product market stability. Notably, 5% of respondents (two companies) observe that their product is in a declining phase. Among these, one company outsources its product production. The other company, experiencing a decline, notes that the product accounts for up to 50% of their total production. The respondent explicitly cites direct production costs, including labor and raw materials, for this company as critical factors impacting its competitive standing.

2.3.4 Competitiveness factors and key performance indicators

Figure 7 shows the main factors identified for competitiveness in order of importance. Customer relationship emerged as the top factor for gaining a competitive advantage, followed by product quality and quick response to orders. When considering responses classified as "important" and "very important", quick response to meet orders is crucial for all participants. Furthermore, meeting orders with the correct due dates are also highlighted as vital for competitive success. However, 15% of respondents concede that they could be more assertive in these market aspects.

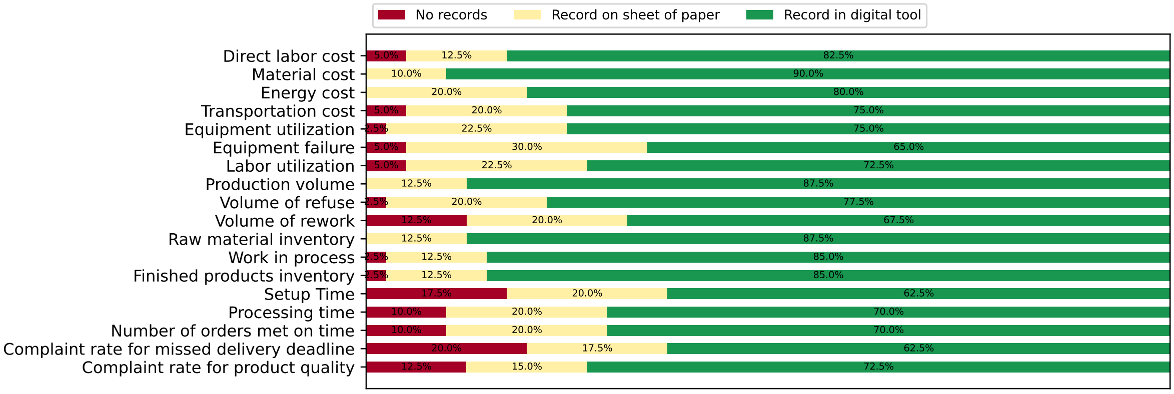
Figure 7 – Critical factors for company competitiveness.



To investigate how companies monitor performance metrics, we asked if they use digital tools (such as spreadsheets or information systems), paper records, or do not track measures.

Figure 8 shows that most KPIs are controlled using a digital tool. However, some answers show that companies do not control production measures such as processing time, setup time, and customer satisfaction with order fulfillment and product quality. A contingency table was created correlating company revenue with the metrics most frequently reported as unrecorded. The analysis shows that companies with an annual revenue of up to 4.8 million, typically small businesses, are more likely to rely on non-computerized record-keeping. This result suggests a possible correlation between revenue and investment in information systems.

Figure 8 – Overview of record methods for key performance indicators.



2.3.5 Production planning problems

In this section, we aim to identify the production problems that significantly impact the competitiveness of the companies. For this purpose, respondents were asked to evaluate a range of production problems on a scale from 1 to 5, where 1 denotes “unimportant” and 5 indicates “very important” factors. Results are shown in Figure 9 in order of importance for the respondents.

Figure 9 – Main production problems in the surveyed textile industries.

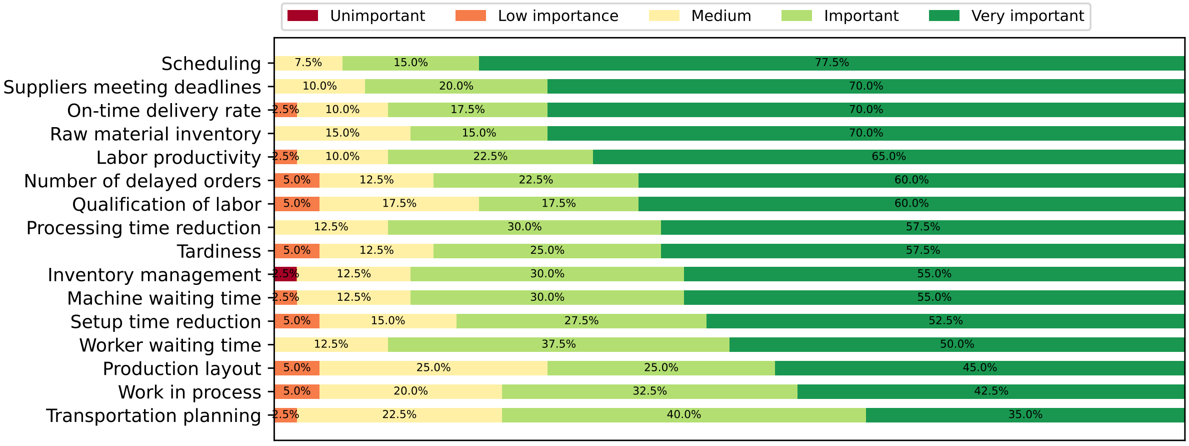
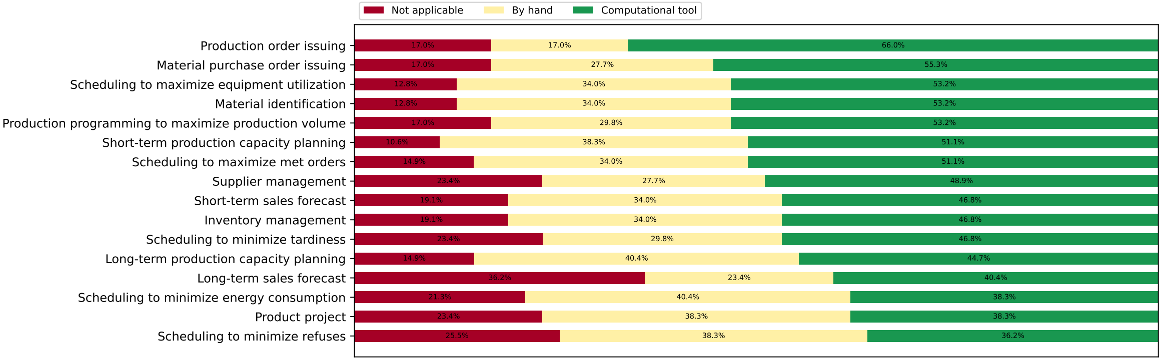


Figure9 highlights the scheduling problem as the most cited production problem for the survey participants. The scheduling problem involves determining the optimal sequence for manufacturing products and assigning the necessary resources. It is particularly relevant in the textile industry, where mixing product families is not feasible, and establishing the most efficient production sequence is crucial for optimal resource utilization. The other significant challenges identified are meeting due dates by suppliers, timely order fulfillment, and managing raw material inventories.

When asked how they evaluate the current method used by the company to deal with the production problems shown in Figure 9, 45% of respondents admit some weaknesses in improving worker productivity, and 40% indicate that employee qualifications are inadequate. Concerning the most significant problems identified, 25% of the respondents highlight that the methods used by the companies are inadequate for scheduling and inventory management, and 35% express dissatisfaction with the management of supplier relations. The strength of the companies is reported in transportation planning, which 82.5% of respondents rated as "good" or "very good".

To investigate how companies manage different aspects of production, such as planning, demand forecasting, capacity planning, material identification, inventory management, and supplier management, we inquired about their use of computer tools, reliance on manual processes, or absence of planning in these areas. Notably, 67.5% of companies use computerized tools for issuing production orders. Regarding production planning, 55% report using a computerized tool to maximize production volume and equipment utilization. However, 40% of respondents indicate that their companies do not forecast long-term demand (over one year). Many of these activities are still manually addressed by company managers. Detailed findings are presented in Figure 10.

Figure 10 – Use of information systems for production planning.



We performed Principal Component Analysis (PCA) to analyze the relation between the answers. PCA applies a vector space transformation to reduce the dimensionality of large datasets. The original dataset can be represented using only a few principal components through mathematical projection. This reduction allows for more precise interpretation, enabling users to identify data trends, patterns, and outliers more efficiently than possible with the complete set of variables (Richardson, 2009). Table 4 presents the original variables being analyzed and their description.

Table 4 – Original Variables and Descriptions Used in PCA.

Variable	Description
1. Direct product costs	Costs directly associated with the production of goods
2. Indirect product costs	Overhead costs not directly tied to production
3. Flexibility to introduce new products	Ability to introduce new products to the production line
4. Flexibility in production volume	Adaptability to adjust production volumes based on demand
5. Quality of the products	Overall quality of the finished goods produced
6. Meeting delivery due dates	Percentage of orders delivered on or before the due date
7. Quick response	Capability to respond quickly to market changes or orders
8. Supplier relationship	Strength of relationship with suppliers in the supply chain
9. Customer relationship	Strength of relationship with customers
10. Labor cost	Cost associated with labor in the production process
11. Material cost	Cost of raw materials used in production
12. Energy cost	Energy consumption cost in the production process
13. Transportation cost	Cost of transportation for materials and finished goods
14. Equipment utilization	Rate at which equipment is used in the production process
15. Equipment failure	Frequency of equipment breakdowns or malfunctions
16. Labor utilization	Effectiveness of labor use in the production process
17. Production volume	Total amount of goods produced in a given period
18. Volume of refuse	Amount of waste produced during the production process
19. Volume of rework	Volume of defective products needing rework
20. Raw material inventory	Inventory of raw materials available for production
21. Work in process	Inventory of goods that are in the process of being manufactured
22. Finished products inventory	Inventory of finished goods awaiting shipment
23. Setup Time	Time taken to set up machines for production
24. Processing Time	Time taken to process goods in the production line
25. Number of orders met on time	Number of orders delivered on time
26. Complaint rate for missed delivery deadline	Rate of customer complaints related to missed delivery deadlines
27. Complaint rate for product quality	Rate of customer complaints regarding the quality of the products

In PCA, using different units of measurement can yield different principal components. To avoid this inconsistency, variables are standardized to have zero mean and unit variance (Jolliffe, 2005). In our case, the questionnaire uses the same scale for all questions. Thus, there is no need to standardize the results. First, we must ensure that the original variables in Table 4 are correlated. The correlation matrix for the original variables is shown in Figure 53 in Appendix A.

The correlation matrix (Figure 53) highlights crucial relationships between various operational variables in the textile industry. Strong positive correlations were found between production volume and work in process, raw material inventory, and finished products inventory, indicating that increased production leads to higher levels of both in-progress inventory and raw material consumption. Additionally, energy cost strongly correlates with equipment utilization, implying that higher machinery usage drives energy consumption. On the negative side, a notable relationship was observed between indirect product costs and flexibility in production volume, suggesting that greater production flexibility can help reduce overhead costs. Flexibility to introduce new products also negatively correlates with the complaint rate for product quality, indicating that higher adaptability in product launches leads to fewer customer complaints. Other significant relationships include a strong positive correlation between supplier relationships and raw material inventory, implying that supplier management is related to inventory control. Furthermore, meeting delivery due dates is closely tied to a reduced complaint rate for missed deadlines.

PCA transforms the original variables into a new set of uncorrelated principal components, ordered so that the first components capture the most variation in the original data (Wold et al., 1987; Ringnér, 2008). We aim to determine the main production-related issues for which companies utilize information systems. We can reduce the original variables in Table 4 into four principal components: PC1, PC2, and PC4 because 81.5% of the variability in the data is explained by these four components (see Appendix A - Tables A2 and A2).

- PC1 represents operational efficiency and the overall production and cost structure (labor, energy, material, and inventory).
- PC2 reflects flexibility and external adaptability, focusing on relationships with suppliers, customers, and the flexibility of production.
- PC3 captures product quality and delivery performance, focusing on ensuring high standards in product quality and meeting delivery timelines.
- PC4 captures the balance between achieving adaptability in production and product offerings while managing associated costs.

From Figure 10 and PCA analysis, we can infer that management inventory systems are essential for controlling operational costs and inventory levels and short-term production planning for textile industries.

2.4 Final remarks and future research

The textile industry plays significant economic value in state of São Paulo, the Brazilian state with the highest concentration of textile companies. In this chapter, we carried out an exploratory survey covering 47 companies to gain a deeper understanding of the prevailing production problems and the adoption of computerized production management systems in these companies. Descriptive statistical methods were employed to analyze the data collected, leading to several important observations that can be summarized as follows:

- *Impact of production management practices on competitiveness:* The survey results from the textile industry highlight several critical factors that influence competitiveness. The predominant reliance on manual processes, especially among small and medium companies with revenues of R$4.8 million, suggests a correlation between financial resources and the adoption of advanced management systems. This result is further evidenced by 67.5% of respondents expressing interest in implementing computerized systems for production management, underscoring the perceived value of technological integration in enhancing operational efficiency.

- *Production planning problems:* The findings also reveal a significant emphasis on customer relationships, product quality, meeting deadlines, and quick response as the main factors for the competitiveness of textile companies. Scheduling, supplier management, and inventory management point to potential room for improvement. Moreover, the fact that some companies do not perform long-term demand forecasting highlights a gap in strategic planning that could impact future growth and adaptability.

- *Employee qualifications and productivity:* A notable concern is the adequacy of employee qualifications, with 40% of respondents indicating it as an issue. This outcome suggests a need for enhanced training programs and skill development initiatives. The fact that 45% of companies acknowledge weaknesses in improving worker productivity further emphasizes the need for more effective human resource management and development strategies.

- *Computerized production management systems:* The interest in adopting computerized systems for production management, particularly in sectors such as production planning and control, internal logistics, and automated inventory management, reflects an industry trend toward digital transformation. The prioritization of these areas indicates that companies recognize the need to adapt to a quickly evolving business environment, where efficiency, agility, and data-driven decision-making are vital to maintaining competitiveness.

- *Future research directions:* A critical aspect of future research in this domain involves conducting comprehensive statistical analyses, including contingency tables, to enhance our understanding of the correlations between various variables in the textile sector. This approach will allow for a more detailed exploration of how factors - such as company size, revenue, technology adoption, and workforce qualifications - interact and influence each other. By applying statistical methods to assess the strength and nature of these relationships, we can gain insights into the underlying dynamics that drive operational efficiency and competitiveness in the sector. This analysis will identify patterns, predict trends, and formulate strategic interventions.

3 Literature review of mathematical programming models and solution approaches for the textile supply chain

3.1 Introduction

The textile supply chain is crucial for the global economy, with China, the European Union, and India being the largest textile sellers of the world (Lu, 2022). Millions of people are employed in the industry in emerging countries such as Turkey, Brazil, Vietnam, and Pakistan (Galatti and Baruque-Ramos, 2022; Tseng et al., 2022). Despite its significant economic importance, the textile industry is known for its high consumption and pollution levels, highlighting the urgent need to address environmental concerns (Zhu et al., 2022). Therefore, exploring production methods that balance the economic growth of the sector is imperative while utilizing resources efficiently.[1]

Previous reviews have conducted analyses of using mathematical programming in the textile sector. In a conference paper, Toledo et al. (2022) provided a brief overview of optimization models used in the textile industry based on twelve papers. Wen et al. (2019) reviewed operational research models for the fashion retail supply chain, including simulation and game theory. Lorente-Leyva et al. (2024) proposed a conceptual framework to support the sustainable and smart planning of textile supply chains in uncertain contexts. However, neither work offers an extensive or comprehensive classification of mathematical programming models across all stages of textile manufacturing, from fiber production to the integrated supply chain. In this paper, we contribute to the state of the art by reviewing 163 papers within this scope published in journals, conferences, and books up to October 2024. This study focuses on studies that apply mathematical programming models, including linear, nonlinear, stochastic, robust, fuzzy logic, and multi-objective programming, to textile supply chain decisions.

The review demonstrates how mathematical models can support decision-making processes in the sector. We identified several optimization strategies to address problems in production planning, transportation planning, network design, order allocation, product quality, sustainability, and social responsibility. Furthermore, by identifying future research gaps, we highlight areas where mathematical programming can be applied to address production problems in this critical industrial and economic sector.

This Chapter is organized as follows. In Section 3.2, we present the methodology and structure used in this review. In Section 3.3, we show the analyzed textile manufacturing models. In Section 3.4, we analyze the integrated textile supply chain models. In Section 3.5, we conclude this review by summarizing the principal findings and pointing out opportunities for

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[1] An article with the contents of this chapter is in the peer review process at Computers & Industrial Engineering. Preprint available in: Alves, Giovanna Abreu; Tavares, Roberto; Amorim, Pedro; Camargo, Victor Claudio Bento. A Systematic Review of Models and Solution Approaches for the Textile Supply Chain. Available at SSRN: `https://ssrn.com/abstract=4577774` or `http://dx.doi.org/10.2139/ssrn.4577774`

future research.

3.2 Methodology

We conducted a systematic literature review of analytical works that apply mathematical programming models to support decision-making in textile manufacturing based on the systematic literature review methodology for operations management proposed in (Thomé et al., 2016), explained as follows.

3.2.1 Search process

Regarding the searching and selection criteria, we searched for papers in the following databases: Elsevier SCOPUS, Google Scholar, IEEE, Informs, Oxford, Science Direct, Springer, Taylor & Francis Online, and Web of Science. The search strings are exhibited in Table 5.

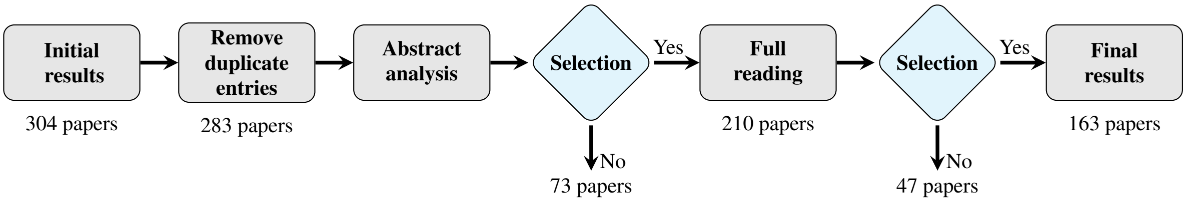
Table 5 – Search strings.

Fiber production	**Yarn manufacturing**	**Fabric manufacturing**	**Apparel manufacturing**	**Textile supply chain**
“cotton production” OR “wool production” OR “silk production” OR “textile fibers” OR “synthetic fibers”	“spinning industry” OR “yarn production” OR “yarn manufacturing”	“knitting” OR “weaving” OR “dyeing” OR “fabric production”	“confection” OR “apparel”	“textile supply chain” OR “textile manufacturing” OR “textile production”
AND “mathematical programming” OR “linear programming”OR “nonlinear programming” OR “optimization” OR “mixed integer programming” OR “integer programming”				

We combined keywords related to each stage of the textile manufacturing process with keywords related to mathematical programming or optimization models. Qualitative or simulation models are not included in the scope of this paper, so the word “models” was not used as a string search. To fit our textile scope well, we use three exclusion criteria: i) those without optimization models (like qualitative approaches, frameworks, and simulations); ii) those not related to the textile industry directly (like optimization models for the process industry, but without application to textile manufacturing); iii) those with specific topics on the textile industry, without optimization problems (e.g., the geometry of cloth structure or computational tools to determine pattern designs). In total, 163 papers were reviewed in this study. The search process can be summarized in Figure 11, which shows all the steps for searching the literature base. The selection process was carried out based on the mentioned exclusion criteria.

Figure 12 illustrates the numerical distribution of reviewed articles over the years. We can see that most publications were made from 2010 to 2024. Moreover, 58% of the papers were

Figure 11 – Literature review search process.



published in the last ten years, showing the recent increase in the relevance of the theme. Figure 13 shows the leading journals for the reviewed papers

Figure 12 – Number of publications during the years.

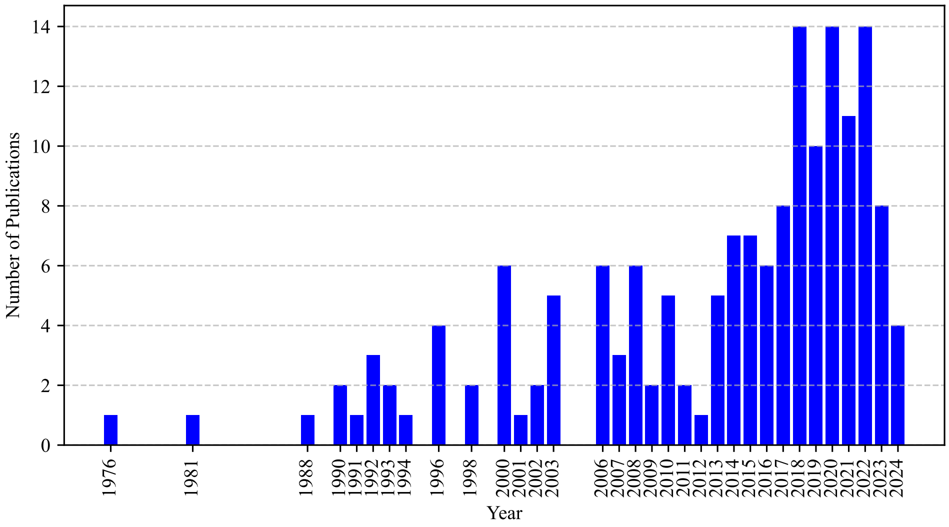
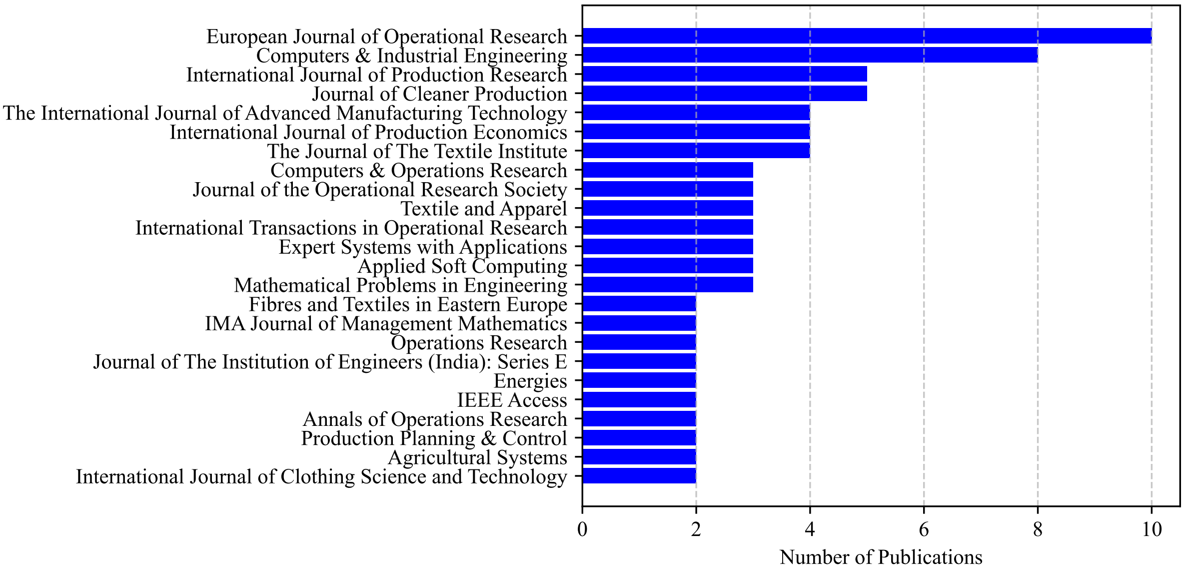


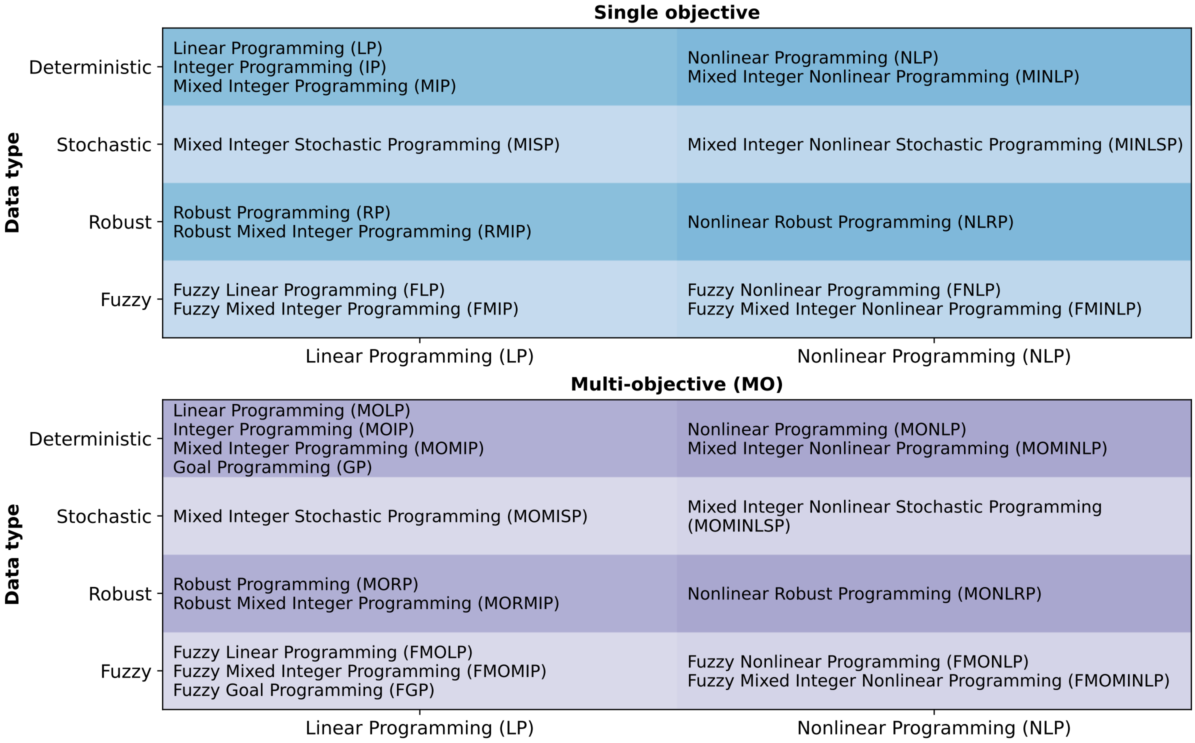
Figure 13 – Leading journals for the reviewed papers.



3.2.2 Data analysis, synthesis, and interpretation

At each stage of textile production, the contents of the papers were summarized in tables showing the type of problem addressed, the presence or absence of multiple items, multiple machines, multiple periods, the type of objective function, and uncertainty in parameters. Furthermore, we highlighted the significant characteristics used in models and the solution methods. The proposed models follow the acronyms in Figure 14.

Figure 14 – Optimization approach present in the papers.



Single objective

Data type	Linear Programming (LP)	Nonlinear Programming (NLP)
Deterministic	Linear Programming (LP) Integer Programming (IP) Mixed Integer Programming (MIP)	Nonlinear Programming (NLP) Mixed Integer Nonlinear Programming (MINLP)
Stochastic	Mixed Integer Stochastic Programming (MISP)	Mixed Integer Nonlinear Stochastic Programming (MINLSP)
Robust	Robust Programming (RP) Robust Mixed Integer Programming (RMIP)	Nonlinear Robust Programming (NLRP)
Fuzzy	Fuzzy Linear Programming (FLP) Fuzzy Mixed Integer Programming (FMIP)	Fuzzy Nonlinear Programming (FNLP) Fuzzy Mixed Integer Nonlinear Programming (FMINLP)

Multi-objective (MO)

Data type	Linear Programming (LP)	Nonlinear Programming (NLP)
Deterministic	Linear Programming (MOLP) Integer Programming (MOIP) Mixed Integer Programming (MOMIP) Goal Programming (GP)	Nonlinear Programming (MONLP) Mixed Integer Nonlinear Programming (MOMINLP)
Stochastic	Mixed Integer Stochastic Programming (MOMISP)	Mixed Integer Nonlinear Stochastic Programming (MOMINLSP)
Robust	Robust Programming (MORP) Robust Mixed Integer Programming (MORMIP)	Nonlinear Robust Programming (MONLRP)
Fuzzy	Fuzzy Linear Programming (FMOLP) Fuzzy Mixed Integer Programming (FMOMIP) Fuzzy Goal Programming (FGP)	Fuzzy Nonlinear Programming (FMONLP) Fuzzy Mixed Integer Nonlinear Programming (FMOMINLP)

3.2.3 Structure for literature review

Based on Wen et al. (2019), we analyzed the existing problems in each stage of the textile supply chain. We have structured the systematic review into two main sections. In Section 3.3, we focus on the problems encountered within a single textile and apparel industry echelon, encompassing the entire process from fiber production to apparel manufacturing. Next, in Section 3.4, we analyze the works concerning an integrated multi-echelon supply chain, investigating strategic, tactical, and operational decision-making problems.

3.3 Mathematical programming and optimization in textile and apparel manufacturing

Production planning studies in the textile industry have faced significant challenges. However, many existing problem formulations only consider some of the constraints of the textile industry, given the complex environment in which these problems are embedded (Rabbani et al., 2016). For instance, to achieve the desired colors and characteristics for textile products, a sequencing of production orders is required to allocate resources better, use full production capacities, and simultaneously reduce cleaning times for different colors. These decisions involve identifying the time and nature of each machine configuration and production demands while considering operational costs, such as setup, transportation costs, and inventory costs(e.g., Zhou et al., 2020; Camargo et al., 2014; Karabuk, 2008). Moreover, efficient production planning becomes more challenging when environmental issues such as water consumption, carbon emissions, and energy savings are considered.(e.g., Zhang and Chen, 2019; Govindan et al., 2015).

3.3.1 Fiber production

Textile manufacturing begins with obtaining raw materials. Generally, natural fibers can be obtained from vegetables (e.g., cotton and flax) or animals (e.g., wool and silk). Man-made fibers can be semi-synthetic, like rayon made from natural sources of regenerated cellulose, or synthetics, such as polyamide, polyester, and acrylic. Desired attributes in textile goods, such as softness, good appearance, and thickness, are obtained from quality fibers (Lord, 2003). In this topic, we discussed problems related to cotton production. No papers were found associated with the other raw materials.

3.3.1.1 Cotton production

Cotton is the most common natural fiber in the textile supply chain (Esteve-Turrillas and de la Guardia, 2017). Producing high-quality cotton fiber begins with growing and harvesting cotton (Kelly et al., 2015). However, only a few papers consider cotton production. For instance, Hong et al. (2019); Wineman and Crawford (2017); Salassi et al. (2013) highlight the importance of crop rotation to achieve better yields in cotton production. Crop rotation is the regular succession of production of different crops on the same land, generating agronomic and economic benefits. Duffy et al. (1994) studied the initial allocation for cotton planting. The objective function was the maximization of discounted before-tax net returns, and the computational results proved a pattern of increasing marginal returns for the initial cotton-base donors.

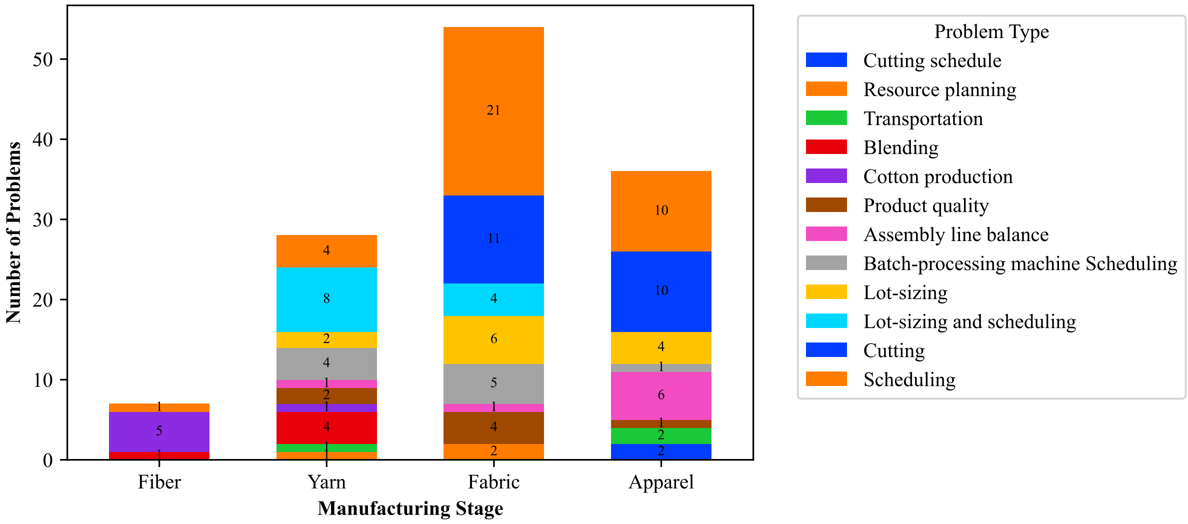
Furthermore, Khalili-Damghani et al. (2015) addressed another critical factor in cotton production: energy consumption. The authors proposed a method based on linear programming to evaluate the relative efficiency of homogeneous decision-making units (fertilizer, pesticide, and seed) to produce cotton and maximize input efficiency.

3.3.2 Yarn, fabric and apparel manufacturing

Textile manufacturing comprises multiple subprocesses that require managerial decision-making. In this review, we have categorized the analyzed papers into the following problem groups: i) blending problems (3.3.2.1), ii) resourcing planning problems (3.3.2.2), iii)lot-sizing problems (3.3.2.3, iv) scheduling problems (3.3.2.4), iv) batch-processing machines scheduling problems (3.3.2.5), vi) integrated lot-sizing and scheduling problems (3.3.2.6), vii) cutting problems (3.3.2.7), viii) cutting schedule problems 3.3.2.8), ix) assembly line balancing problems (3.3.2.9), x) product quality problems (3.3.2.10), and xi) distribution problems (3.3.2.11).

Figure 15 shows the distribution of reviewed papers across fiber, yarn, fabric, and apparel manufacturing stages, highlighting the dominance of research in the fabric stage. It also provides insights into the specific problem types explored within each stage, emphasizing key problems in textile manufacturing.

Figure 15 – Problem types by textile manufacturing stage.



3.3.2.1 Blending problems

Blending different raw materials is crucial in determining clothing softness, comfort, thickness, and strength. High-quality yarns are obtained by mixing different types of fibers. (El Mogahzy, 1992; Biadgligne et al., 2020; Bhattacharyya et al., 2008) have addressed the cotton-blending problem and determined the right mix required for manufacturing at the minimum cost. Zhang et al. (2014) formulated a nonlinear model to determine a suitable blending ratio of cotton yarns.

3.3.2.2 Resource planning problems

A strategic production plan to optimize the use of capital-intensive equipment in the apparel industry was analyzed by Wong et al. (2001). A two-level model was applied to determine the number of spreading and cutting machines to minimize the payback time. Rabbani et al. (2016) presented a MIP model for technology and capacity planning in textile manufacturing that considers water consumption, workforce constraints, and setup times to maximize profits. The model decides the amounts of each type of available technology and capacity planning allocated for each product at each period to maximize profits. Regarding energy consumption, Kousar et al. (2022) presented eight models to determine energy source allocation in a multi-stage textile facility.

3.3.2.3 Lot-sizing problems

The lot-sizing problem (LSP) consists of determining the amount to be manufactured for each product to meet customer demand and respect resource constraints. Bhatnagar (1981) discussed the implementation of LP to determine the optimal product mix, showing the challenges and the advantages of using LP formulation for textile manufacturing. Also, Gunasekaran et al. (1993) deals with the economic LSP in a multi-stage, multi-facility, and multi-product, production-inventory textile system, considering setup and in-process inventory carrying costs.

Motivated by financial planning decisions for a mixed make-to-order/make-to-stock environment when demand exhibits predictable fluctuations, a MIP model for LSP is proposed in (Elmehanny et al., 2018) for the apparel industry. The model has to decide the production amount in regular time and overtime, the inventory levels, and the area of fabric kept in inventory over a season. Also, an LP model is presented by Ghosh et al. (2020) to solve the production planning problem of a composite textile industry considering the manufacturing lead time.

Research dealing with single objective functions could ignore some critical aspects of the textile industry. Some aspects are reducing machine time, maximizing demand fulfillment, utilizing raw materials, and lowering operation times. Malik et al. (2022) addressed these issues in a multi-objective problem for a small apparel industry, considering eight different objectives simultaneously.

To address the labor shortage and environmental issues, Tsai and Jhong (2019) proposed a model combining workforce planning, carbon emission reduction, energy recycling, and waste reuse. Similarly, Tsai (2018) addressed a lot-sizing problem while improving environmental sustainability. Tayyab et al. (2020) addressed production planning in a multi-stage system considering effluent treatment and carbon emission costs. Also, Wu and Chang (2003a,b) proposed NLP models for determining textile dyeing amounts while respecting waste minimization alternatives, new environmental regulations, and the limitations of production resources.

3.3.2.4 Scheduling problems

Scheduling involves determining the job sequence and allocating necessary resources. An example of resource allocation can be found in (Sumathy and Amirthalingam, 2021), which tackles workforce scheduling in the textile industry. Mainly, scheduling in the textile processes is crucial to maintaining the desired features of the products, using materials and resources efficiently (Zhou et al., 2020; Srinath et al., 2022).

Jobs can be seen as items that should be manufactured, like yarns, fabrics, or clothing. Each job has attributes like color, weight, fibers, processing times, and other characteristics that determine the product family. Typically, items from the same family can be processed in the same production batch. However, setup times and costs can significantly impact the allocation of resources required to switch from one family to another.

Setup times and costs can be categorized as sequence-dependent or sequence-independent. A setup is sequence-dependent if it depends on the current and previous jobs processed. A setup is sequence-independent if it depends only on the current job, regardless of the prior one (Allahverdi, 2016). Mathematical programming models considering setup times and/or costs are applied in (Frendewey and Sumichrast, 1988; Guinet, 1991; Serafini and Speranza, 1992; Morales et al., 1996; Maldonado et al., 2000; Wong et al., 2000; Qiu et al., 2002; Guo et al., 2006; Hsu et al., 2009; Sumihartati et al., 2011; Eroglu and Ozmutlu, 2014; Zhang et al., 2017; El Hachemi et al., 2018; Zhou et al., 2020; Mourtos et al., 2021; Li et al., 2021a; Demir and Inan, 2022; Srinath et al., 2022; Berthier et al., 2022).

Performance measures are essential for evaluating scheduling production. Common performance measures include makespan, total processing time, tardiness, and earliness. The completion time (C_j) of job j is the instant at which its processing is completed. Makespan deals with the total processing time required to complete all jobs. MIP models and metaheuristics for minimizing makespan in textiles are in (Wong et al., 2000; Jungwattanakit et al., 2008; Huang and Yu, 2013; Berthier et al., 2022). Croft et al. (2021) proposed models to minimize makespan while considering water consumption. Unlike most studies, Wang et al. (2022) treated makespan as a constraint rather than an objective in an energy consumption-focused scheduling problem. The authors investigated energy-efficient scheduling on unrelated parallel machines with position-based deterioration in the textile industry.

Tardiness occurs when a job is completed after its due date (d_j). The number of tardy jobs represents late completed jobs. Tardiness (T_j) is the difference between the completion time of tardy jobs and their due dates $(T_j = \max C_j - d_j, 0)$. Early completed jobs may incur inventory-carrying costs. Earliness (E_j) is the difference between the early completion due dates $(E_j = d_j - C_j)$. To minimize tardiness and earliness, Tomastik et al. (1996) used an IP model and Lagrangian relaxation in a circular, automated material handling system. MIP models and genetic algorithms (GA) have been applied in (Min and Cheng, 2006; Jungwattanakit et al., 2008; Hsu et al., 2009; Celikbilek et al., 2016) to minimize costs related to earliness and tardiness. Huang and Yu (2013) analyzed a cutting and sewing flow shop to minimize the sum of weighted earliness, tardiness, and makespan. Azadeh et al. (2010) investigated three textile sub-processes (dyeing, printing, and finishing operations) to minimize makespan and total tardiness. Sánchez-Herrera et al. (2019) suggested a MIP model and greedy search procedure to minimize maximum tardiness, emphasizing human resource importance.

Sometimes, job splitting is required to process sub-jobs on separate machines to meet due dates. Eroglu and Ozmutlu (2014) focused on scheduling jobs with splitting and sequence-dependent setup times across nonidentical and unrelated parallel machines to minimize makespan in weaving. Job splitting and preemption are have also studied in previous works by Serafini

(1996) and Stern and Avivi (1990). Li et al. (2021a) and Srinath et al. (2022) explore machine eligibility by assigning specific machines to certain colors. Furthermore, Srinath et al. (2022) introduced scheduling preferences and shade differences as new objectives, alongside traditional ones like makespan, tardiness, and total setup time.

LP models in (Saydam and Cooper, 2002; Cooper and Saydam, 2003) to maximize machine utilization and generate optimal loads for scheduling jobs on multi-port dyeing machines. In a different scheduling application, Zaharie et al. (2017) used an IP model to determine order acceptance, scheduling, and allocation to work teams in the apparel industry, considering penalties for delays or rejections. Du et al. (2018) addressed robust order scheduling in apparel by assigning orders to production lines, considering preproduction events and daily production uncertainties to minimize preproduction events and tardiness.

3.3.2.5 Batch-processing machine scheduling problem

The scheduling model that best fits the dyeing process in literature is the batch-processing machine scheduling problem (BPMSP). BPMSP integrates he batch and the scheduling problems. In textile dyeing, the batch problem involves grouping yarn or fabric with different characteristics and due dates for processing in dyeing boilers. Uzsoy (1994) showed that the BPMSP is equivalent to a bin-packing problem. A classical bin packing problem aims to pack a finite set of objects into a minimum number of equal-sized bins. BPMSP was formulated as MIP models and solved with heuristics in (Puigjaner et al., 1996) to minimize costs and in (Demir and Inan, 2022; Demir, 2023) to minimize the total tardiness and the total number of boiler washings. (Zhang et al., 2017), proposed multiobjective formulations and metaheuristics to minimize tardiness and machine finishing time, while (Demir, 2022, 2024), focused on optimizing over-capacity usage and boiler costs. Duran et al. (2024) maximized jobs processed while minimizing machine usage. Li et al. (2022) proposed a bi-objective model to minimize maximum lateness and pollution cost on parallel batch-processing machines with varying capacities.

3.3.2.6 Integrated lot-sizing and scheduling problems

Integrated lot-sizing and scheduling problems combine decisions regarding the amount of production (lot sizes) and scheduling of several products on single or multiple capacitated machines. Integrating the lot-sizing and scheduling problems aims for efficiency and cost reductions. This class of problems is well-known as NP-hard since lot-sizing and scheduling problems are typically NP-hard, and algorithms are developed to solve them. Different approaches have been used in (Frendewey and Sumichrast, 1988; Gunasekaran et al., 1993; Akinc, 1993; Dumoulin and Vercellis, 2000; Beraldi et al., 2006, 2008; Silva and Magalhaes, 2006; Camargo et al., 2014, 2021). Pimentel et al. (2011, 2008) studied an integrated lot-splitting and scheduling problem in knitting manufacturing. Each item can be split into one or several different sizes during production, and each lot will be produced independently on identical parallel machines.

Camargo et al. (2021) analyzed blending integrated with scheduling and lot-sizing in spinning production planning. In the first stage, the blending problem determines the number of cotton bales in each blend load to feed the spinning machine. The lot-sizing and scheduling problem in the second stage determines the timing, level, and production sequence to meet yarn demand over time.

In general, the productive environment of textile industries is characterized by unpredictable demand, meaning that companies need to adapt to demand fluctuations over the planning horizon. However, most literature on mathematical programming in textile manufacturing considers deterministic parameters. Few papers consider parameter uncertainty. Uncertain data are represented by stochastic programming in (Karabuk, 2008; Beraldi et al., 2006) for yarn manufacturing. The most uncertain parameters for textile supply chain papers are discussed in Section 3.4.

3.3.2.7 Cutting problems

Cutting stock problems (CSP) involve cutting objects available to produce smaller pieces in specified amounts. CSP establishes cutting patterns in fabric production to minimize waste and costs or maximize profits. MIP models in (Richter, 1992; Degraeve and Vandebroek, 1998) address one-dimensional cutting problems (1D-CSP) to minimize cutting operations and waste while maximizing profits. In 1D-CSP, a fabric roll is only cut into smaller pieces in one direction. Ozdamar (2000) handled the cutting-wrapping problem, cutting large fabric lengths into smaller pieces wrapped around rolls.

In the two-dimensional rectangular cutting stock problem (2D-CSP), small rectangular pieces are cut from a large quantity of fixed-sized rectangular sheets. For instance, Wuttke and Heese (2018) proposed a MIP model and heuristic to minimize trim loss in 2D-CSP for the weaving industry. de Armas et al. (2008) also addressed a 2D-CSP with a Graphical User Interface in the textile industry. Farley (1990) presented a variant of 2D-CSP to minimize waste over multiple stock plates for the canvas industry. Peric et al. (2009) and Li et al. (2016) aimed to reduce waste and production time in a multicriteria MIP model and stochastic quadratic programming, respectively.

Gonçalves (2015) applied a biased random-key genetic algorithm to solve 2D-CSP to minimize the total fabric quantity needed to fulfill all orders. Salem et al. (2023) Salem et al. (2023) proposed a 2D-CSP variant with variable cutting pattern lengths between company-defined limits. They presented MIP formulations to minimize the total fabric area and the number of cuts.

Irregular packing problems (nesting) involve allocating irregular and regular pieces to a larger sheet while minimizing material or space waste (Leao et al., 2020). For instance, Heckmann and Lengauer (1998) and Hu et al. (2020) considered the 2D nesting problem to minimize the length of the sheet.

Some papers address fabric spreading and assigning garment sizes onto a table before cutting. This problem is known as cut order planning (COP). Tsao et al. (2020) formulated COP as a MIP model to determine the length of used fabrics and the number of opened sections while minimizing the total cost. Moreover, Ünal and Yüksel (2020) and Shang et al. (2019) proposed formulations to minimize the total usage of fabrics for COP. Also, Xu et al. (2020) analyzed the cost-oriented garment COP system in the context of mass customization when products must deal with fit and design issues.

Silva et al. (2015) considered minimizing the material waste problem in a vertically integrated textile company. The authors analyzed the integrated production planning and cutting problem. The proposed MIP model defines fabric roll dimensions, the number of rolls from inventory or purchase, and cutting patterns for each piece.

3.3.2.8 Cutting schedule problems

In apparel manufacturing, the pieces produced in the cutting process are required as work in progress to avoid bottleneck downtime in the sewing process. However, due to the limited area for storage and inventory costs, holding high inventory levels of cut pieces is not appropriate. In this context, Hung et al. (2014) proposed a MIP model to deal with the cutting schedule problem. The model determines optimal cutting times of fabric lays to meet the needs of the sewing process, minimizing piece inventory. For Wang et al. (2016), scheduling a cutting operation is similar to a 2D bin packing problem. By minimizing the makespan, the cutting schedule provides the cutting table, the location on the cutting table, and the start time of the cutting operation for each fabric lay.

3.3.2.9 Assembly line balancing problems

Assembly line balancing is a critical operational decision in manufacturing systems where products flow through workstations until the final product is obtained. The assembly line balancing problem (ALBP) aims to maximize the efficiency of an assembly line by distributing workstations throughout the line. Pereira (2018) provided two MIP formulations to minimize the total cost of stations while Efe et al. (2018) aimed to reduce the number of workstations. Gürsoy (2012); Gürsoy and Gürsoy (2015) Gürsoy (2012); Gürsoy and Gürsoy (2015) explored ALBP in a lean environment, aiming to minimize idle time per operator, using constructive heuristics and GA approaches. For multi-line apparel industries, Zhang and Chen (2019) and Zhang et al. (2019) used multi-objective optimization to reduce the transfer distance of semi-finished products and the area occupied by the sewing assembly line. Considering sustainable aspects, Zhang and Chen (2019) addressed the ALBP with a carbon emission evaluation to minimize the time loss rate and provide the smoothness index of the assembly line.

3.3.2.10 Product quality problems

Physical properties of textile products are crucial for their quality, and several multi-objective programming models have been proposed to assess textile quality. Ünal and Koç (2010) Ghosh et al. (2013), and Chakraborty and Diyaley (2018) developed models to improve yarn and fabric characteristics such as strength, unevenness, hairiness, imperfections, and breaking elongation, among others, at a minimum cost. Majumdar et al. (2017) proposed a model to optimize fabric air permeability and thermal conductivity. He et al. (2022) proposed a multi-objective optimization system for helping textile manufacturing firms optimize overall process performance and product quality. For certain textiles, such as jeans or denim garments, prewashed fabrics are highly valued by customers due to their appearance and softness. In this context, Ke et al. (2019) proposed a MINLP model to minimize costs and meet hydrogen peroxide concentration, temperature, and treatment time requirements in a bleach-washing process for denim garments.

3.3.2.11 Transportation problems

Distribution operations involve transporting materials from origin to destination. Distribution decisions are crucial as they impact costs, flexibility, and inventory management. For instance, El Hachemi et al. (2018) proposed a two-stage method to address the synchronized bin-forklift scheduling problem, which involves scheduling dye jets and planning forklift transportation. The objective is to dye and transport all jobs to the wringing section at the lowest cost while respecting the dye-jet capacity. Similarly, Smirnov et al. (1976) developed an LP model to optimize the distribution of rayon yarns and staple fibers by maximizing the daily output produced at each plant.

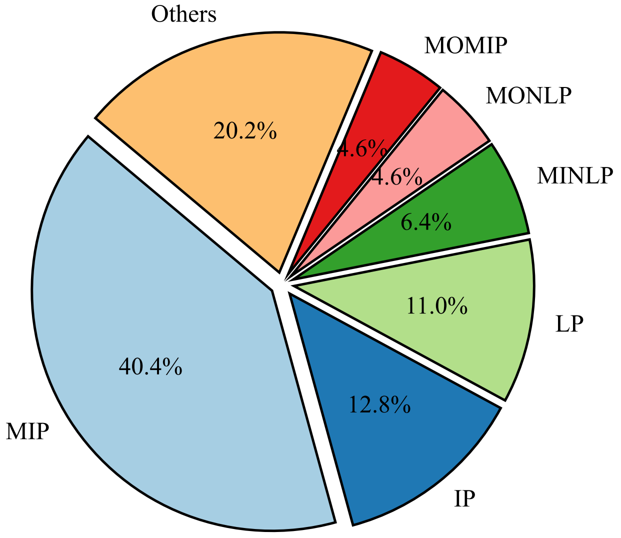
Hu et al. (2015) investigated the uncertain try-on service time for apparel distribution. Try-on service is a benefit some apparel companies offer customers when choosing home clothes, improving customer satisfaction. However, the uncertainty of try-on service time can make the apparel distribution process uncertain and incur higher logistics costs and times. In this sense, Hu et al. (2015) formulated this problem as a vehicle routing problem (VRP). The model was extended to support the solution strategies for uncertain try-on times. Another VRP for the textile industry can be found in (Eliguzel et al., 2021), which investigated the problem of picking up employees at a textile company.

3.3.3 Remarks

The reviewed literature highlights various mathematical programming models and techniques to address production and distribution problems in textile and apparel manufacturing. These models seek to improve the overall efficiency and sustainability of textile manufacturing in different contexts. Given the analysis, we can point out the following:

- *Model characteristics*: The analysis of the model characteristics reveals a clear dominance of linear programmings in the reviewed papers, where MIP is the predominant approach as illustrated in Figure 16. Models appearing in less than 3% of the papers are grouped in the *Others* class. Detailed models are presented in Table B2.

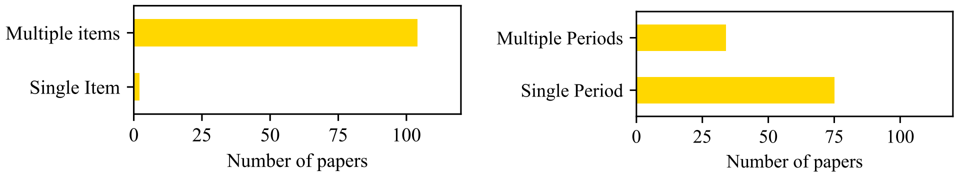
Figure 16 – Distribution of mathematical programming models in textile and apparel manufacturing



As Figure 17a indicates, most papers deal with multiple items. Figure 17b shows that most studies consider a single planning period rather than multiple periods, indicating a preference for simpler models and immediate operational focus. The limited exploration of multi-period scenarios highlights an opportunity for future research to address dynamic, long-term planning. Figure 17c suggests that most studies focus on complex machine environments, reflecting a preference for real-world production settings. More details can be found in Tables B3, B5, and B7).

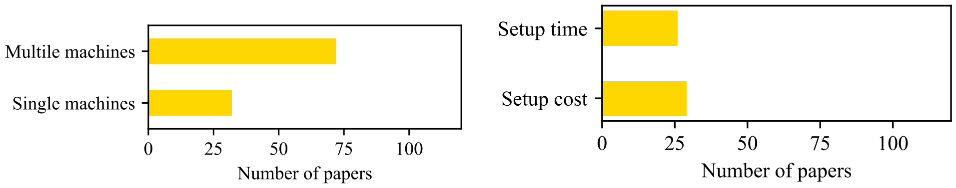
- *Setup*: Figure 17d shows that 27% of the reviewed textile manufacturing papers consider setup times or costs in their formulations. Tables B3, B5 and B7 summarize the characteristics of studies incorporating setup costs or times, mainly focusing on scheduling and lot-sizing problems. Most of these studies assume sequence-dependent setups, highlighting their importance. Despite the benefits of setup carryover for cost reduction (Gopalakrishnan et al., 1995), only Camargo et al. (2021, 2014) have incorporated it. This presents opportunities for further research on cost and setup improvements in textile production planning.
- *Objective function*: Figure 18 shows that most models are single objective function models, with only a few studies considering multiple objectives. Cost-related factors such as inventory, backorder, and setup are the main focus in cost minimization studies, while profit maximization has been little explored. In scheduling studies, the main objectives are minimizing tardiness and makespan, and a small number of studies consider the number

Figure 17 – Summary of model characteristics analyzed in the reviewed textile and apparel literature.



(a) Distribution of studies by the number of items.

(b) Distribution of studies by planning horizon.

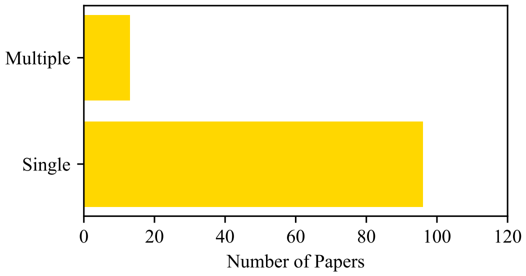


(c) Distribution of studies by machine configuration.

(d) Setup considerations in studies.

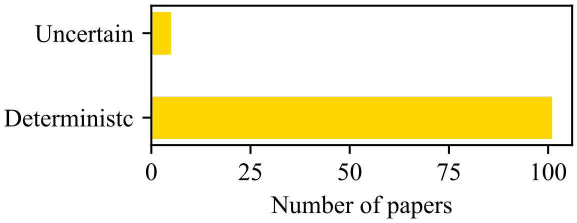
of setups or setup time minimization. Operational performance is addressed through objectives like maximizing machine utilization and minimizing waste. Furthermore, the quality improvement of textile items is addressed through factors such as strength and softness. Details are presented in Tables B3, B5 and B7.

Figure 18 – Distribution of objective function types in models for textile and apparel manufacturing.



- *Uncertainties*: Figure 19 shows that only 6% of the reviewed papers address parameter uncertainties, primarily focusing on uncertain demand. Common methods used to represent these uncertainties include randomly generated numbers and stochastic programming. One study applies robust optimization to manage uncertainties in daily production quantities. One work applies fuzzy numbers to represent uncertain parameters such as costs and worker productivity. For further details, see Tables B3, B5, and B7. More research is needed to investigate a broader range of textile and apparel manufacturing uncertainties, such as supply disruptions, market fluctuations, and machine failures.
- *Solution approach*: Commercial solvers are employed to obtain exact solutions on 44% of the papers. Authors predominantly count on approximate methods, particularly heuristics

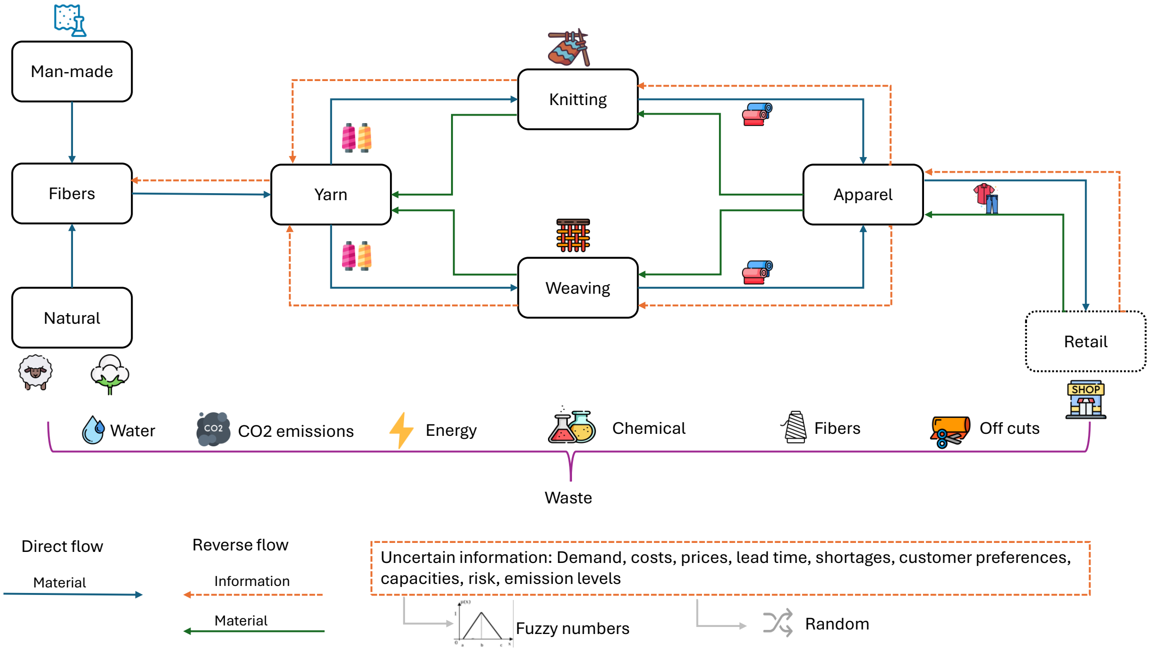
Figure 19 – Distribution of data type in textile and apparel manufacturing models.



and meta-heuristics as the solution approach (Table B2). Among the approximate methods, genetic algorithms are the most used solution method, followed by search algorithms and constructive heuristics.

3.4 Mathematical programming and optimization in textile and apparel supply chain

Figure 20 – Textile supply chain flow diagram.



The demand for textile products is expected to triple by 2050, driven by the growing consumption of different textile applications, such as fashion, health care, military, automobile, space, and sports (Shirvanimoghaddam et al., 2020; Li et al., 2021b). At the same time, the textile supply chain is one of the most polluted chains in the world, leaving tons of waste in the environment (Zhu et al., 2022; Xu et al., 2024; del Mar Barbero-Barrera et al., 2016). Estimates show that 45% of textile products, ranging from fibers to clothing, are wasted (Li et al., 2021b). These issues differentiate the planning process in the textile supply chain.

Companies make integrated decisions to manage material distribution within the chain, covering direct and reverse flows. The information flow involves uncertainties, often represented by fuzzy numbers, with few studies using random scenario generation. Additionally, the authors emphasize the importance of integrated decisions prioritizing waste reduction, such as reducing water and energy consumption and carbon emissions. In this section, we review works that explore multi-echelon supply chains, categorizing the planning decisions into three levels: strategic, tactical, and operational. Figure 20 illustrates the relationships between stages in the textile supply chain, highlighting material and information flows. Retail operations are not within the scope of this review.

3.4.1 Strategic level decisions

Strategic planning is long-term planning (5-10 years), generally related to decisions such as plant or warehouse locations, capacity levels, technology and equipment acquisitions, activity outsourcing, transportation networks, suppliers, and order fulfillment approaches. At this level, we have works addressing supply chain network design (3.4.1.1), location-allocation problems (3.4.1.2), and closed-loop supply chain (3.4.1.3).

3.4.1.1 Supply chain network design

Supply chain network design (SCND) decisions involve plant and distribution center locations, capacities, customer zones, supplier allocation, transportation modes, and other factors. An efficient SCND enables textile companies to meet customer orders while reducing travel times and global costs. Bouzembrak et al. (2013) analyzed SCND under uncertain demands and supplier levels, with costs modeled as fuzzy numbers.

Paydar et al. (2021) developed a bi-objective stochastic model for apparel SCND, optimizing total profit while minimizing downside risk. Ying-Hua (2010) used a co-evolutionary model and constraint-satisfaction mode to solve SCND Berthier et al. (2020) addressed SCND using a MIP model to determine optimal fabric production locations, minimizing costs across the whole chain. Additionally,Shaw et al. (2013); Jafari et al. (2017); Moreno-Camacho et al. (2020); Mezatio et al. (2022, 2023a,b); Kian et al. (2024); Shefa et al. (2024) considered sustainability aspects such as water recycling, carbon emissions, and green processes for SCND.

Sarma et al. (2021) investigated fashion retail supply chain strategies to deal with the COVID-19 pandemic. The proposed model presented the optimal retailing strategies for selling fashion goods over physical and online platforms, analyzing the effect of the pandemic on the supply chain.

3.4.1.2 Location-allocation problem

Li et al. (2017) focused on the location-allocation problem within a reverse network involving customer zones, collection points, and repair centers. The authors proposed a MIP model to minimize costs by assigning repair centers to collection points and allocating collection points to customer zones. Khannan et al. (2018) used linear programming to optimize the warehouse allocation considering cross-docking operations. Also, Zheng and Song (2019) proposed a stochastic model to optimize capacity allocation among clothing suppliers to maximize shared resource utilization.

3.4.1.3 Closed-loop supply chain and sustainable supply chain

Concern with environmental issues and developing a sustainable supply chain has grown in recent decades. Thus, the entire SC needs to be designed by incorporating sustainability concerns into several echelons of the SC. Some companies implement reuse or recycling policies. Others introduce environmental considerations, like carbon emissions, into planning. The forward chain combines processes from raw material producers and manufacturers to the final customers. A backward flow is needed for end-of-life management. The reverse flow starts with consumers, collecting discarded products that return to earlier production stages. Considering both flows in an SC will result in a new configuration known as a closed-loop supply chain (CLSC) (Govindan et al., 2015).

Masoudipour et al. (2017) developed a MINLP to deal with CLSC based on the quality of returned products. Their study explores the impact of CLSC on network decisions and profits. Oh and Jeong (2014) developed a multi-objective model to determine the trade-off between CLSC profit and carbon emissions. The model must decide the production, transportation, and inventory amounts for a CLSC network.

Jakhar (2015) proposed a set of sustainable SC performance measures for an apparel SC network. Using fuzzy logic, the author proposed a method to maximize sustainable purchasing, production, delivery, and logistics while minimizing costs and carbon emissions. Also, a MOMIP is presented by Jafari et al. (2017) to design a sustainable CLSC concentrating on water recycling and justice-oriented employment levels. Abbas et al. (2021) integrated cotton crop waste into the textile energy supply chain with an LP model, addressing sustainability and cost-effectiveness. The model converts waste into bioenergy, reducing fossil fuel dependency and emissions.

3.4.2 Tactical level decisions

Tactical planning is mid-term planning (12-18 months), ensuring that the firm meets the goals established at the strategic level. Commonly, tactical decisions include assigning production capacity to product families, supplier selection, capacity manufacturing planning, workforce requirements, distribution centers, shipment plans, inventory management, and transportation mode. At this level, we grouped works in supplier selection (3.4.2.1), aggregate production planning (3.4.2.2), and integrated production and distribution planning problems (3.4.2.3).

3.4.2.1 Supplier Selection

Supplier selection seeks to identify suppliers capable of meeting manufacturer needs with acceptable performance. Factors such as capacity, price, quality, and transportation further complicate decision-making, directly impacting customer satisfaction. Araz et al. (2007) proposed an integrated multi-criteria decision-making method using fuzzy goal programming to select suitable strategic suppliers and allocate order quantities.

Integrated decisions on supplier selection, order allocation, and transportation under uncertainty were studied in (Ghasemy Yaghin and Darvishi, 2019; Ghasemy Yaghin and Sarlak, 2019; Ghasemy Yaghin and Darvishi, 2022; Ali and Zhang, 2023). The authors proposed multi-objective linear programming, fuzzy goal programming, and fuzzy mixed integer nonlinear models. Ghasemy Yaghin and Sarlak (2019) considered corporate social responsibility and environmental variables, like air and water pollution and energy consumption. Hashim et al. (2017), Tayyab and Sarkar (2021), andAli and Zhang (2023) also use fuzzy logic to tackle the sustainable supplier selection problem in a textile SC for purchasing raw materials. Sustainable supplier selection was also addressed by Mezatio et al. (2022). The MIP model proposed by the authors considers selecting suppliers, subcontractors, opening sites and warehouses, transportation modes, and raw material quantities based on carbon footprints.

Karami et al. (2020) developed a systematic approach incorporating environmental, social, and economic factors for supplier selection in the apparel industry. An LP approach was used to determine efficient suppliers in a three-stage framework. Similarly, Jatuphatwarodom et al. (2018) The EGP is explicitly used to focus on inventory optimization analysis.

3.4.2.2 Aggregate Production planning

Aggregate Production Planning (APP) is a crucial medium-term production planning process that typically spans a planning horizon of 2 to 18 months. The primary objectives of APP involve determining optimal production, inventory, and employment levels. Several studies have explored the complexities of multiple suppliers, manufacturers, and customers within multi-site, multi-period, and multi-product APP models.

Leung et al. (2003, 2006, 2007) proposed different approaches for a multi-site APP for apparel SC. Data uncertainty (Table B10) were considered in (Leung et al., 2007, 2006). Likewise, Ghiani et al. (2003) presented a GP model with uncertain productivity for allocating production batches to subcontractors in a textile SC, using a fuzzy logic approach to handle data uncertainty. Moreover, a rolling-horizon APP method was proposed by Demirel et al. (2018), incorporating an alternative stabilizing approach into the conventional APP.

Darvishi et al. (2020), Ghasemy Yaghin et al. (2020) and Ghasemy Yaghin and Darvishi (2022) studied jointly inbound logistics and multi-site aggregate production planning (APP) decisions with uncertainties along the tactical planning horizon in a textile SC. The authors proposed nonlinear models with stochastic-fuzzy to integrate supplier selection and social responsibility related to the APP. Furthermore, considering the trade-off between carbon emissions, social performance, and supply chain total profit, Ghasemy Yaghin and Sarlak (2022) studied textile SC tactical planning under demand fuzziness.

Ghasemy Yaghin (2020) proposed a nonlinear model to combine marketing decisions into APP. Marketing planning involves product selection, sales channels, and pricing, while production planning focuses on resource allocation to achieve these goals. Similarly, Guan et al. (2000) examined APP and proposed a fuzzy MIP formulation to determine production and capacity planning for a manufacturer operating within a supply chain that experiences seasonal demand.

3.4.2.3 Integrated production and distribution planning

To improve the performance of an SC, it is necessary to efficiently plan and manage production and distribution activities by coordinating information, services, and goods. Therefore, some papers seek SC coordination and overall cost-reduction approaches to the integrated production and distribution problem. Safra et al. (2019, 2021) proposed a planning approach involving tactical and operational decisions. The authors considered receiving preseason orders at the tactical level to determine production capacity and the need to hire outsourced labor. A weekly rolling horizon integrates the new replenishment orders received during the weeks.

Felfel et al. (2018, 2016a,b, 2015) studied an SC network composed of medium and small companies that comprises different textile stages. The authors proposed stochastic and multi-objective linear programming models for integrated production and distribution planning. Similarly, Ait-Alla et al. (2014) analyzed a production planning problem for a textile SC. Robust optimization represents the conditional value theory of uncertain data at risk by introducing and constraining a loss function. Wang et al. (2021) developed a stochastic multi-objective model to tackle sustainable production planning, considering workforce change and customer satisfaction.

3.4.3 Operational level decisions

Operational planning is related to short-term (daily or weekly) decisions regarding resource allocation and further steps on the shop floor to follow the tactical plans. Decisions on this level include problems such as scheduling machines, inventory balancing, customer order processing, warehouse operations scheduling, labor scheduling for manufacturing, vehicle routing, carrier selection for individual loads, and sales promotions. At this level, we grouped works in production planning (3.4.4.1) and distribution and transportation (3.4.4.2).

3.4.4 Operational level decisions

3.4.4.1 Production planning

De Toni and Meneghetti (2000) focused on the production planning process in a knitting SC aiming for synchronization across a large network. The network operates using seasonal campaigns within a make-to-order manufacturing system. The authors analyzed the impact of production planning on supply chain performance, particularly from a time-based perspective.

3.4.4.2 Transportation

The success of textile and apparel companies depends on supply chain management to ensure timely product flow at minimal cost (Safra et al., 2021). Distribution and transportation decisions are critical, encompassing determining shipment quantities to satisfy demand, scheduling daily inventory movement, and coordinating pickup and delivery activities.

Caro and Gallien (2010) addressed the distribution problem of allocating limited inventory across all stores in a large apparel supply chain. The authors developed a stochastic model to predict sales during replenishment, considering demand forecasts, initial inventory, and policy inventory. A MIP model calculated store shipments to maximize predicted sales while adhering to inventory constraints. The study evaluated operational performance metrics, including shipments, sales, and missed demand. In a different context, Mas'ud and Wahid (2022) analyzed a distribution problem in the processing of silk products, focusing on the challenges posed by digital disruption during the COVID-19 pandemic.

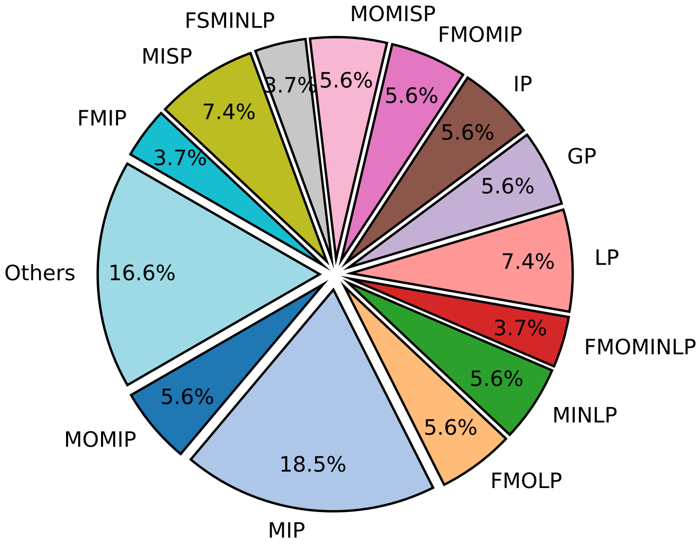
Companies often outsource logistics activities to third-party logistics providers (3PL). 3PLs specialize in warehousing, transport, freight consolidation, inventory management, and other logistics services. In this context, Kayvanfar et al. (2018) proposed an FMOGP for the distribution problem of a textile industrial cluster, using a 3PL for logistics services. The model had three objective functions: minimizing the total logistics costs, maximizing the demand satisfaction rate, and maximizing the quality of delivery. Also, Karabuk (2007) studied the transportation problem of a textile producer that operates many manufacturing facilities at all SC. Cotton and synthetic fibers yarns are shipped to weaving plants to produce fabrics. Fabrics are shipped from weaving to dyeing and finishing plants and sent to customers. The truck fleet is heterogeneous, allowing different loading shipments. The problem involves scheduling pickups and deliveries for daily inventory movements between plants.

3.4.5 Remarks

- *Model characteristics*: Figure 21 shows the distribution of mathematical programming models in the textile supply chain. The analysis of the model attributes reveals that linear programming is predominant in supply chain papers, with MIP as the most popular approach. Nonlinear models appear in 17% of the articles. Models that appear only once are grouped under the *Others* category. Detailed models are presented in Table B9.

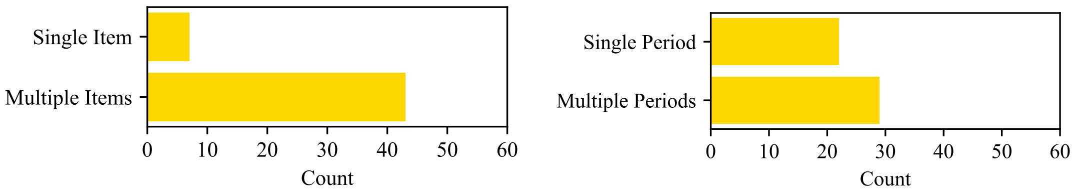
  Figure 22 illustrates that most integrated supply chain studies focus on multiple items, multiple periods, multi-site production plants, and multiple suppliers. Yet, 42% of the studies still address single-period problems. Given the multi-echelon nature of these studies, our findings indicate a stronger research emphasis on the relationships between

Figure 21 – Distribution of mathematical programming models in textile supply chain.



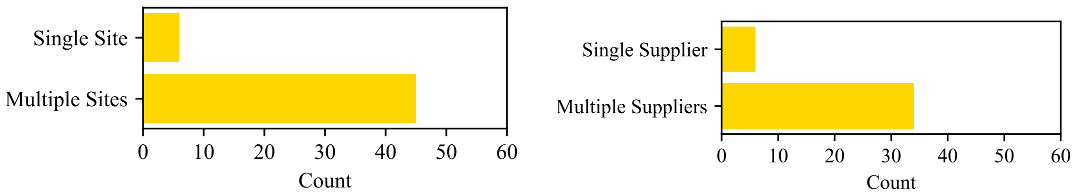
companies and suppliers (upstream supply chain) compared to the relationships between companies and customers (downstream supply chain). Future research could explore customer-centered studies to address gaps in downstream supply chain dynamics.

Figure 22 – Summary of model characteristics analyzed in the reviewed textile supply chain literature.



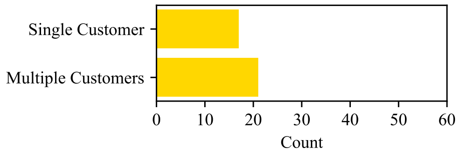
(a) Distribution of studies by the number of items.

(b) Distribution of studies by planning horizon.



(c) Distribution of studies by the number of plants.

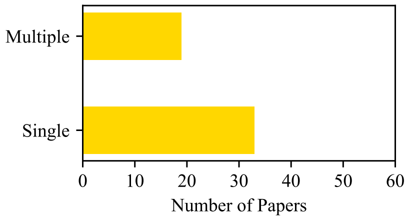
(d) Distribution of studies by the number of suppliers.



(e) Distribution of studies by the number of customers.

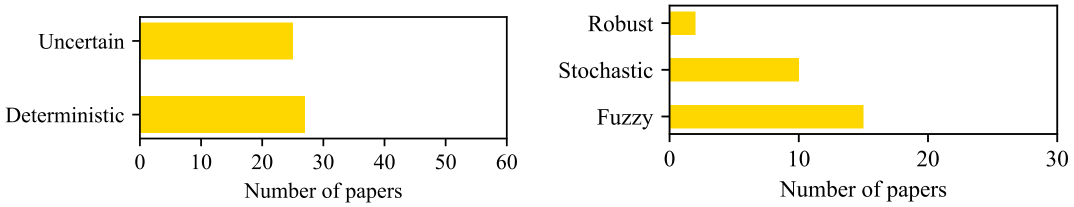
- *Objective function*: Figure 23 shows that most models are single objective function models. Table B11 indicates that minimizing costs—including inventory, transportation, labor, production, material, lost sales, and backorder costs—is the focus of most studies. It is worth mentioning that 36% of the studies use multi-objective models, targeting goals such as optimizing social value, minimizing water consumption and carbon emissions, maximizing capacity utilization, mitigating risk, reducing production time, improving product quality, and selecting green suppliers. These multifaceted objectives help capture the broader implications and sustainability considerations within the textile supply chain, highlighting a field for future research.

Figure 23 – Distribution of objective function types in textile supply chain models.



- *Uncertainties*: The presence of uncertain data in supply chain articles is higher compared to the articles discussed in Section 3.3. Figure 24a reveals that half of the reviewed studies address uncertain environments. In these works, 55% formulated the uncertainty as Fuzzy numbers, as shown in Figure 24b. Table B10 demonstrates several sources of uncertainty that are analyzed, including production times, capacity levels, sales prices, costs, lead times, customer preferences, and others, with demand being the primary source of uncertainty.

Figure 24 – Distribution of studies by data type in textile supply chain models.



(a) Distribution of studies by data type

(b) Distribution of studies by type of uncertainty.

- *Solution approach*: In the field of the textile SC, 50% of the studies use only exact methods offered by commercial solvers, as shown in Table B9. In 34% of the papers, approximate methods such as genetic and search algorithms are used to solve the proposed models. Both exact and approximate methods are applied in 11% of the studies. Some works employ mathematical programming as part of multi-criteria decision-making processes, including data envelopment analysis and analytical hierarchy process, particularly for supplier selection.

3.5 Final remarks, future research, and limitations

The textile sector is crucial, attracting significant academic interest across various aspects. In recent years, there has been a notable growth in research focused on this field. Given its specific characteristics, such as short product life cycles, high volatility, low predictability, and high demand accompanied by substantial energy and water consumption, as well as carbon emissions, the development of efficient management plans are essential to ensure competitiveness. To contribute to this field, we conducted a systematic review of mathematical programming models used in the decision-making process for the textile supply chain, spanning different publication years. By categorizing the reviewed papers based on manufacturing stages and problem types, we identified key features, objective functions, and solution approaches employed in this domain.

Scheduling: Our findings emphasize the significance of scheduling problems in textile manufacturing. It is important avoiding mixing certain items and colors to maintain product quality. In this sense, each machine can process only one job at a time, and each job can be processed on only one machine. Several works have proposed different scheduling approaches on various machines, considering sequence-dependent setup costs or times. However, there is still room for further research on scheduling problems, especially when considering integrated problems encompassing multiple textile manufacturing aspects. Also, more practical concerns should be considered, including machine maintenance, machine eligibility, failure, product life-cycle, defective items, and re-dyeing.

Economic, environmental, and social aspects: While some models primarily focus on environmental aspects such as carbon emission reduction and energy and water consumption as indicators of sustainable production, it is crucial to recognize that sustainability encompasses the triple-bottom line: economic, environmental, and social dimensions (Jafari et al., 2017; Ghasemy Yaghin and Sarlak, 2019). Hence, it is vital to consider the economic and environmental impacts, including cost reduction through efficient resource utilization, integration of reverse flows, including carbon trade, minimizing waste, and reusing resources and products. Equally important is incorporating social responsibility factors, such as fair labor practices and community engagement, to ensure a comprehensive approach to sustainable production (Jafari et al., 2017; Sánchez-Herrera et al., 2019). Here, it is important to note that while sustainable aspects have been incorporated into supply chain models, this topic remains underexplored in individual manufacturing stages.

Uncertainties: Several papers highlight the challenges faced in textile production planning, primarily due to various sources of uncertainty (e.g., Karabuk, 2008; Rabbani et al., 2016; Felfel et al., 2018). However, we observed that most of these studies still focus on deterministic parameters, especially for the individual manufacturing stages. Although demand is recognized as the primary source of uncertainty, further research is needed to explore demand modeling, considering factors such as sales channels, customer segmentation, and supplier prices. One aspect that has received limited attention is using safety stock to mitigate the impact of demand variability (Ghasemy Yaghin et al., 2020). Additionally, to closely resemble real-world scenarios, it is crucial to incorporate uncertain data into the models for production costs, purchasing costs, capacity levels, disruption, labor productivity, and sales prices. These factors play a key role in capturing the complexity and dynamics of textile production planning.

Operational performance metrics: Operational performance metrics are essential in the textile and apparel supply chain, providing valuable insights into the efficiency and effectiveness of operational activities. Our research highlights the significance of performance measures such as makespan, total processing times, tardiness, and earliness in addressing scheduling problems. Caro and Gallien (2010) have included metrics like shipments, returns, sales, and lost sales to quantify operational performance in the apparel supply chain. Additionally, Zhang et al. (2017) evaluated time machine utilization, and Tayyab et al. (2020) suggested including service-level constraints to improve production planning. These metrics enable organizations to track and measure key performance indicators (KPIs) related to production, inventory management, order fulfillment, and logistics. Companies can identify bottlenecks, optimize processes, and enhance operational performance by monitoring cycle time, throughput, on-time delivery, order accuracy, and inventory turnover. Further studies should include constraints and objective functions to evaluate operational performance metrics.

Solution approach: Several papers primarily concentrate on cost minimization using single objective functions. However, it is essential to recognize the significance of incorporating multiple objective functions to achieve a more holistic approach. By incorporating different goals like quality, customer satisfaction, sustainability, and production efficiency, textile companies can align their decision-making processes more effectively with the diverse requirements of the industry and stakeholders. In terms of solving these problems, developing exact or approximate solution algorithms, instead of solely relying on commercial solvers, can ensure successful resolutions for large instances in the textile supply chain.

Limitations: The current study had certain limitations regarding the method used. Firstly, while we used multiple databases for our search process, certain databases, such as Emerald, JSTOR, and ACM Digital Library, were not included. Secondly, our study focused exclusively on research articles published in the English language, missing valuable literature published in other languages. Additionally, we specifically concentrated on mathematical programming models, thus excluding other operational research techniques like simulations and game theory from the scope of this review. Furthermore, our study primarily centered around manufacturing stages and did not delve into retailer operations such as pricing, selling strategies, or customer behavior. We compensated for these limitations by presenting key problems and listing research gaps in the textile supply chain. We hope this work will inspire further research on mathematical programming in the textile industry.

4 Using mathematical modeling to meet service levels in production planning in textile companies

Selecting the product delivery strategy in manufacturing systems is a complex managerial decision. One challenge is choosing a production strategy that allows firms to offer high-quality, customized products while maintaining competitive costs and high service levels Hemmati and Rabbani (2010). Increasing customer satisfaction by meeting their needs is a primary goal for companies Chong and Chen (2010). This satisfaction, measured by logistical performance, primarily depends on promised delivery lead time and service level related to meeting orders on time Zäpfel (1998); Uvet (2020); Tian et al. (2021).[1]

Su and Gargeya (2016) pointed out that the textile supply chain is highly fragmented, composed of most small and medium companies with low coordination, making them more vulnerable to global competition. In this sense, it is vital for the survival of these companies on-time delivery, product quality, quick response time, and better communication. The textile and apparel industries are significantly vulnerable to time-based management due to their dependence on fashion trends. Unsold products often require markdowns, while delayed production or delivery risks losing customers to competitors (Seuring et al., 2004).

In this chapter, we address the lot-sizing problem focusing on customer orders. As shown in chapter 3 several authors address the lot-sizing problem focusing on items production (e.g.: Ghosh et al. (2020); Camargo et al. (2021); Malik et al. (2022)). An order-oriented lot-sizing problem is addressed in Furtado et al. (2019) and Alves et al. (2024) for small foundries, aiming to minimize the sum of backlogged order costs. The production planning of orders is a case of lot-sizing problems where items are grouped according to customer orders, and production sequencing is performed for alloy families. An order is considered completed when all component items are delivered. This model can be extended to other process industries considering item families, such as the textile, glass container, or soft-drink industries.

When an order is met after its due date, it becomes a backlogged order. This can lead to lost sales if the order remains unmet in the planning horizon, and estimating the cost of lost sales, including revenue and customer goodwill loss, is a complex task (Brahimi et al., 2017). One approach to limit backlogged orders and mitigate lost sales is to ensure a given service level which can be modeled as service-level constraints.

Service-level constraints are primarily studied in stochastic inventory management problems (Bookbinder and Tan, 1988; Aardal et al., 1989; Tempelmeier and Herpers, 2010; Helber et al., 2013; Tunc et al., 2014; Tsai and Jhong, 2019; Sereshti et al., 2021). According to Gruson et al. (2018), the service-level constraints are usually not considered in deterministic problems due to an assumption that there should be no delays if the demand is previously

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[1] An article with the contents of this chapter is in the peer review process at Flexible Services and Manufacturing Journal.

known. In multi-item capacitated problems, the demand of a lower-priority customer may be delayed to meet the demand of a higher-priority customer on time (Gruson et al., 2018; Gade and Küçükyavuz, 2013). Additionally, Stadtler and Meistering (2019) affirm that deterministic formulations offer a more practical approach to addressing real-world production planning challenges and can be helpful for decision-makers controlling specific service levels.

We extend the γ service-level constraints to limit the total of backlogged orders. In the original constraint, the γ service level limits backlogging items. In our work, we used the γ constraint in an aggregate manner because we propose the constraint to limit the number of backlogging orders that may include different items. Furthermore, Bhatti et al. (2014) pointed out that for some companies like textile industries put more focus on the customer satisfaction and delivery reliability. The authors listed the importance of key performance indicators (KPIs) and their impact on overall organizational performance. In this sense, we propose the μ service-level constraint to increase the number of orders delivered during the planning horizon and seek to increase the production rate measured by the throughput. Finally, a efficient use of the resources, such as machine utilization, is important for textile industries (Zhang et al., 2017). Thus, the third proposed constraint is capacity utilization (θ).

Considering the production planning problem focusing on customer orders, we propose a set of service-level constraints to limit backlogging orders, increase the order production rate in the planning horizon, and improve the equipment capacity utilization. For this purpose, we extend the model proposed by Furtado et al. (2019), creating five new variations of this model according to the service level or capacity utilization constraints. To solve these models, we adapt the Alves et al. (2024) solution method based on Surrogate relaxation of the capacity constraints.

The impact of the proposed constraints is analyzed on the solution structure related to the costs and the number of orders met on time, on delay, and on unmet orders. We also analyze the impact of these constraints on KPIs such as lead time, throughput, work-in-process, and average delay, which are considered essential control measures for manufacturing systems Clark et al. (2011); Battesini et al. (2021).

The remainder of this chapter is organized as follows: in Section 4.1 we report the related works on the literature. In Section 4.2 we present the proposed service-level constraints. The instances description used for computational experiments is presented in Section 4.3. Numerical results for three different scenarios are shown in Section 4.4. Finally, conclusions and future research are pointed out in Section 4.5.

4.1 Related works

Service-level constraints are primarily studied in stochastic inventory management problems (Bookbinder and Tan, 1988; Tempelmeier and Herpers, 2010; Helber et al., 2013; Tunc et al., 2014; Tsai and Jhong, 2019; Sereshti et al., 2021). The cycle service-level (α service-level) represents the probability that no stockout occurs during a cycle or in a planning period of discrete-time models (Silver et al., 1998; Helber et al., 2013). In Bookbinder and Tan (1988), the α service-level is incorporated into the stochastic lot-sizing problem, and different strategies for the probabilistic lot-sizing problem are studied. Equivalent deterministic problems are proposed to tackle the computational complexities of stochastic problems.

Fill rate constraint, known as β service-level, is frequently used in the industry to measure inventory management performance, understood as the fraction of the demand immediately met by the inventory (Tempelmeier and Herpers, 2010; Helber et al., 2013). The works in Tempelmeier and Herpers (2010) and Tempelmeier (2011) deal with the stochastic capacitated lot-sizing problem (SCLSP) formulation with random demand over a discrete and finite time horizon and β service-level constraints. The authors use the fill rate constraint to count the number of periods covered by production.

Two other service-levels for SCLSP are considered in Helber et al. (2013): γ service-level and δ service-level. The γ service-level measures the delay and, somehow, the customer waiting time. This measurement can also be expressed as an average of the entire planning horizon. By considering the waiting time of customers and the size of backorders, the authors develop the δ service-level constraint to limit the total expected backlog.

Several mathematical formulations for aggregate service-level constraints in the SCLSP are proposed in Sereshti et al. (2021). These aggregate formulations enable the decision-maker to allocate individual service-levels to multiple products while ensuring that the overall aggregate service-level is met. Sereshti et al. (2024) developed deterministic and two stochastic models for more flexible handling of stochastic, distinguishing between known customer demands and variable demands. The models aim to optimize production setup and volumes to minimize total costs—including setup, inventory, overtime, and backlog costs—while meeting service-level requirements for demand fulfillment.

Some papers have considered service-level constraints in lot-sizing problems with deterministic demand. For example, Zangwill (1966) addressed a deterministic production scheduling with a backlog and a limited number of delays in a period to represent a service-level. An uncapacitated lot-sizing problem (ULSP) is studied in Gade and Küçükyavuz (2013). The α service-level constraint limits the number of periods with backlogs. In addition, the authors presented models with the β service-level to impose the percentage of demand satisfied on time above a given limit. Wei et al. (2021) affirm that stochastic models, often used to deal with service-level constraints, are challenging to solve and are typically approximated by deterministic formulations. The authors analyzed two inventory models (with backorder and lost sales) with independent demands, positive lead times, and service-level constraints. These parameters can be calculated using the optimal solution of a deterministic approximation of the backorder inventory system. The authors highlight the relevance of using deterministic formulations to solve complex inventory problems.

The work of Gruson et al. (2018) introduced different service-levels for CLSP and ULSP deterministic problems. An adaptation of the α service-level is exhibited to determine the percentage of periods in which no backorder occurs. A formulation including the δ service-level is also considered. In Stadtler and Meistering (2019) different formulations for CLSP and service-level constraints were studied. The authors addressed α, β, γ, and η service-levels. The η service-level is the customer order waiting for time service-level, a customer/buyer-oriented performance criterion. Furthermore, Tomazella et al. (2023) examined the integrated procurement and lot-sizing problem, incorporating β service-level constraints for items and customers to minimize costs. Moreover, a bi-objective approach is proposed where service-levels are optimized and costs are minimized.

Several approaches have been adopted to address lot-sizing problems involving service-level constraints. An overview of the papers discussed in this section reveals a limited focus on customer orders. We contribute to incorporating orders into production planning, thereby advancing this field. Furthermore, this study extends the existing literature on service-level constraints with deterministic demands.

Table 6 – Related works on lot-sizing with service-level constraints.

		Demand type		service-level type					Customer
Authors	Year	D	S	α	β	γ	δ	Others	orders
Bookbinder and Tan	1988		✓	✓					
Tempelmeier and Herpers	2010		✓		✓				
Tempelmeier	2011		✓		✓				
Tempelmeier and Herpers	2011		✓		✓				
Helber et al.	2013		✓				✓		
Gade and Küçükyavuz	2013		✓			✓			
Tunc et al.	2014		✓	✓					
Gruson et al.	2018	✓		✓	✓		✓	✓	
Stadtler and Meistering	2019	✓		✓	✓	✓		✓	
Sereshti et al.	2020		✓	✓	✓	✓	✓		
Wei et al.	2021	✓		✓	✓				
Tomazella et al.	2023	✓			✓				✓
Our work	2023	✓				✓		✓	✓
Caption	D	Deterministic		S	Stochastic				

In the original constraint, the γ service-level limits backlogging items. In this work, the constraint is adapted to restrict the number of backlogging orders that may include several items. Thus, this service-level constraint seeks to meet the orders as much as possible on time. In addition, to increase the number of orders delivered during the planning horizon, μ service-level constraint is proposed. The third proposed constraint is machine capacity utilization (θ). This measure is not considered a service-level. However, it is essential to ensure efficient capacity utilization, especially for process industries (Clark et al., 2011), thus justifying its inclusion.

4.2 Modeling constraints

In this chapter, we propose adding service-level and capacity utilization constraints to the Furtado et al. (2019) model. The authors addressed the NP-hard production planning problem of orders in small foundries to determine the alloys to be melted and the items to produce. Orders from several customers are composed of different items for production during the planning horizon. We can extend the process to the textile industry by considering that alloys are product families, in which the products must be made from the same material, such as yarn or fabric. Therefore, the mathematical model for the production planning problem of orders is given as follows:

Indices and sets	
$k \in \{1, \cdots, K\}$	families;
$i \in \{1, \cdots, NP\}$	orders;
$j \in \{1, \cdots, N\}$	items;
$t \in \{1, \cdots, T\}$	periods;
$\eta \in \{1, \cdots, L_T\}$	subperiods;
$S(i)$	Items that belong to order i;
$L(k)$	Items belonging to the family k.
Parameters	
F_t	First subperiod in period t ($F_1 = 1$);
L_t	Last subperiod in period t ;
cap	Single machine load capacity (kg);
a_{ji}	Units of item j demanded in order i;
p_j	Gross weight (kg) of item j;
d_{it}	Takes 1 if the due date of order i is in period t; 0 otherwise;
bo_{it}	Penalty for backlogging order i in period t;
h_j	Benefit of holding item j in the end of planning horizon (period T).
Decision variables	
XO_{it}	Takes 1 if order i is delivered in period t; 0 otherwise;
BO_{it}	Takes 1 if order i is delayed in period t; 0 otherwise;
$X_{j\eta}$	Number of items j to be produced in subperiod η;
I_{jt}	Number of items j held at the end of period t;
Y_η^k	Takes 1 if the machine has been used for the production of family k in subperiod η; 0 otherwise;

$$\min \quad \sum_{i=1}^{NP}\sum_{t=1}^{T} bo_{it}BO_{it} - \sum_{j=1}^{N} h_j I_{jT} \tag{4.1}$$

$S.t:$

$$XO_{it} + BO_{it} = d_{it} + BO_{it-1} \qquad \forall i, \quad \forall t \tag{4.2}$$

$$I_{jt-1} + \sum_{\eta=F_t}^{L_t} X_{j\eta} = I_{jt} + \sum_{\substack{i=1,\\ j\in S(i)}}^{NP} a_{ji}XO_{it}, \qquad \forall j, \quad \forall t \tag{4.3}$$

$$\sum_{j\in L(k)} p_j X_{j\eta} \le capY_\eta^k \qquad \forall \eta, \quad \forall k \tag{4.4}$$

$$\sum_{k=1}^{K} Y_\eta^k \le 1 \qquad \forall \eta \tag{4.5}$$

$$\sum_{\eta=F_1}^{L_T} X_{j\eta} \le \sum_{i=1}^{NP} a_{ji} \qquad \forall j \tag{4.6}$$

$$\sum_{k=1}^{K} Y_\eta^k \ge \sum_{k=1}^{K} Y_{\eta+1}^k \qquad \forall \eta \in \{1,\cdots,L_t\}\setminus L_t \tag{4.7}$$

$$Y_\eta^k \in \{0,1\} \qquad \forall \eta, \quad \forall k \tag{4.8}$$

$$XO_{it}, BO_{it} \in \{0,1\} \qquad \forall i, \quad \forall t \tag{4.9}$$

$$X_{j\eta} \ge 0 \quad \text{and integer} \qquad \forall j, \quad \forall \eta \tag{4.10}$$

$$I_{jt} \ge 0 \qquad \forall j, \quad \forall t \tag{4.11}$$

The objective function (4.1) aims to minimize the backlogging costs of orders and considers the benefit of stocking items at the last production period to improve equipment usage.

Constraints (4.2) determine when an order is completed. Equations (4.3) represent the inventory flow balance and exhibit the relationship between items and orders such that an order is considered completed only when all its items are delivered. Constraints (4.4) determine that production does not exceed machine capacity and Constraints (4.5) guarantee that only one family product can be used per load. Inequalities (4.6) limit the number of items produced to the total demanded. Constraints (4.7) are used to avoid symmetric solutions. Finally, Constraints (4.8) - (4.11) represent the variable domains.

4.2.1 The γ service-level

In Helber et al. (2013), the γ service-level for a specific period t, reflects backlog, is defined as

$$\gamma_t = 1 - \frac{\text{expected backlog in period t}}{\text{expected demand in period t}}$$

In our case, the expected backlog can be seen as the number of orders planned for production in period t that are not met on time t, i.e., $\sum_{i=1}^{NP} BO_{it} \cdot d_{it}$ and the expected demand in period t is determined by the number of orders which have a due date for the period t: $\sum_{i=1}^{NP} d_{it}$, considering period by period case, the γ service-level constraint is

$$\sum_{i=1}^{NP} BO_{it} \cdot d_{it} \leq (1-\gamma_t) \sum_{i=1}^{NP} d_{it} \quad \forall t \tag{4.12}$$

By adding (4.12) to model (4.2) - (4.10) we have the Period Expected Backlog Problem (PEBP) that limits the number of orders unmet on time in each period. This measure can also be expressed as an average over the entire planning horizon as shown in the inequality (4.13):

$$\sum_{i=1}^{NP} \sum_{t=1}^{T} BO_{it} \cdot d_{it} \leq (1-\gamma) \sum_{i=1}^{NP} \sum_{t=1}^{T} d_{it} \tag{4.13}$$

We nominate the resulting problem obtained by adding (4.13) to (4.2) - (4.10) as Global Expected Backlog Problem (GEBP).

4.2.2 The μ service-level

In order to maximize the number of orders delivered during the planning horizon, we propose a new constraint called μ service-level. Note that the γ service-level constraints seek to minimize the number of backlogs, while μ service-level aims to maximize the total number of orders delivered. The μ service-level constraint is defined as follows:

$$\mu = \frac{\text{total met orders}}{\text{total demanded orders}}$$

The total number of met orders is given by $\sum_{i=1}^{NP} \sum_{t=1}^{T} XO_{it}$, and the total demanded order is parameter NP. Therefore, the μ service-level constraint is

$$\sum_{i=1}^{NP} \sum_{t=1}^{T} XO_{it} \geq \mu \cdot NP, \tag{4.14}$$

where μ defines the percentage of orders met within the horizon planning.

In this sense, increasing the number of orders met improves the throughput and the productivity of the company. By adding constraints (4.14) to the (4.2) - (4.10), we obtain the Total Met Orders Problem (TMOP).

4.2.3 The θ capacity utilization

Lindberg et al. (2015) studied important KPIs that improve industrial performance. One is capacity utilization, which measures equipment effectiveness. We propose a new constraint, named θ, to measure the machine usage: the total gross weight of items produced compared to the total machine capacity.

This measure can also be represented load by load or globally by considering the average usage over the planning horizon. The θ service-level constraint is defined as follows:

$$\theta_\eta = \frac{\text{total gross weight of items in machine load in subperiod } \eta}{\text{machine capacity}}$$

Since the total gross weight of items is given by $\sum_{j=1}^{N} p_j X_{j\eta}$, we have:

$$\sum_{j=1}^{N} p_j X_{j\eta} \geq \theta_\eta \cdot cap \quad \forall \eta \tag{4.15}$$

By adding constraints (4.15) to (4.2) - (4.10) we obtain the Individual Loading Usage Problem (ILUP). To measure the average usage over the entire planning horizon, we have:

$$\sum_{j=1}^{N} \sum_{\eta=F_1}^{L_T} p_j X_{j\eta} \geq \theta \cdot L_T \cdot cap, \tag{4.16}$$

where the right side of constraint (4.16) represents the total capacity available in the entire horizon planning. The resulting problem, adding (4.16) to (4.2) - (4.10), is named Global Loading Usage Problem (GLUP).

Table 7 summarizes all the proposed service-level constraints and the correspondent models.

Table 7 – Proposed service-level constraints.

service-level constraint	Correspondent model	Constraint
γ_t	PEBP	(4.12)
γ	GEBP	(4.13)
μ	TMOP	(4.14)
θ_η	ILUP	(4.15)
θ	GLUP	(4.16)

4.3 Instances description

The computational tests were conducted using the instances of Furtado et al. (2019). The planning horizon spans five periods $(T = 5)$. The equipment used in these tests has a capacity of 360 kg per load that can be used at most 10 times per day,i.e., the number of subperiods equals 10. The order book contains 19 product families and 383 items to be produced.

The orders were created based on the item due dates, and three classes of instances are obtained: (M1) all items that have the same due date constitute the same order; (M2) items were randomly allocated in the purchase orders; (M3) each item type is considered an order. Each class has 11 instances, differing from each other about the number of parameters and cases of delayed items. M1-11, M2-11, and M3-11 are the most extensive instances for each class.

In order to evaluate the impact of the proposed constraints on the objective function and KPIs, we use M1-11, M2-11, and M3-11 instances proposed by Furtado et al. (2019), and we determine three scenarios:

- Scenario A: High demand with delayed orders presented in the order book. These are the original instances from classes M1, M2, and M3 proposed by Furtado et al. (2019).
- Scenario B: High demand without delayed orders in the order book: new due dates are generated using uniform distribution $U[1,T]$
- Scenario C: Low demand without delayed orders in the order book. Using the instance obtained in Scenario B, we generated a random number $U[1,N]$ and withdrew the item from the original order book. This process is repeated until total demand is reduced to 67% (Gopal and Ramesh, 2014) of the production capacity of 5 days.

Table 8 summarizes some parameters used in the instances

Table 8 – Instances parameters.

	Amount of Orders				
	M1	M2	M3	Items (N)	Families (K)
High demand	52	217	383	383	19
Low demand	46	160	209	209	8

For the service-level and capacity intensities, we consider different levels for each problem:

- The intensities for PEBP: $\gamma_t \in \{0, 0.1, 0.2, \cdots, \gamma_t^{max}\}$;
- The intensities for GEBP: $\gamma_t \in \{0, 0.1, 0.2, \cdots, \gamma_t^{max}\}$;
- The intensities for TMOP: $\mu \in \{0.5, 0.6, \cdots, \mu_{max}\}$;
- The intensities for ILUP $\theta_\eta \in \{0.5, 0.6, \cdots, \theta_\eta^{max}\}$;
- The intensities for GLUP: $\theta \in \{0.5, 0.6, \cdots, \theta_{max}\}$.

The number of intensities varies according to the scenario analyzed. To find the maximum values for γ, μ and θ (γ_t^{max},γ_{max}, μ_{max}, and θ_η^{max}, θ_{max}), we solve the respective problems with the objective function of maximizing these parameters.

4.3.1 Costs determination

The inventory and backlogging costs are calculated based on item weights, determined by Furtado et al. (2019), as follows:

- Let max O be the heaviest order, calculated as max $O = \max_{i \in \mathscr{I}} \left\{ \sum_{j \in S(i)} p_j a_{ji} \right\}$.

- In case an order i be delayed in period t, the backlogging cost is calculated by $bo_{it} = \frac{\sum_{j \in S(i)} (p_j a_{ji} (\alpha_i + 1 + t))}{\max O}$, where α_i is delay of order i at $t = 0$. If the order i is not delayed in period t, bo_{it} is a large number.
- The benefit of holding item j at the last period is: $h_j = \frac{p_j}{\max O}$

For example, suppose an order i is delayed 5 days, then $\alpha_i = 5$. Suppose it is the haviest order $\max O = \sum_{j \in S(i)} p_j a_{ji} = 1000$. Then, $bo_{i1} = 7$; $bo_{i2} = 8$; $bo_{i3} = 9$.

4.4 Numerical Results

We compare the obtained solutions with three different groups of indicators: i) objective function, ii) orders, and iii) KPIs. Group (i) contains the objective function value (Solution cost) and the optimality gap. Group (ii) exhibits the number of orders met on time, delayed, or unmet. Finally, group (iii) presents the KPIs: average delay, maximum delay, throughput, lead time, work in process (WIP), and capacity utilization.

We have a backlogging order if an order is met after its due date. Let dt_i be the number of delayed periods of an order i. The average lead time is given by:

$$\text{Average delay} = \frac{\sum_i dt_i}{\sum_{i=1}^{NP} \sum_{t=1}^{T} XO_{it}}$$

In this sense, the maximum delay is the largest number of periods of delay, obtained by:

$$\text{Maximum delay} = \max(dt_i)$$

An important productivity measure is throughput. The throughput measures the rate at which products are delivered to customers in a given period. We define the throughput as the ratio of total orders delivered to the number of periods in the planning horizon, which means:

$$\text{Throughput} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{NP} XO_{it}}{T}$$

We determine the lead as the time to complete an order. Let o_i be the date the order is received, and t_i be the period in which the order is fulfilled, then the average lead time is calculated by:

$$\text{Average lead time} = \frac{\sum_i (t_i - o_i)}{\sum_{i=1}^{NP} \sum_{t=1}^{T} XO_{it}}$$

Note that the average delay, maximum delay, and lead time are related only to orders fulfilled because it is not possible to determine these measures for unmet orders.

As the production of items is limited to demand, items are held for meet future orders, so the work in process (WIP) is related to orders that are in progress. Thus, the amount of items (in kg) held in inventory was calculated as follows:

$$WIP = \sum_{j=1}^{N} \sum_{t=1}^{T} p_j I_{jt}$$

Capacity utilization was obtained from the ratio of total weight produced to total available capacity:

$$\text{Capacity utilization} = \frac{\sum_{j=1}^{N} \sum_{\eta=F_1}^{L_T} p_j X_{j\eta}}{L_T \cdot cap}$$

We want to evaluate the correlation between the intensity of the service-level and the results obtained for the objective function, orders, and KPIs. To this end, we calculated the Pearson correlation coefficient (r), which is determined as follows:

$$r = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}},$$

where: n: number of service-level intensities,
x_i: service-level intensity,
y_i: objective function value or KPI measure value,
$\bar{x}$: average of service-level intensities,
$\bar{y}$: average of objective function values or KPI measure values.

The Pearson correlation coefficient indicates if there is an association between two variables. In positive correlation, if the value of one variable increases, the value of the second variable also increases. Likewise, there is a negative correlation if the value of one variable increases and the value of the second variable decreases (Schober and Schwarte, 2018). Table 9 exhibits how to interpret the Pearson correlation coefficient.

Table 9 – Interpreting a Correlation Coefficient.

r absolute value	**Interpretation**
0.00–0.10	Negligible correlation
0.10–0.39	Weak correlation
0.40–0.69	Moderate correlation
0.70–0.89	Strong correlation
0.90–1.00	Very strong correlation

We use the solution method, the Surrogate-based heuristic (SUBH), proposed by Alves et al. (2024) for solving the models. The SUBH (Algorithm 1) comprises three main steps: i) surrogate relaxation of the capacity constraints, ii) checking the relaxed solution feasibility for the original models, and iii) feasibility procedure.

According to Alidaee (2014), when optimal solutions are not found in a Surrogate relaxation, there is a need to update surrogate multipliers. We do not update surrogate multipliers because we obtain solutions with small optimality gaps for most tested instances, with some optimal solutions (see Appendix C).

Algorithm 1: Surrogate-based heuristic (SUBH)

```
Let S be the surrogate relaxation model and P the original problem.
$x^s$ ← Solve S model
if $x^s$ is feasible for P then
    if $x^s$ is optimal for S then
        $x^s$ is optimal for P.
    else
        Use S lower bound to calculate optimality gap.
        $x^s$ is a P upper bound.
else
    Use S lower bound to calculate optimality gap.
    Use a feasibility procedure to search P upper bounds from $x^s$.
```

The models were coded using Python 3.8 language and the Gurobi 9.5.2 optimization software, with default settings and a time limit of 3,600s. The experiments were performed on an Intel Core i7 with 2.9 GHz and 32 GB of RAM on a Windows 10 operational system.

4.4.1 Cost oriented *versus* order oriented production planning

To assess whether minimizing delay costs achieves the same goal of the service level constraints, we examined the results with the original model (baseline), PEBP ($\gamma = 0.5833$), GEBP ($\gamma = 0.61$), and TMOP ($\mu = 0.923$), as presented in Table 10. The analysis reveals that minimizing delay costs does not necessarily correlate to fewer delayed orders but instead prioritizes the fulfillment of orders with higher costs. For instance, in the original model, orders $i = 47$ and $i = 50$ are met in the first period due to their high delay costs, resulting in 25 other orders being delayed. The PEBP and GEBP models impose a maximum delay to be accepted to improve the service level, so order delays decrease and total costs increase. Conversely, the TMOP model improves order fulfillment rates from 86% in the baseline to 92% by setting a minimum fulfillment threshold while respect capacity constraints. However, TMOP does not necessarily reduce order delays.

Table 10 – Comparison of delayed and unmet orders of the models.

	Delayed Orders	Total	Unmet Orders	Total
Baseline	16,18,19,24,25,28,29,30,31,36,37,38,45,52,9,10,11,12,23,7,8,13,15,20,5	25	1,2,3,4,6,14,17	12
PEBP	9,11,16,18,19,23,24,29,31,33,47,50	12	5,6,8,10,12,14,15,20	8
GEBP	9,11,16,18,19,23,24,29,31,33,47,50	12	5,6,8,10,12,13,15,20	8
TMOP	3,4,7,8,9,10,11,12,13,14,15,16,18,19,20,23,24,25,28,29,30,31,36,37,38,45,52	27	1,2,5,6	4

4.4.2 Managerial implications

In general, the constraints proposed in this chapter demonstrate that improving service-levels comes with higher costs. The γ and μ constraints optimize service-levels by improving KPIs related to order deliveries and customer satisfaction. However, choosing between these constraints depends on the specific planning horizon and existing backlogs. If the planning horizon already starts with backlogs, the μ constraint is more appropriate than the γ constraint, as it can deliver more orders. Completing as many orders as possible on the correct due date is preferable without delayed orders in the order book. Therefore, the γ constraint is recommended.

The findings from the GEBP and GLUP models align with those presented by Sereshti et al. (2021). From the consistent results, it can be deduced that the individual models are more strict than the global models. This inference is illustrated by analyzing the costs associated with the same γ values in GEBP and PEBP, as well as θ values in GLUP and ILUP. One advantage of employing the global models is their increased flexibility in item production. Additionally, considering that orders comprise multiple items, the constraints are imposed on aggregated service-level values. This approach enables a comprehensive overview of how service-levels collectively influence different orders or periods, ultimately aiming to improve overall operational efficiency and customer satisfaction. By adopting this perspective, a more holistic understanding emerges regarding the interplay of service-levels and their impact on crucial performance metrics.

In Furtado et al. (2019), the $-h_j$ component of the objective function is described as a method to increase equipment utilization. In real-world scenarios, this element of the objective function is atypical. We removed the $-h_j$ part of the objective function and repeated all experiments, yielding results close to those reported in this Section. This minor difference occurs because the cost of holding inventory, calculated based on the weight of each item, is relatively low compared to the cost incurred from order delays, thereby little affecting the number of orders fulfilled. Nevertheless, employing the model without the $-h_j$ part is advisable in high inventory costs, which can influence the results. Moreover, if elevated equipment utilization is crucial, the ILUP model is recommended.

In a process industry, such as the textile industry, it is common for managers to plan high-capacity utilization to accommodate existing variability in customer orders (Hussain and Figueiredo, 2023). However, our findings reveal that expanding production utilization does not intrinsically result in fulfilling more orders and improving service-levels. This outcome aligns with the phenomenon described by Karmarkar (1987), where elevated utilization rates can cause high lead times due to elements such as lot sizes, setup times or costs, and the queue effect in a multi-item production process. This scenario is more challenging when we consider setup costs because they directly affect the total number of orders that are met. Therefore, pursuing high equipment utilization might not be advisable in a scenario with significant item variability. Instead, the focus should shift toward encouraging production flexibility. This flexibility becomes even more crucial in a make-to-order context with multiple items, as just increasing the number of items produced does not necessarily mean an increase in fulfilled orders.

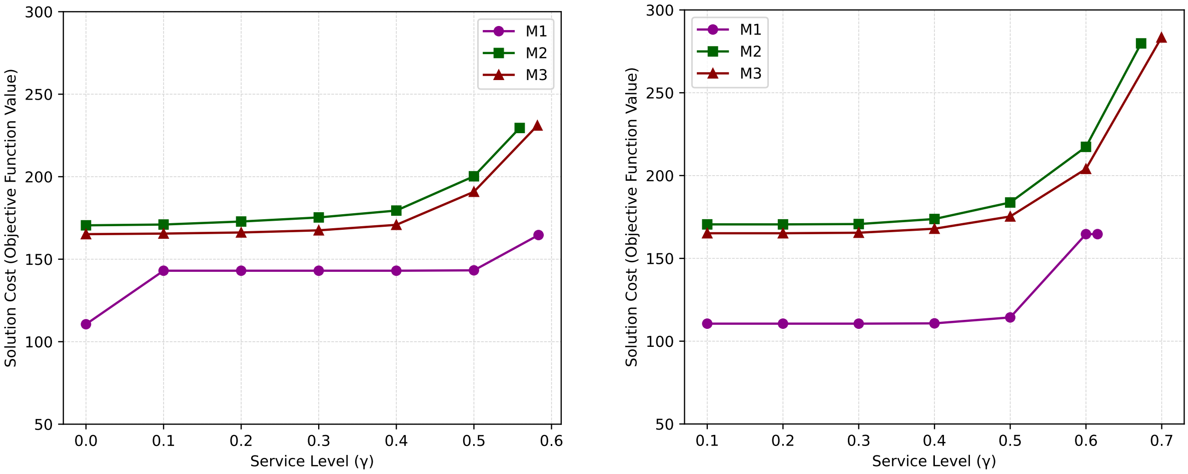
In the following sections, we present extensive numerical results for each problem introduced in Section 4.2, according to each proposed service level. We divided the sections by service-level constraints and examined the outcomes related to costs, orders, and KPIs for each demand scenario. We present graphs illustrating how service-levels or capacity utilization intensities affect costs and orders. Tables containing detailed results are available in Appendix C. Furthermore, it is worth mentioning that in practical situations, the $-h_j$ part of the objective function is not common. Thus, we removed the h_j part of the objective function and repeated all experiments, and we obtained similar results due to the cost structure inherent in our instances.

4.4.3 γ service-level constraints

Considering that the γ service-level is related to its ability to meet orders on time, it is necessary to minimize delays. In this sense, the Period Expected Backlogging Problem (PEBP) and Global Expected Backlog Problem (GEBP) limit the number of backlogged orders. We analyzed the results obtained regarding costs, orders, and KPIs. In the presented graphics, we have the baseline when $\gamma = 0$.

4.4.3.1 Scenario A: High demand with delayed orders presented in the order book

Figure 25 – Solution costs results for Scenario A for γ constraints.



(a) PEBP

(b) GEBP

Costs: Figure 25 shows that service-level improvement is accompanied by an expected trade-off involving increased costs, particularly when $\gamma \geq 0.5$. To fulfill more orders on time, the model may overlook specific orders that would incur higher delay costs. Suppose a scenario where a company receives a mix of orders, some of which are of high value but have relatively flexible delivery due dates, while others are of lower value but require immediate delivery. In this case, the γ service-level would ensure that the lower-value orders are processed and delivered promptly, even if it means that some high-value orders are fulfilled later.

It is possible to notice that GEBP service-level intensities until 0.5 little affect the costs. Also, GEBP has lower costs than PEBP for the same γ intensities, particularly for the M1 instance. This suggests that a global service level offers more flexibility in fulfilling orders than an individual service level, providing better solutions.

Orders: Figure 26 shows that an increase in γ intensities positively impacts the number of orders met on time. This improvement is associated with enhanced customer satisfaction and supports the reliability of the company. As Chen (2014) pointed out, when the order fulfillment timing does not meet expectations in real-world applications, planners may adjust the production schedule to align with delivery dates to ensure customer satisfaction. In this context, limiting the overall backlogging of orders is a strategic approach that can assist companies in reaching due dates and improving customer satisfaction.

Within the scope of the PEBP model, optimizing to the highest γ intensity significantly increases the number of orders met on time — by 1.6, 2.3, and 2.6 for instances M1, M2, and M3, respectively, compared to the baseline. The GEBP model outperforms the PEBP in instances M2 and M3, with an increment of 2.75 and 3.07 additional orders met on time, respectively.

KPIs: Data in Appendix ... shows that for M2 and M3 instances, there is a strong positive correlation between the γ value, average delay, and lead time. A very strong positive correlation exists between the γ value and throughput. These findings demonstrate that increasing the γ intensity significantly improves the quality of these KPIs by reducing delayed orders.

Regarding the M1 instance, the relationship between the γ values and KPIs is unclear, as the r-value results indicate a weak or negligible correlation. This result can be explained by meeting a close number of orders for most tested γ intensities, indicating that average delay and throughput are almost the same regardless of γ values. There is limited room to improve the number of met orders because M1 comprises a few orders with many different items.

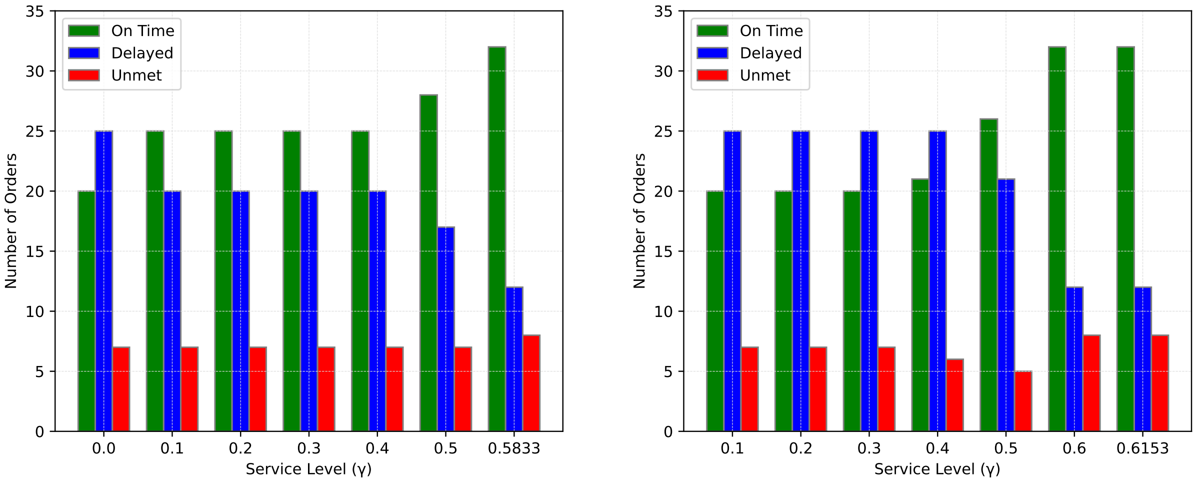
The WIP presents higher values for M1 than for M2 and M3. Once again, this fact is explained by the fact that M1 has orders for many component items. Then, holding several items until the whole order is complete is necessary, raising the WIP. The GEPB model is less restrictive than the PEPB, allowing it to hold more items than the PEPB, as seen with WIP values. This result is advantageous, mainly when inventory costs are not a primary concern.

On average, the capacity utilization is 93%, and increasing γ intensities have little impact on capacity utilization. This outcome is within the expected range, considering the high demand for orders. It is worth noting that the column “unmet orders" indicates instances where capacity is insufficient to meet the demand, leading to unfulfilled orders.

4.4.3.2 Scenario B: High demand without delayed orders in the order book

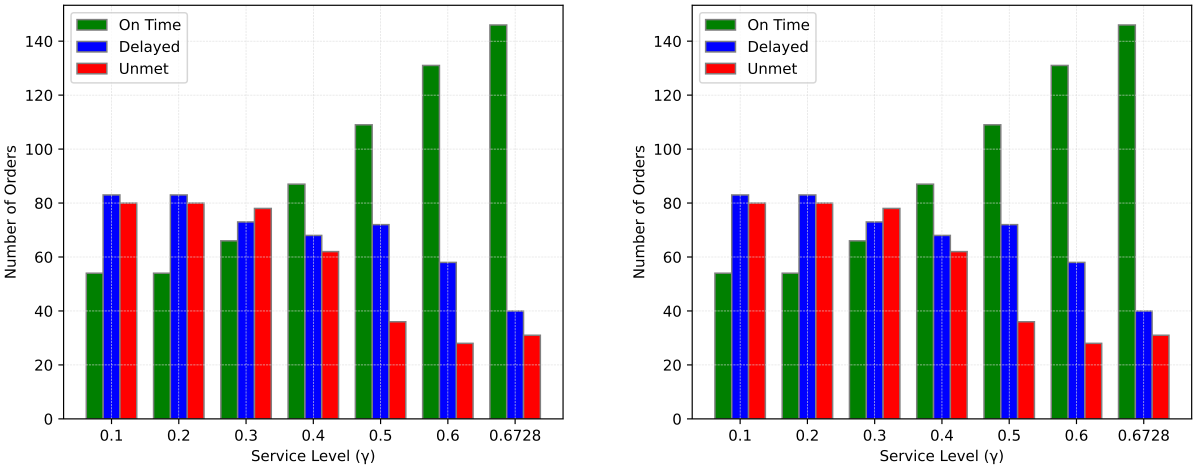
Costs: Figure 27 displays the cost results for Scenario B, comparing the PEBP and GEBP models. In Scenario B, accommodating more γ intensity levels is feasible since there are no backlogged orders at the beginning of the planning horizon. For both PEBP and GEBP models, γ values in the range of $\{0, 0.5\}$ have low impact on costs. However, for $\gamma > 0.5$, a significant

Figure 26 – Fulfilling orders for Scenario A for γ constraints.



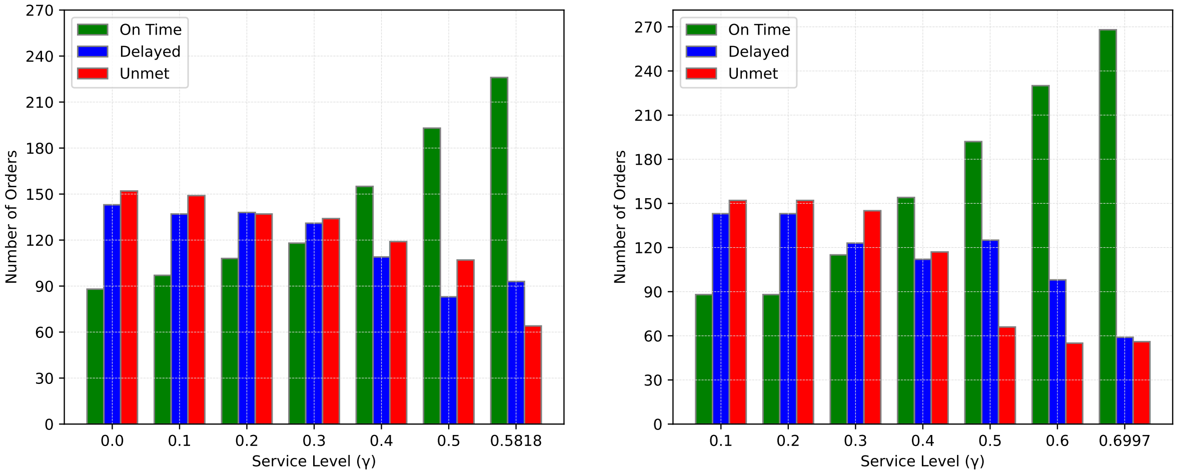
(a) PEBP - M1

(b) GEBP - M1



(c) PEBP - M2

(d) GEBP - M2



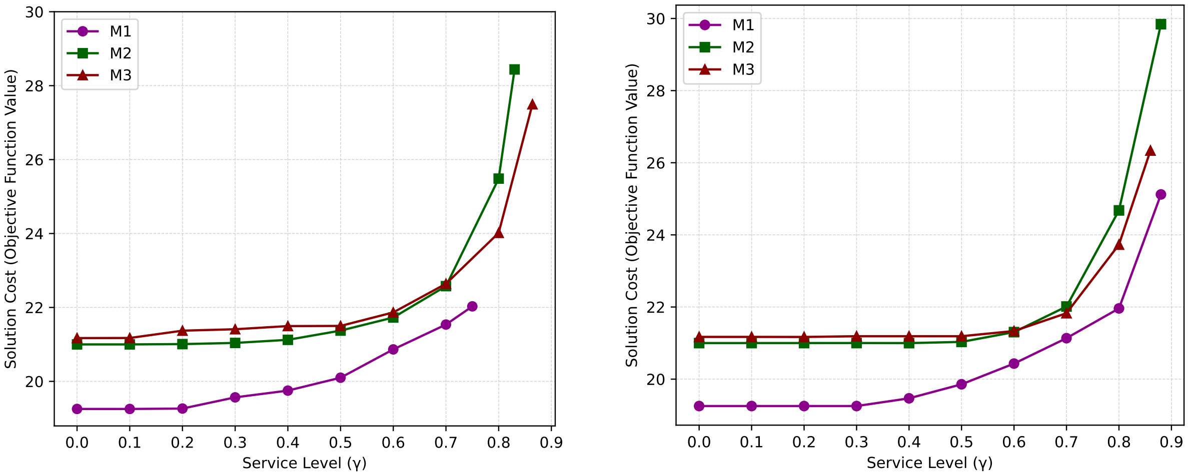
(e) PEBP - M3

(f) GEBP - M3

cost increase is observed. The costs in Scenario B are lower than in Scenario A, and the absence of delayed orders at $t = 0$ underscores the benefits of timely order fulfillment.

Orders: Figure 28 illustrates that at the baseline ($\gamma = 0$), numerous orders are delayed

Figure 27 – Solution costs results for Scenario B for γ constraints.



(a) PEBP

(b) GEBP

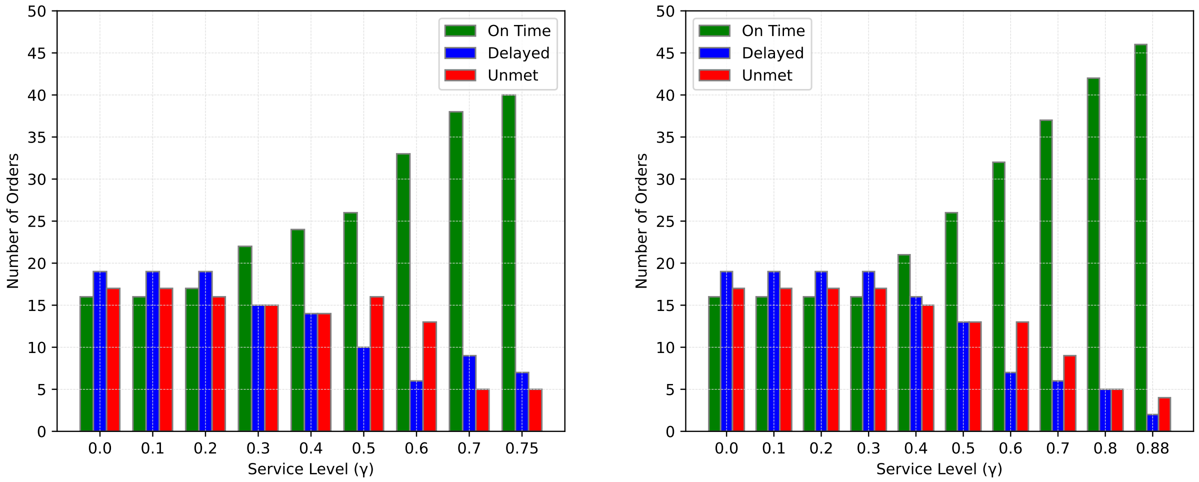
or unmet because the objective function prioritizes meeting more costly backlogging orders. However, in the PEBP model, applying the maximum γ intensity significantly improves on-time order fulfillment, increasing the number of orders met on time by 2.5, 2.1, and 2.3 for instances M1, M2, and M3, respectively. The GEBP model demonstrates even better performance, delivering an increase of 3.2, 2.4, and 2.5 more orders met on time for each respective instance. These results highlight the enhanced flexibility and efficiency in meeting order deadlines that the GEBP model brings, especially at higher service levels.

KPIs: As shown in Appendix . Fulfilling more orders on time increases throughput, reduces average and maximum delays, and necessitates holding multiple items until an order is complete, thereby increasing the WIP. The correlation between KPIs and γ values aligns with interpretations previously discussed for Scenario A.

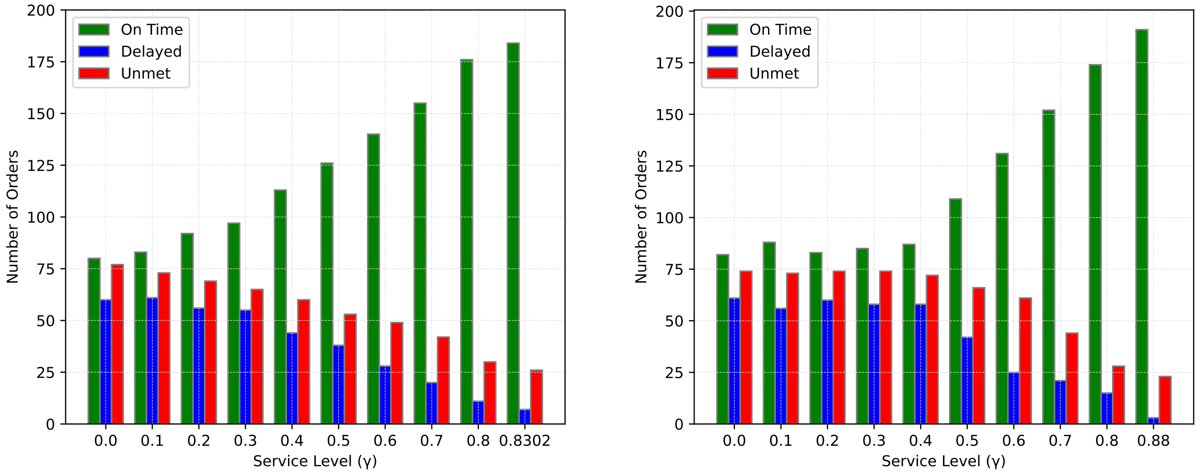
Better capacity utilization is possible in Scenario B than in Scenario A. For both the PEBP and GEBP models, average capacity utilization was 94%, 97%, and 98% for M1, M2, and M3 instances, respectively. However, a reduction in utilization can be observed with higher γ values. This result can be attributed to the fulfillment of orders containing only a few items made of the same family, which decreases the overall capacity utilization. Notably, PEBP and GEBP yielded similar results in the order book under high-demand conditions without delayed orders.

Figure 28 – Fulfilling orders for Scenario B for γ constraints.

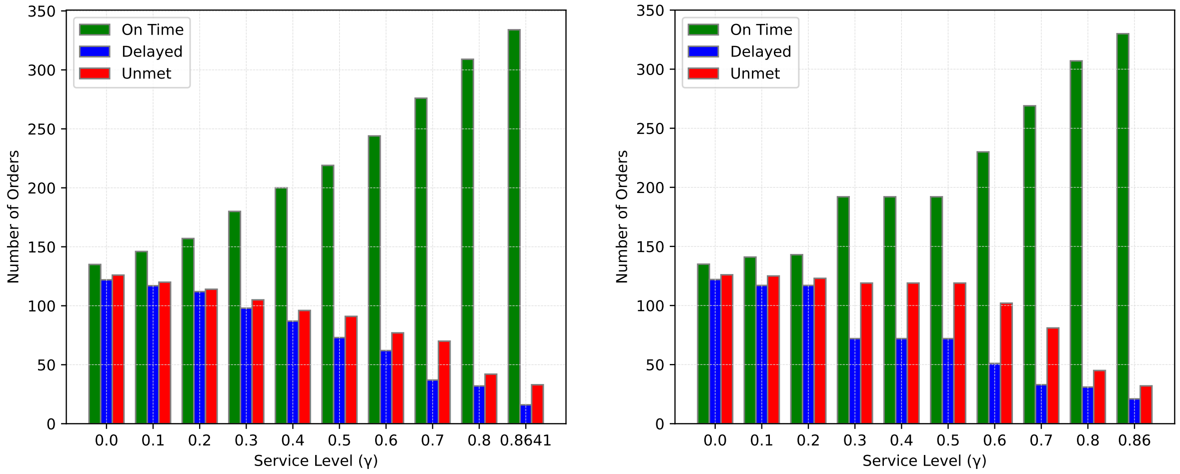
(a) PEBP - M1 (b) GEBP - M1



(c) PEBP - M2 (d) GEBP - M2



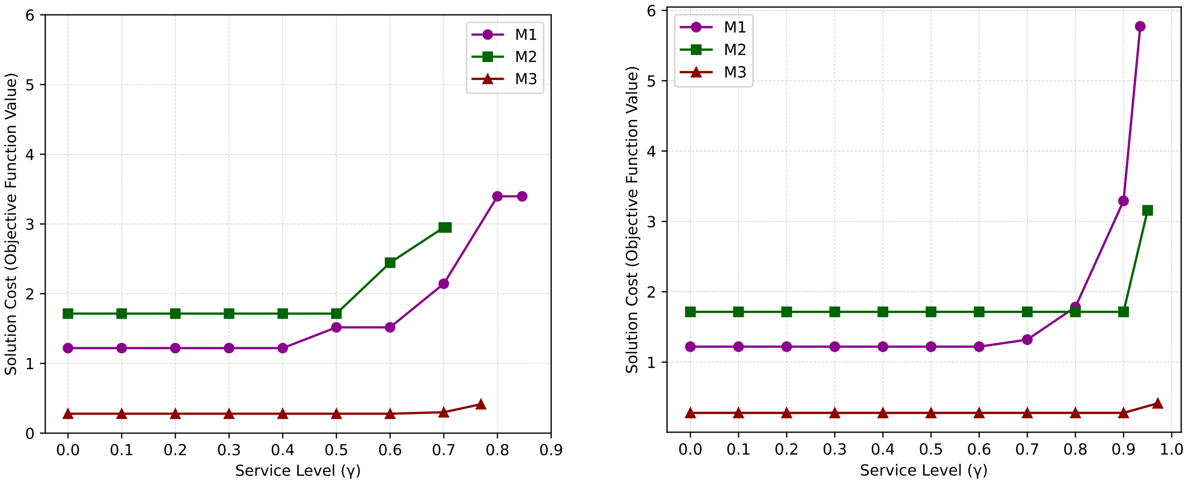
(e) PEBP (f) GEBP



4.4.3.3 Scenario A: High demand with delayed orders presented in the order book

In this scenario, the demand corresponds to approximately 67% of the available capacity, and no delayed orders exist in the order book. The same optimal solutions were identified for different γ intensities, implying that various settings of γ yield equivalent results.

Figure 29 – Solution costs results for Scenario C.


(a) PEBP

(b) GEBP

Costs: Figure 29 shows that the costs are the same for γ values in range $\{0, 0.4\}$ for all instances in both models. We have found the same solutions for GEBP with γ values in range $\{0, 0.9\}$ for M1 and M2 instances. It is feasible to achieve more γ intensities for GEBP than PEBP, but it means higher costs, as expected.

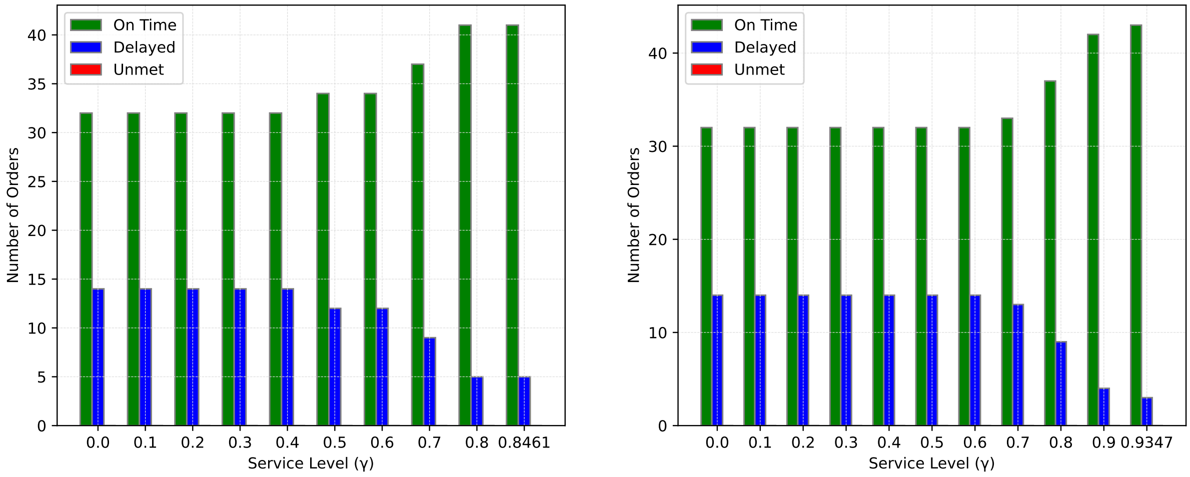
Orders: As the demand is lower than the capacity in all instances, all orders are successfully fulfilled. Increasing γ intensities results in a few delayed orders. Figures show that the service-level constraints bring little gain in a low-demand scenario.

KPIs: For the M1 instance, it was possible to reduce the average delay and maximum delay for both models. For M2 and M3, little gain was obtained for those KPIs as several γ intensities produced the same results. Since all orders are met, the throughput remains constant across all outcomes. Results in Scenario C presented higher WIP values than Scenarios A and B. This result indicates that items are held to complete the equipment load and fill future orders within the planning horizon.

In general, the costs for GEBP are lower than PEBP for all Scenarios. In addition, concerning the total number of orders met, it is noticeable that the GEBP performance is superior to the PEBP performance, producing a larger number of orders for the same level of γ intensity. Therefore, we can infer that with the same γ value, the period-by-period model is more strict than the global model. Thus, the global model presents more flexibility in determining production planning, enabling production capacity to be used more efficiently.

Figure 30 – Fulfilling orders for Scenario C, instance M1.

(a) PEBP (b) GEBP

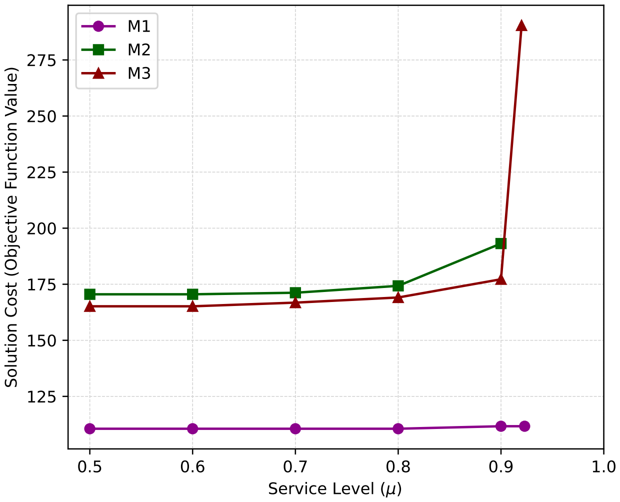


4.4.4 μ service-level constraints

In order to meet more orders in the planning horizon, we present results concerning TMOP model that contain μ service-level constraint. In this case, the baseline is represented by $\mu = 0.5$

4.4.4.1 Scenario A results

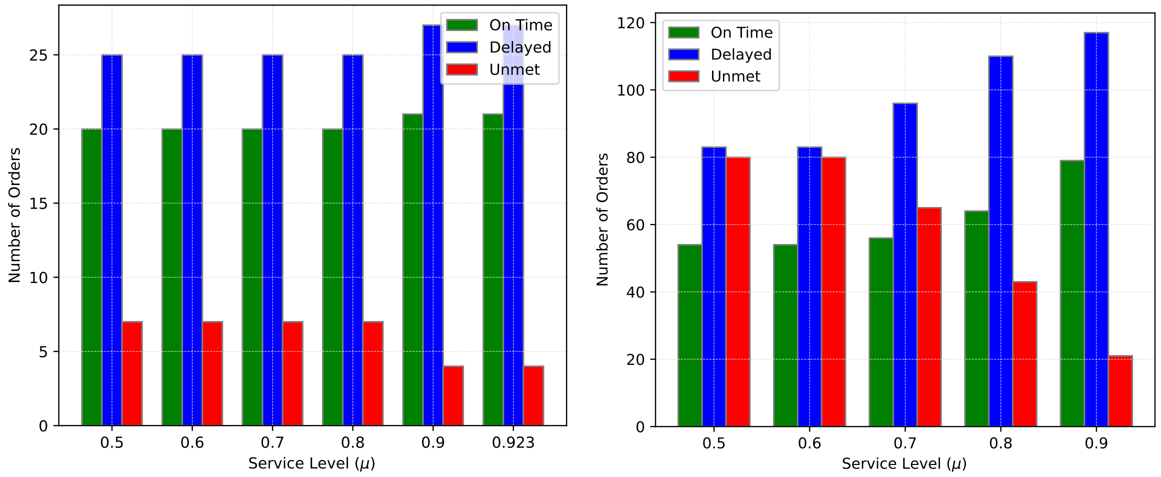
Figure 31 – Solution costs results for TMOP Scenario A for μ constraint.



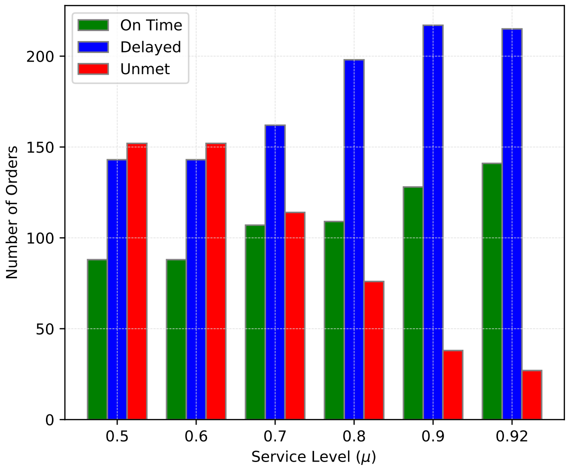
Costs: Figure 31 shows that higher levels of μ intensities increase the costs for M2 and M3 instances. There is little change in the costs for M1 instance. In comparison with Figure 25, the results for the μ service-level constraint met more orders with lower solution costs. In this case, there is no requirement to fulfill orders according to the due date stipulated by the γ constraint. Thus, the model prioritizes fulfilling more costly backlogging orders, reducing the total cost.

Figure 32 – Fulfilling orders for TMOP and Scenario A for μ constraint.

(a) M1 (b) M2



(c) M3



Orders: Figure 32 demonstrates that the service level constraint leads to more orders being fulfilled by the end of the planning horizon. However, simply increasing the amount of fulfilled orders does not guarantee their timeliness. There is a strong correlation between μ and the number of delayed orders. This fact can be explained because, to satisfy the μ constraints, some orders are completed past their due date. Regardless, the number of unmet orders has significantly decreased.

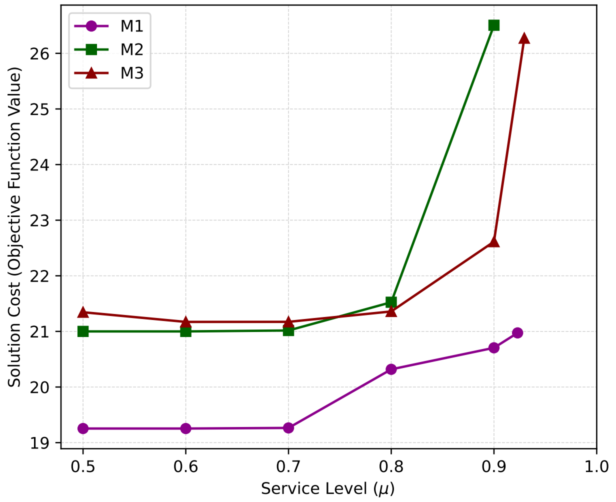
KPIs: Despite the presence of delayed orders, we have a negative correlation between μ intensities and average delays. This observation can be attributed to prioritizing and reducing the delays for higher-cost orders. However, it is important to note that some orders still experience delays, resulting in a higher average delay than the γ service-level. As anticipated, a strong positive correlation exists between μ values and throughput in the M1 instance and very strong positive correlation between μ and throughput in the M2 and M3 instances. Furthermore, there is a reduction in the average lead time, which, when combined with the increased throughput, can confer a competitive advantage in a time-sensitive environment (Tersine and Hummingbird, 1995).

For the M1 instance, the WIP is higher than that obtained by the γ service-level constraint, as it represents items that must be held to complete orders. On the other hand, M2 and M3 instances achieved lower WIP values because they handled orders with fewer items than M1. The μ constraint does not significantly impact capacity utilization, which remains close to 93%.

4.4.4.2 Scenario B results

Costs: The graph in Figure 33 shows that solution costs are less than or equal to results obtained with the GEBP model for this Scenario. presents solution cost results for TMOP Scenario B across three instances: M1, M2, and M3. It is possible to notice that the costs remain relatively flat as the service level increases from 0.5 to 0.8, suggesting that raising the service level in this range does not substantially increase costs. However, costs sharply increase as the service level approaches 1.0. The increase in costs at higher service-levels could indicate that fulfilling nearly all orders comes with significantly higher costs. This fact can be explained by the sequence imposed on orders to meet the mu-constraint, so that some orders were fulfilled tardily, increasing costs.

Figure 33 – Solution costs results for TMOP Scenario B for μ constraint.

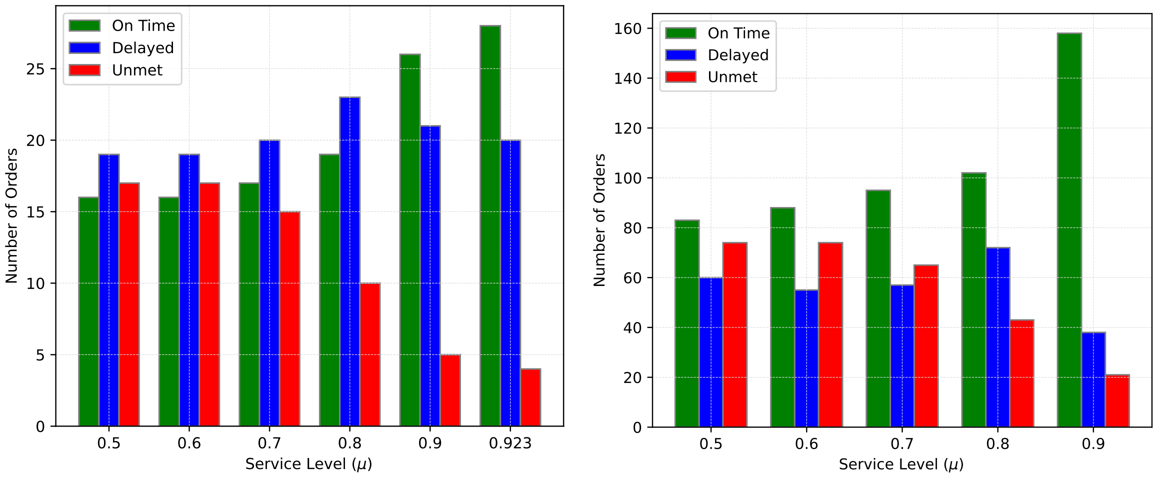


Orders: A strong negative correlation between μ intensities and the unmet orders indicates that TMOP improves the overall number of orders met within the planning horizon. However, some orders will be delayed at the end of the planning horizon.

KPIs: A strong negative correlation between μ and average delay implies that large μ intensity reduces some backlog orders. As expected, the r-value analyses show that larger μ intensities improve the throughput as a strong positive correlation exists between μ and throughput. Some backlogging may still occur, increasing the overall lead time average.

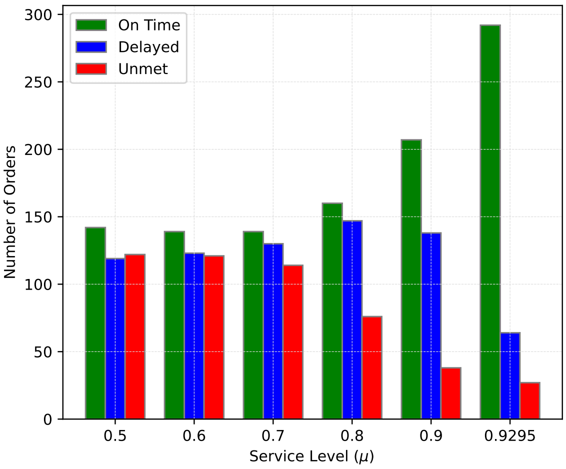
The WIP values obtained are lower than using GEBP, as illustrated in Appendix C. This suggests that more items must be held to meet more orders on time. On average, the M1 instance used 94% of its capacity, M2 used 97%, and M3 used 98%. However, it is observed that there is a drop in capacity utilization for values of μ above 0.9. By seeking to fulfill as many orders as possible, some orders that consist of families with a few items are prioritized, leading to a decrease in the overall use of the equipment.

Figure 34 – Fulfilling orders for TMOP and Scenario B.



(a) M1

(b) M2



(c) M3

4.4.4.3 Scenario C: Low demand without delayed orders in the order book

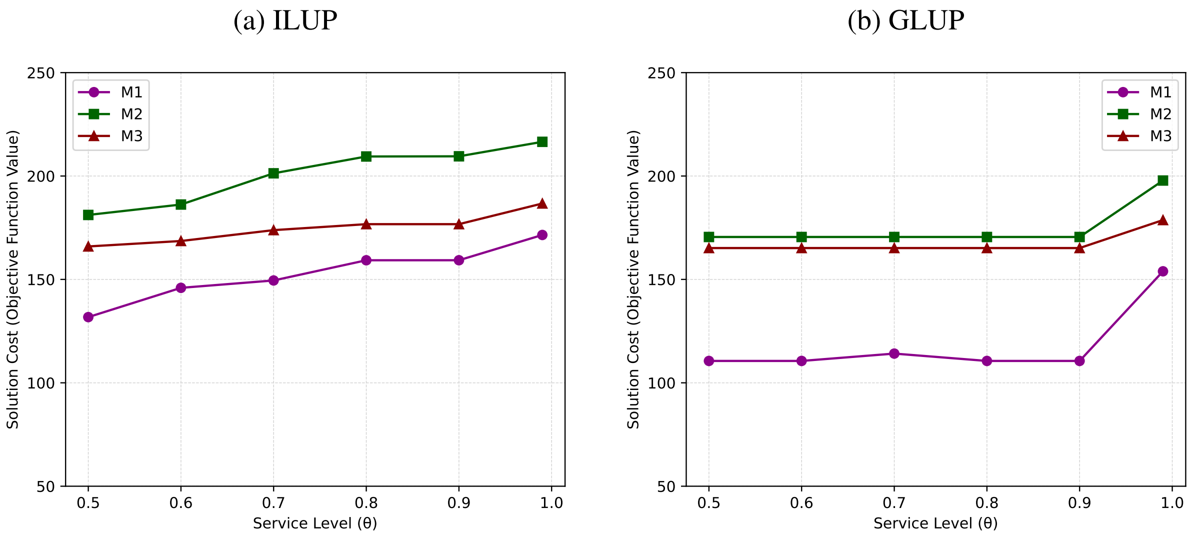
In Scenario C, the capacity exceeds the demand. Thus, all orders are fully met within the horizon planning. As a result, the μ service-level does not provide any additional advantages for production planning, obtaining the same baseline results. There is more than enough capacity to meet the demand, making the μ constraint redundant.

4.4.5 θ capacity utilization

Capacity utilization measures equipment effectiveness. To assess the impact of capacity utilization on meeting orders and KPIs quality, we analyze results obtained with ILUP and GLUP models, which are discussed in this section.

4.4.5.1 Scenario A: High demand with delayed orders presented in the order book

Figure 35 – Solution costs results for Scenario A for θ constraints.

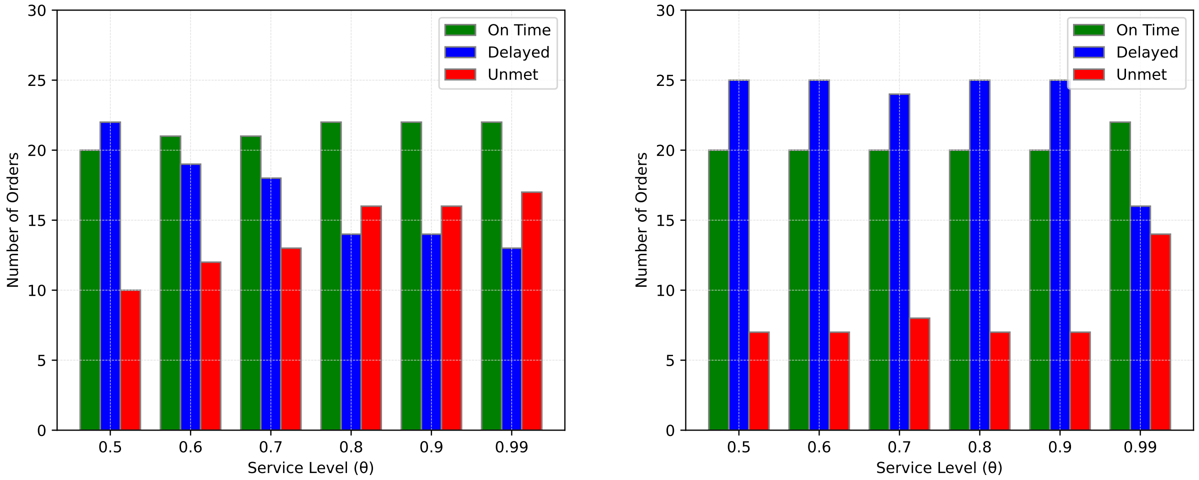

(a) ILUP

(b) GLUP

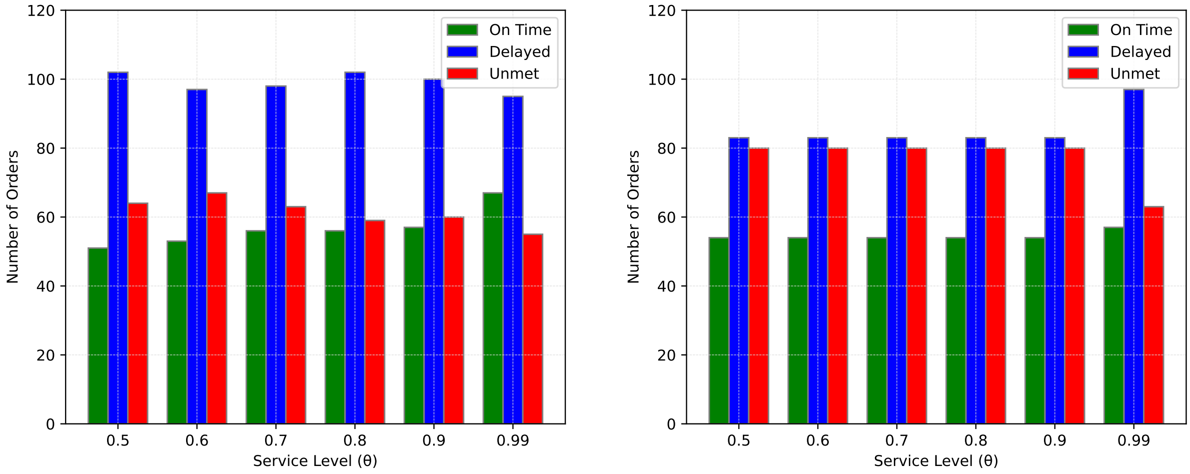
Costs: For ILUP, results in Figure 35 show that increasing θ raises costs, specially for M1 instance. Scenario A presents a high demand. Thus, the production system naturally uses the equipment above 90%. Using the GLUP model, the results indicate that θ intensities between 0.5 and 0.9 do not affect costs. However, there is a considerable increase in costs for the maximum capacity ($\theta = 99\%$). Using the ILUP model, there is an increase in the costs because the theta constraint imposes a minimum for equipment usage, requiring the production of additional items. This increase in production, however, does not mean fulfilling a greater number of orders. Therefore, some orders are backlogged, increasing the costs.

Orders: Figure 36 shows that producing additional items can enhance capacity utilization but does not ensure automatic order fulfillment. Despite the intention to optimize resource allocation, an order can contain multiple items of different families, and the equipment can only be loaded with one family at a time. Thus, it is feasible to see high capacity utilization with many unmet or delayed orders, as observed in the M1 instance results. For the M2 and M3 instances, which have fewer items per order, capacity utilization can be increased with more fulfilled orders, but there remains a significant number of delays.

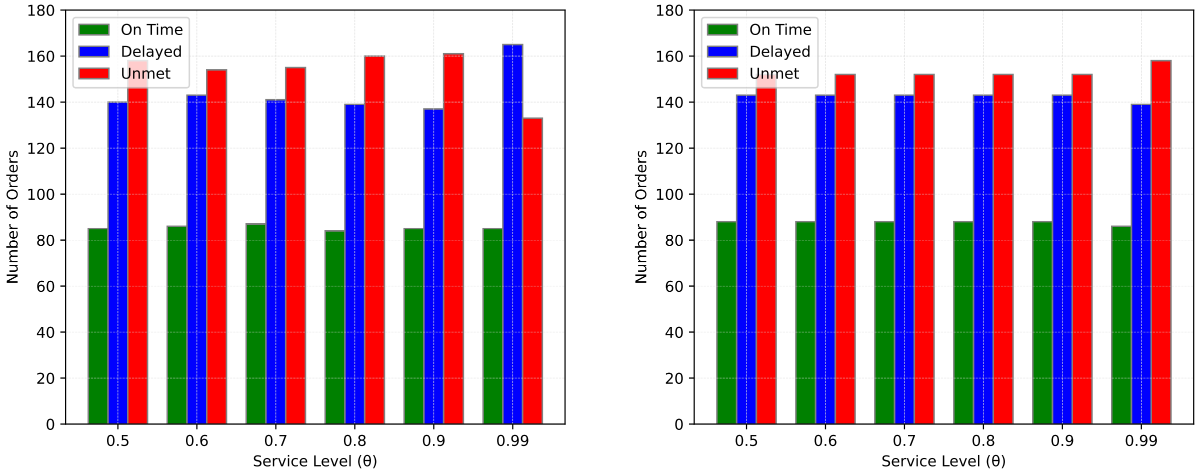
Figure 36 – Fulfilling orders for Scenario A for θ constraints.


(a) ILUP- M1

(b) GLUP - M1


(c) ILUP - M2

(d) GLUP - M2


(a) ILUP - M3

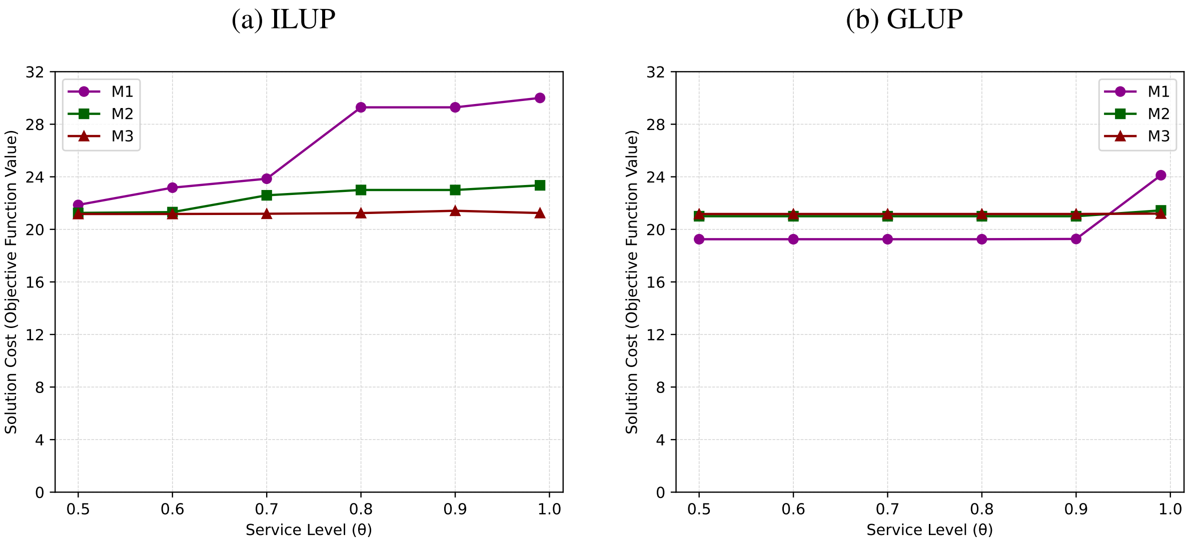
(b) GLUP - M3

KPIs: The results from the M1 instance indicate a positive correlation between θ and average delay. Nevertheless, it is crucial to understand that this average delay is calculated based on the number of orders fulfilled, and there are fewer such orders under the θ constraint compared to the γ or μ constraints. As a result, for the M1 instance, the lead time increases due to the extended duration required to complete some orders. With fewer items per order, both ILUP and GLUP models were able to reduce the average delay and lead time for the M2 instance. In the M3 instance, every order contains just one type of item. The ILUP results suggest that expanding capacity utilization has little impact on the number of orders met on time. However, by raising θ intensities, some previously unmet orders are completed, reducing the average delay and lead time. The maximum delay remains the same in all tests.

The throughput for the M1 instance in ILUP and GLUP models and M3 in GLUP is negatively affected by the number of orders met. The increase in capacity utilization was obtained by producing more items for inventory, as seen from WIP.

4.4.5.2 Scenario B: High demand without delayed orders in the order book

Figure 38 – Solution costs results for Scenario B for θ constraints.


(a) ILUP

(b) GLUP

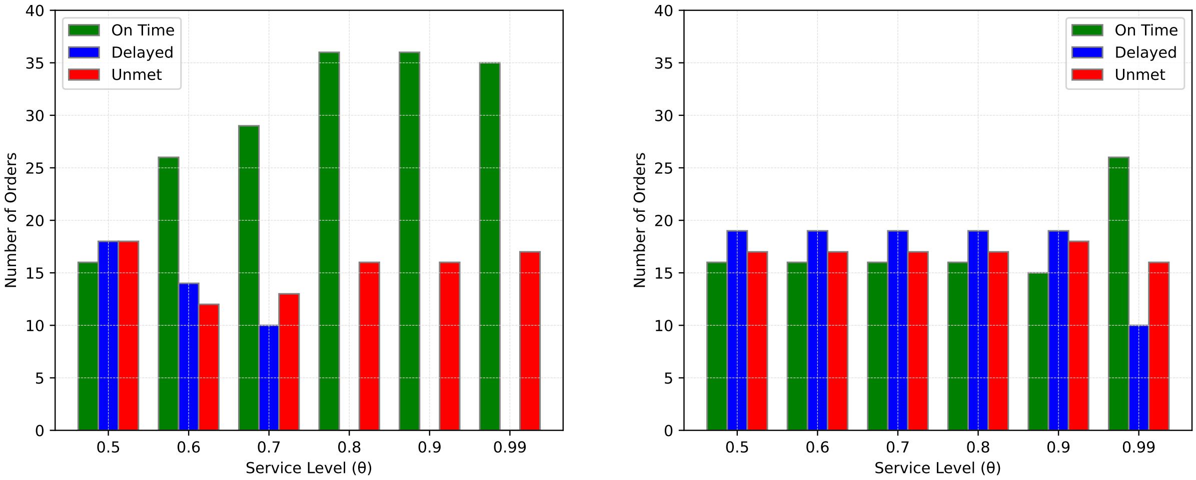
Costs: As with Scenario A, Scenario B is characterized by high demand, leading to the production system routinely operating the equipment at over 90% capacity. In the context of ILUP, the results shown in Figure 38 indicate that incremental increases in the θ threshold cause only a slight rise in costs for the M2 and M3 instances. A similar analysis to that of Scenario A is applicable here. In the GLUP model, adjusting θ values within the range of 0.5 to 0.9 has no impact on costs, likely because this range does not change the core parameters of the original problem.

Orders: In Scenario B, where there were no pre-existing delayed orders, both the ILUP and GLUP models fulfill more orders on time compared to Scenario A, as seen in Figure 39. Particularly, there were zero delayed orders for the M1 instance utilizing the ILUP model when the θ values were set above 0.8. This result suggests that the production of extra items allowed the model to satisfy several orders by their correct due date, although a substantial quantity of orders still went unmet. The results indicate that the ILUP model outperforms the GLUP in meeting more timely orders.

Figure 39 – Fulfilling orders for Scenario B for θ constraints.

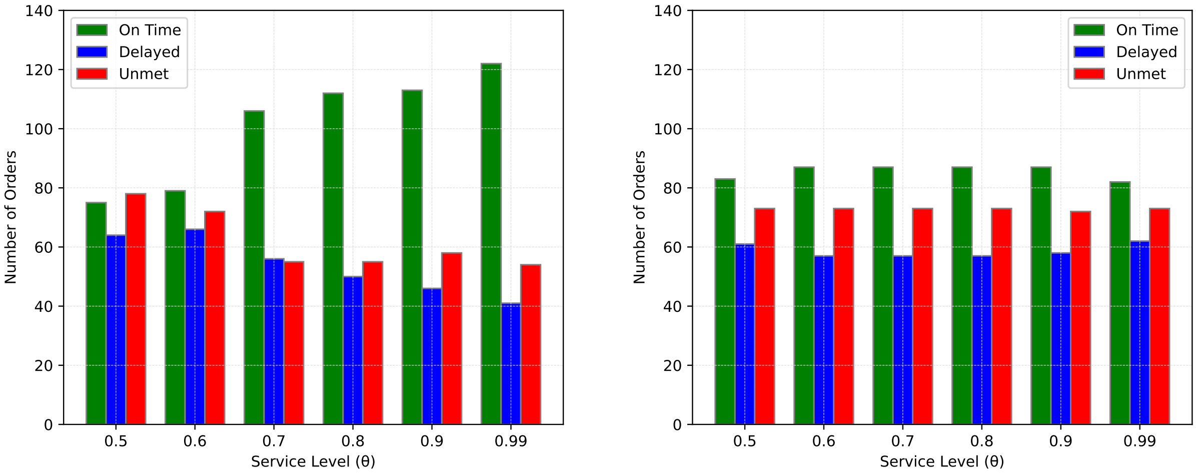
(a) ILUP- M1

(b) GLUP - M1

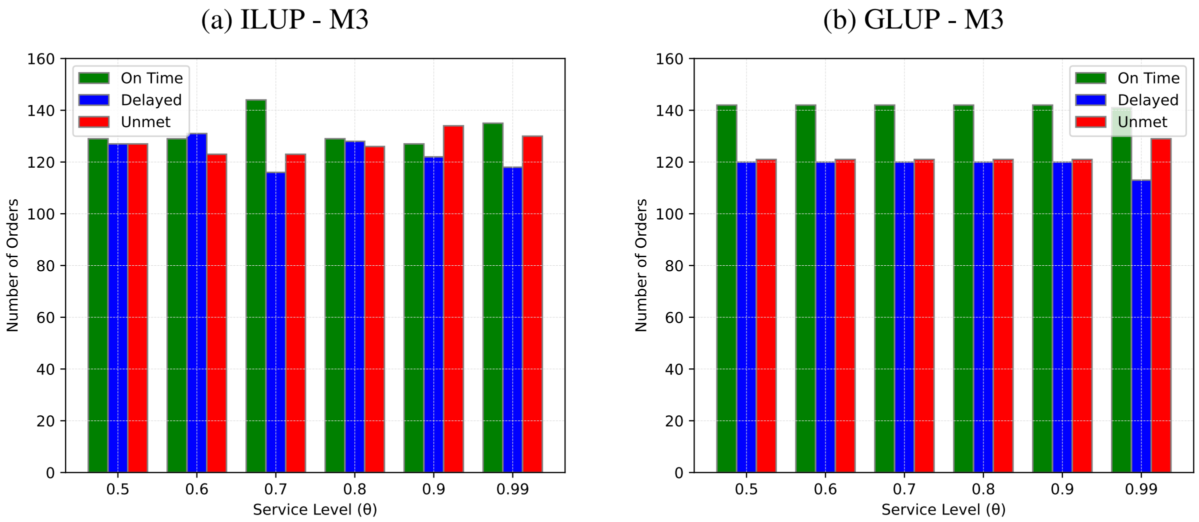


(c) ILUP - M2

(d) GLUP - M2



KPIs: Results in Appendix show that in the ILUP model, a negative correlation between θ and average delay indicates a potential to decrease the average delay for some orders across all instances. One period was reduced for the maximum delay for M2 and M3 instances in ILUP. In the GLUP model, a moderate negative correlation exists between θ intensities and average delay for the M1 instance, with a weak correlation observed for M2 and M3 instances. The maximum delay remains unchanged. These results suggest that increasing θ intensities wield a minor influence on the final solutions. The ILUP model also registered reduced lead times for M1 and M3 instances. The gain capacity utilization was obtained by holding items, as we can see by WIP values, particularly for the M1 instance in the ILUP model.


(a) ILUP - M3

(b) GLUP - M3

4.4.5.3 Scenario C: Low demand without delayed orders in the order book

As the demand is 67% of the capacity, few θ intensities were found, and we only found a feasible solution for $\theta = 0.5$, using ILUP. For the GLUP, the solutions are the same as obtained in the original problem, without the θ constraint. Establishing a minimum number of orders fulfilled or a minimum average utilization of the equipments does not add any gain to the original problem.

4.4.6 Inventory and setup costs in the objective function

As shown in chapter 3, inventory and setup costs are essential for textile industries. Thus, in this section, we investigate the impact on costs and met orders when we include these costs in the objective function. A fixed setup cost s is incurred whenever we have a machine configuration for a family k ($Y_\eta^k = 1$). Therefore, we consider the following model:

$$\min \sum_{i=1}^{NP}\sum_{t=1}^{T} bo_{it}BO_{it} + \sum_{j=1}^{N}\sum_{j=1}^{T} h_j I_{jt} + \sum_{k=1}^{K}\sum_{\eta=F_1}^{L_T} sY_\eta^k \tag{4.17}$$

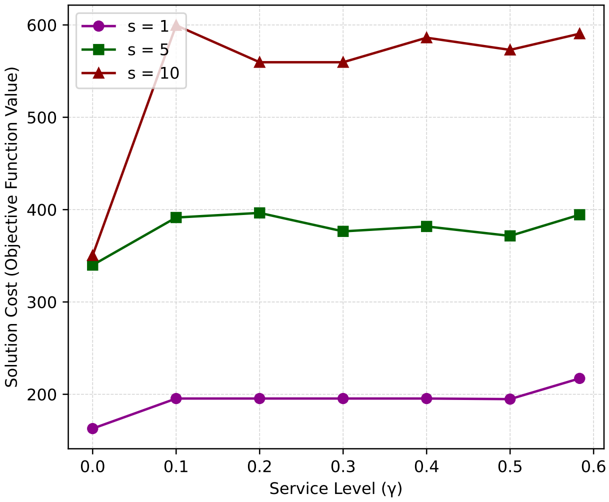
$$S.t:$$

$$(4.2)-(4.11)$$

To use SUBH solution method, we add a binary variable and a constraint to account when a setup occurs in the relaxation model proposed by Alves et al. (2024) (see Appendix C.1) . We ran the tests for M1 instance in Scenario A, with $s = \{1, 5, 10\}$.

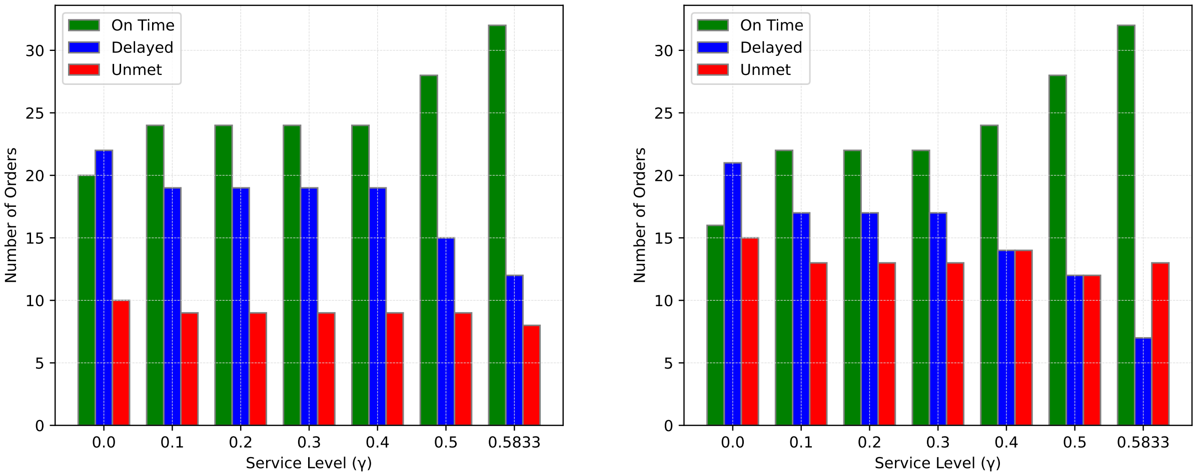
Costs: Figure 41 illustrates that the setup cost directly influences the total cost. When $s = 1$, the results are near those observed in previous sections. However, as the setup cost parameter increases to $s = 5$ and $s = 10$, there is a significant rise in total costs. This trend highlights the impact of setup costs on production planning and operational costs.

Figure 41 – Solution costs results considering inventory and setup costs for Scenario A.



Orders: When we analyze order fulfillment, the impact of incorporating setup costs becomes evident in the number of delayed and unmet orders during the planning process, the results can be seen in Figure 42. Setup activities due to changeovers represent costly disruptions to production processes. In this case, we have a more considerable backlog of orders, especially when setup costs are high. Therefore, including these costs in the planning model directly affects meeting order due dates.

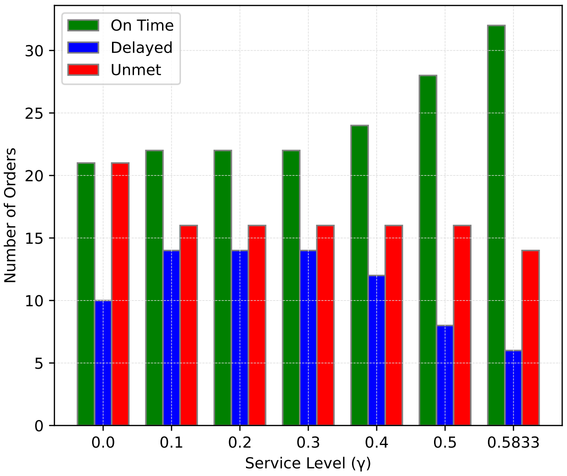
Figure 42 – Fulfilling orders considering inventory and setup costs for Scenario A.


(a) $s = 1$

(b) $s = 5$

KPIs: As the number of unmet orders increases, we observe a negative impact on throughput. Higher setup costs increase the average delay and lead times. Setup activities due to changeovers represent costly disruptions to production processes (Allahverdi and Soroush, 2008). When $s = 1$, the WIP inventory is reduced because inventory costs are incurred on a period-by-period basis. However, for $s = 5$ and $s = 10$, we notice a significant increase in WIP levels. In Scenario A, which features high demand, the initial average equipment utilization was

(c) $s = 10$



93%. This utilization rate drops to 79% for s=1, 71% for s=5, and 63% for s=10. This decrease reflects the impact of higher setup costs.

4.5 Final remarks

In this chapter, we investigate two service-levels and capacity utilization constraints in lot-sizing problems with an order-oriented approach. This problem arises in a textile industry context to gain competitive advantage. The five proposed constraints consider the presence of several customers, filling a gap in the literature. To analyze the behavior of the problem, a set of problem instances was solved. These scenarios encompass high-demand (M1 with 52 orders, M2 with 217 orders, and M3 with 383 orders) and low-demand (M1 with 46 orders, M2 with 160 orders, and M3 with 209 orders) contexts, with and without initially delayed orders. This study illustrates how service-level and capacity utilization constraints impact decision-making processes.

Introducing service-level constraints brings about favorable outcomes for key performance indicators (KPIs) such as average delay, lead time, maximum delay, throughput, and work in process. On average, limiting the number of backorders (γ constraints) can increase the number of orders fulfilled on time by up to 114% in high-demand with initial delayed orders and 123% in high-demand without initial delayed orders scenarios. These results reduce the average delay and lead time, improving customer satisfaction. In order to increase throughput, we set a constraint on the minimum number of orders to be fulfilled (μ constraints), resulting in an average increase of 35% in throughput in high-demand scenarios. In low-demand scenarios, service level constraints bring little gain in improving KPIs.

We also analyzed the relationship between capacity utilization (θ constraints) and other KPIs, determining that increased capacity does not necessarily correlate with enhanced productivity. It is consequential that higher service-level intensities or capacity utilization come with higher costs. The significance of this trade-off varies by instance. However, the data provided by the models provides the decision-maker with sufficient insight to determine if equity-driven solutions are relevant.

Notably, the conducted numerical experiments highlight that global constraints produce lower solution costs compared to period-based or equipment-based constraints. Individual models are recommended when KPIs need to be monitored over shorter periods than the planning horizon. Global models offer flexibility in producing individual items, collectively contributing to achieving average or global service-level targets.

This work can be extended in future research by providing new individual and aggregate service-level constraints. We also suggest extending this study to a multi-objective approach, in which several service-levels and costs are optimized.

It is noteworthy that while those experiments offer valuable insights into service-levels and capacity utilization constraints, the results presented are specific to the set of instances tested. The implications and findings might change in different operational contexts and scenarios. Therefore, there is room for further research and testing to prove the more general applicability of the proposed models.

5 Integrated production and distribution problem with order consideration and cargo arrangement

In a process industry with sequential production, storage, and distribution activities, operations planning is usually performed individually, from predetermined decisions from previous activities. However, production and distribution are two functions that need to be viewed in an integrated way to obtain better operational performance of the organization (Chen, 2010). Over the years, the concern about integrated production and distribution (IPD) problems has grown. Chen (2010), Fahimnia et al. (2013), and Darvish et al. (2021) presented literature reviews about IPD problems, showing model variations related to the IPD problems applied to supply chain management. However, those surveys do not cover the IPD with order considerations and cargo arrangement.[1] [2]

By covering lot-sizing problems integrated with transportation decisions, Amorim et al. (2013) and Belo-Filho et al. (2015) explored lot-sizing in IPD operational-level problems. The lot-sizing decisions must define the amounts of items to be produced and the production sequence in the machines. Thus, a planner must simultaneously decide on production planning and vehicle routing. Recently, Bank et al. (2022) presented two MIP models and optimality properties for the lot-sizing IPD problem. These papers focus on the routing vehicles instead of the loading problem.

Concerning cargo arrangement, Molina et al. (2016) proposed MIP models for lot-sizing problems with distribution costs using unit load devices such as pallets and containers. Lot-sizing decisions must respect limited capacity and meet the product demand. Therefore, distribution decisions are related to the loading and transporting products in cargo unitization. Another important aspect of operations management is order fulfillment (Amorim et al., 2013). To the best of our knowledge, the grouping of the items in the orders is done for batch delivery, and order fulfillment is explored in a few lot-sizing problems.

The integrated production and distribution planning problem with order consideration and cargo arrangement appears in the production environment of a textile spinning mill located in the interior of São Paulo, inspiring this chapter. A multi-stage process with multiple parallel machines characterizes the spinning production system. These machines generally have different production characteristics, such as processing and setup times. The configurations depend on the sequence of products manufactured by the machines (Camargo et al., 2014).

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[1] An article with contents of this chapter was published by Giovanna Abreu Alves, Roberto Tavares, and Victor Claudio Bento Camargo. MIP model for integrated production and distribution problem with order consideration and cargo arrangement. SIMPÓSIO BRASILEIRO DE PESQUISA OPERACIONAL, 2022, Juiz de Fora. Anais eletrônicos. Available in `https://proceedings.science/sbpo/sbpo-2022/trabalhos/mip-model-for-integrated-production-and-distribution-problem-with-order-consider?lang=pt-br>.`

[2] A working paper based on the solution method presented in this chapter is in development by Giovanna Abreu Alves, Guilherme Ferreira De Lima Tonon, Roberto Tavares, and Victor Claudio Bento Camargo.

Yarn manufacturing encompasses steps, beginning with fiber cleaning and preparation. Fibers undergo a thorough cleaning process to eliminate impurities and are blended to combine different fiber types. This stage sets the foundation for the subsequent combing process, aligning the fibers and reading them for carding. During carding, fibers are aligned and twisted into slivers, enhancing their strength while reducing their thickness. Following this, an intermediary process involves twisting a delicate network of fibers to fortify them, thus imparting the necessary characteristics to the yarn and priming it for spinning. The spinning process culminates in the yarn wound onto bobbins. Post-spinning, the bobbins are arranged on pallets for distribution, where each pallet carries only a single yarn type. Once palletized, they are prepped for distribution.

Integrated production and distribution problems, recognized for their NP-hard complexity, typically necessitate heuristic or metaheuristic techniques to derive workable solutions for their models (Darvish et al., 2021). In a comprehensive review, Adulyasak et al. (2015) solutions methods for integrated production and routing challenges. Their analysis of benchmark instances, which included scenarios with several customers, revealed that the Adaptive Large Neighborhood Search (ALNS) metaheuristic presented a good performance for the tested problems. In IPD models involving direct delivery, ALNS has the potential to effectively solve complex scenarios with multiple customers.

In this chapter, we present a MIP model designed to support integrated production and distribution decisions at the operational level, focusing on order fulfillment, lot-sizing, and scheduling. The model incorporates sequence-dependent setup and setup carryover constraints in production and distribution logistics through heterogeneous vehicle fleets responsible for pallet transportation. Additionally, we propose an ALNS to solve the model efficiently.

The remainder of this chapter is organized as follows. In Section 5.1, we present the related works in the literature. In Section 5.2, we describe the considered problem and the mathematical formulation for the production and distribution problem with order consideration and cargo arrangement. The proposed ALNS is presented in Section 5.3. Then, in Section 5.4, the results and analysis of the computational study are presented. Conclusions and future research are pointed out in Section 5.4.

5.1 Related works

This section presents the related literature for this work, divided into two parts. Subsection 5.1.1 reviews studies that employ mathematical programming for integrated production and distribution problems with direct delivery. Subsection 5.1.2 explores applications of ALNS in solving MIP models.

5.1.1 Integrated production and distribution problems with direct delivery

In this problem, products are transported directly from the manufacturer to customers, and various production and distribution constraints are considered. Production constraints include costs associated with manufacturing and setup times. The objective is to minimize the total costs within the planning horizon, encompassing production, machine configuration, inventory, and transport costs. This problem typically incorporates various aspects of production, for example, production cost and setup time, and involves distribution decisions where fixed and unit delivery costs are customer-specific (Adulyasak et al., 2015).

Some authors consider the integrated production and distribution problem with direct delivery for a single item. Li et al. (2004), Jaruphongsa et al. (2007) and Hwang (2010) addressed variants of integrated lot-sizing, batch ordering, and distribution problems with a piece-wise linear transportation cost function and the possibility of full or split loading for vehicles. The authors presented dynamic programming algorithms to solve the models. A comparative approach between just-in-time (JIT) and time window (TW) policies is analyzed by Akbalik and Penz (2011) for a lot-sizing problem integrated with transportation decisions. In the JIT policy, customer demand has to be satisfied by a specific date, while in the TW policy, delivery can be made a few days before the due date. A MIP model and a dynamic pseudo-polynomial program are proposed to solve the models. A heuristic based on dynamic programming is proposed to solve the model.

Still considering the production of a single item, Darvish et al. (2016) investigated the production and distribution planning problem for the simultaneous optimization of production, inventory control, demand allocation, and distribution decisions. The authors considered a fixed delivery date to be distributed from any of the selected plants. The branch-and-bound algorithm is used to solve the model. Furthermore, Gruson et al. (2019) compared 13 formulations for the lot-sizing and distribution problem on three levels (plant-warehouse-retail). Inventory can be held at all three levels of the supply chain at one cost, and a commercial solver is used to solve and compare the models.

A more general piece-wise linear transportation cost function for the production and distribution of multiple items was addressed by Rizk et al. (2006). The authors proposed a MIP model for integrated production and distribution problems with purchase cost discounts. Lagrangian relaxation and heuristics based on the subgradient method are solution methods.

van Norden and van de Velde (2005) studied an integrated lot-sizing and multi-item distribution model in which delivery costs depend on the type of contract established with the carrier without necessarily depending on the volume to be transported. The authors proposed an algorithm based on Lagrangean relaxation to solve the model. A solution heuristic for the van Norden and van de Velde (2005) model is proposed by Molina et al. (2009), and three extensions of the model are proposed by Molina et al. (2013) to represent pallets or trucks needed to pack and transport the items. In addition, Molina et al. (2016) presented different MIP models for integrated lot-sizing and distribution problems with cargo unitization on pallets or containers. The models are solved using the branch-and-cut method in commercial optimization software.

As integrated production and distribution problems grow increasingly complex, involving multiple layers of production, inventory, and distribution constraints, authors look for methods that provide timely and high-quality solutions. Adulyasak et al. (2015) and Mara et al. (2022) pointed out the potential of the ALNS to solve a range of problems and its possibility of being extended for different issues. In this sense, the following section explores ALNS methodology and effectiveness in integrated production and distribution contexts.

5.1.2 Adaptive large neighborhood search - ALNS

Local search heuristics are often built on neighborhood moves that make small changes to the current solution, such as moving a request from one route to another or swapping two requests. These types of local search heuristics can investigate many solutions quickly, but one solution is little changed in each iteration. For Ropke and Pisinger (2006), such heuristics can have difficulties moving from one promising area of the solution space to another when faced with restricted problems, even when inserted into metaheuristics. The ALNS algorithm was introduced by Ropke and Pisinger (2006) as an extension of the heuristic proposed by Shaw (1998) to solve the problem of routing vehicles with pickup and delivery. The basic idea behind ALNS is to repeatedly destroy and repair part of a solution to obtain a better solution using search operators. These operators are selected probabilistically based on empirical scores. A complete review of ALNS methodology is presented by Mara et al. (2022).

Adulyasak et al. (2014) used ALNS for an integrated production and routing problem and incorporated three main features into ALNS to decompose the problem into easier-to-solve subproblems. An enumeration scheme is used to create several different initial solutions. Different output configurations generate small initial solutions in the initialization phase. The authors developed two operator types: selection and transformation. At each iteration, one operator of each type is selected probabilistically. The selection operator is first applied to create a list of node candidates (client-period combinations). Then, the transformation operator is applied to remove and reinsert node candidates into the list for the current solution. When a new solution is found during the transformation process, a minimum cost flow problem is solved to optimize production, stock, and delivery quantities. The algorithm ends when it reaches the maximum number of iterations. ALNS has recently been applied to various routing applications (examples in Liu et al. (2019); Liu and Liu (2020); Chen et al. (2021); Gobbi et al. (2023)).

Although ALNS is primarily used in routing problems, several works have applied ALNS as the solution method for other contexts. For example, Muller et al. (2012) presented an ALNS to solve a capacitated lot-sizing problem with setup times. The authors detailed various types of destroyed neighborhoods used in the heuristic: random removal, production that causes inventory, capacity critical, inventory items, periods with high inventory density, and production higher than demand. The heuristic employs two methods for repairing neighborhoods: bounding variables by a fraction of their current value and fixing variables by their value in the current solution when production equals demand. Rifai et al. (2021, 2016) applied ALNS to deal with a multi-objective scheduling problem with sequence-dependent setup times in a flow shop manufacturing system. The authors used ALNS to optimize job allocation and sequencing, focusing on minimizing makespan, production costs, and tardiness. The heuristic incorporates advanced solution acceptance, non-dominated set updating mechanisms, and new heuristics to handle varying setup times, demonstrating its effectiveness in quickly finding high-quality solutions. The scheduling problem is also addressed by Lusby et al. (2016), which uses ALNS to solve the dynamic patient admission scheduling problem in a healthcare context. Furthermore, Praseeratasang et al. (2019) addressed the production scheduling and assignment in broiler farms, aiming for the maximum profit. The authors developed an ALNS algorithm to find a good solution to the problem quickly. These works exemplify the effectiveness of ALNS in solving MIP problems in different fields.

5.2 Problem definition

The problem considered in this chapter consists of nonidentical parallel capacitated machines producing multiple items grouped in customer orders. The big bucket planning horizon is finite, and the dynamic demand is deterministic. The inventory capacity is limited.

Each machine can make only one type of item per load. The setup changeover (time and cost) between different items on a machine is sequence-dependent. In addition, machine configuration is carried out from the end of a previous period until the beginning of the next.

In this problem, the weight of the pallets and the loading time of vehicles are not considered limitations. In distribution decisions, items are loaded into pallets without mixing item types. The distribution fleet is heterogeneous and limited, with vehicles required to be loaded exclusively with pallets. Each vehicle serves only one order per period and must be delivered on its due date. Delays result in additional costs. Consequently, the model must generate a cost-minimizing plan that integrates lot sizing and delivery scheduling to support both production and distribution planning.

Consider the following indices, parameters, and decision variables used in the Integrated model.

Indices	
$i, j \in \{1, \cdots, N\}$	items;
$m \in \{1, \cdots, M\}$	machines;
$k \in \{1, \cdots, K\}$	orders;
$v \in \{1, \cdots, V\}$	vehicles;
$t, t' \in \{1, \cdots, T\}$	periods;
Parameters	
d_{ik}	demand (kg) for item i in order k;
p_{im}	processing time to produce 1kg of item i in machine m ;
s_{ijm}	setup time of a changeover from item i to j in machine m;
c_{ijm}	setup cost of a changeover from item i to j in machine m;
cap_m	production capacity time of machine m;
ch	total storage capacity;
b_i	Maximum amount of (kg) items of type i that can be loaded on the same pallet;
r_v	Number of vehicles of type v available for delivery;
q_v	Maximum number of pallets that can be transported on a vehicle v;
dd_{kt}	1 if the due date of order k is planned to period t, 0 otherwise;
h_i	holding cost of 1kg of item i;
tr_{vkt}	cost to use vehicle of type v, for delivery the order k, in period t;
dc_{kt}	backorder cost of the order k in period t.
Decision variables	
XO_{kt}	Takes 1 if order k is delivered in period t; 0 otherwise;
BO_{kt}	Takes 1 if order k is delayed in period t; 0 otherwise;
X_{imt}	Amount (kg) of item i to be produced in machine m at period t;
Y_{ijmt}	Takes on 1, if there is a changeover from item i to item j in machine m in period t; 0 otherwise;
Z_{imt}	Takes 1, if item i is prepared to produce into machine m at the beginning of period t; 0 otherwise;
V_{imt}	Auxiliary variable to design the item i to machine m in period t;
I_{it}	Amount (kg) of item i held at the end of the period t;
W_{ikt}	Amount (kg) of item i delivered into order k in period t;
A_{ikt}	Number of pallets loaded with item i, delivered to meet order k, in period t
B_{vkt}	Number of vehicles of type v used to delivery order k in period t.

Integrated model is given by:

$$min \quad \sum_i \sum_t h_i I_{it} + \sum_i \sum_j \sum_m \sum_t c_{ijm} Y_{ijmt} + \sum_v \sum_k \sum_t tr_{vkt} B_{vkt} + \sum_k \sum_t dc_{kt} BO_{kt} \tag{5.1}$$

S.t:

$$I_{it-1} + \sum_{m} X_{imt} = \sum_{k} W_{ikt} + I_{it} \qquad \forall i, \quad \forall t \tag{5.2}$$

$$\sum_{i} I_{it} \leq ch \qquad \forall t \tag{5.3}$$

$$\sum_{i} p_{im} X_{imt} + \sum_{i} \sum_{j} s_{ijmt} Y_{ijmt} \leq cap_m \qquad \forall m, \quad \forall t \tag{5.4}$$

$$X_{imt} \leq \sum_{k} d_{ik} (Z_{imt} + \sum_{j} Y_{jimt}) \qquad \forall i, \quad \forall m, \quad \forall t \tag{5.5}$$

$$\sum_{i} Z_{imt} = 1 \qquad \forall m, \quad \forall t \tag{5.6}$$

$$Z_{imt} + \sum_{j} Y_{jimt} = Z_{im(t+1)} + \sum_{j} Y_{ijmt} \qquad \forall i, \quad \forall m, \quad \forall t \tag{5.7}$$

$$V_{imt} + N \cdot Y_{ijmt} - (N-1) - N \cdot Z_{imt} \leq V_{jmt} \qquad \forall i, j \quad i \neq j, \quad \forall m, \quad \forall t \tag{5.8}$$

$$\sum_{m} \sum_{t} X_{imt} \leq \sum_{k} d_{ik} \qquad \forall i \tag{5.9}$$

$$\sum_{t} W_{ikt} \leq d_{ik} \qquad \forall i, \quad \forall k, \quad \forall t \tag{5.10}$$

$$\sum_{t'=1}^{t} W_{ikt'} \geq d_{ik} XO_{kt} \qquad \forall i, \quad \forall k, \quad \forall t \tag{5.11}$$

$$\sum_{i} W_{ikt} \geq XO_{kt} \qquad \forall k, \quad \forall t \tag{5.12}$$

$$A_{ikt} \geq \frac{W_{ikt}}{b_i} \qquad \forall i, \quad \forall k, \quad \forall t \tag{5.13}$$

$$\sum_{v} q_v B_{vkt} = \sum_{i} A_{ikt} \qquad \forall k, \quad \forall t \tag{5.14}$$

$$\sum_{k} B_{vkt} \leq r_v \qquad \forall v \quad \forall t \tag{5.15}$$

$$XO_{kt} + BO_{kt} = dd_{kt} + BO_{kt-1} \qquad \forall k \quad \forall t \tag{5.16}$$

$$X_{imt}, V_{imt} \geq 0, \qquad \forall i \quad \forall m \quad \forall t \tag{5.17}$$

$$I_{it} \geq 0, I_{i0} = 0 \qquad \forall i \quad \forall t \tag{5.18}$$

$$W_{ikt} \geq 0, \qquad \forall i \quad \forall k \quad \forall t \tag{5.19}$$

$$A_{ikt} \in \mathbb{Z}^{+}, \qquad \forall i \quad \forall k \quad \forall t \tag{5.20}$$

$$B_{vkt} \in \mathbb{Z}^{+}, \qquad \forall v \quad \forall k \quad \forall t \tag{5.21}$$

$$Y_{ijmt} \in \{0,1\} \qquad \forall i \quad \forall j \quad \forall m \quad \forall t \tag{5.22}$$

$$Z_{imt} \in \{0,1\} \qquad \forall i \quad \forall m \quad \forall t \tag{5.23}$$

$$XO_{kt}, BO_{kt} \in \{0,1\} \qquad \forall k \quad \forall t \tag{5.24}$$

The objective function (5.1) aims to minimize the total costs of inventory, machine setup, delivery, and backlogging costs, respectively. Constraints (5.2) represent the inventory balancing, establishing that the total amount produced and stored is sufficient to deliver the items in period t.

Constraints (5.3) limit the total capacity to store the items. Constraints (5.4) are the time capacity constraints of the machines, considering processing and the changeover times of the items.

Constraints(5.5) guarantee that the production of an item i can only occur if machine m is prepared for this item, while constraints (5.6) - (5.8) determine the sequence of items to be produced on each machine in each period. Constraints (5.6) assure that each machine can only be set up for a single item at the beginning of each period. Constraints (5.7) ensure a balanced network flow of the machine configuration states and carry the setup configuration state of the machine to the next period. Constraints (5.8) avoid sub-tours from occurring in the item preparation sequence. If no changeover is performed in machine m in period t, then $Y_{ijmt} = 0$ for all i and j, and the configuration state of the machine is carried from period $t-1$ to period $t+1$.

Constraints (5.9) ensure that the total produced is, at most, the amount demanded by each item. Constraints (5.10) ensure that the amount of items delivered for each order does not exceed the quantity demanded per item. Constraints (5.11) determine that an order is only considered complete when all items in the order are delivered. Constraints (5.12) impose that at least one delivery is made on the period the order is considered complete. The number of pallets loaded with item i, delivered to meet order k, in period t is defined by constraints (5.13).

The entire vehicle capacity, in pallets, will be transported. Such condition is ensured by constraints (5.14). Constraints (5.14) define the number of vehicles needed to perform the deliveries for each order, and the total number of vehicles is bounded by constraints (5.15).

Constraints (5.16) represent the flow balance in the delivery of orders. When an order k is delivered in period t, $XO_{kt} = 1$. Note that this constraint only allows the order to be completed on the planned due date, or it is delayed. After the expected due date, as long as the order is not delivered, $BO_{kt} = 1$. Finally, the non-negativity and variable dominance conditions are represented in constraints (5.17) - (5.24).

5.2.1 Example problem

In this section, a small data set is considered, with two machines with capacities of 2000 and 3000 time units, respectively. The planning horizon has $T = 8$ periods, and the storage capacity is not bound. Order $k = 1$ has a due date at $t = 3$ and order $k = 2$ at $t = 8$. If orders are not delivered on time, costs of $dc_{kt} = 15000$ occur per delayed period. When an order is not delayed, $dc_{kt} = 100000$ (prohibitive delay cost). The rest of the example data is given in Table 11, s_{ijm}/c_{ijm} is valid for all m and tr_{vkt} for all t.

Using a commercial solver to solve the problem, the optimal solution found is shown in Figure 43. The initial configuration of each machine at the beginning of period t is given by $Z_{12t} = 1$ and $Z_{21t} = 1$. There was idle time on machine 1 at the end of periods $t = 1$ and $t = 8$ and a configuration changeover from item $i = 2$ to $j = 1$ on machine 1 at $t = 8$ ($Y_{2118} = 1$). Deliveries occur at periods $t = 3$ and $t = 6$ to meet order $k = 1$ and at period $t = 8$ to meet order $k = 2$. In other periods, production quantities are stored to delivery the orders in due date. Table 12 displays the values of variable I_{it} in the optimal solution of the example.

Table 11 – Data for illustrative example with two items, two production machines, and two vehicles.

	d_{ik}		s_{ijm}/c_{ijm}			
	$k=1$	$k=2$	$j=1$	$j=2$	h_i	b_i
$i=1$	8000	3500	0/0	1.3/2	0.001	880
$i=2$	4000	2200	22	0/0	0.001	704
			tr_{vkt}			
	q_v	r_v	$k=1$	$k=2$		
$v=1$	8	1	1000	1100		
$v=2$	8	1	800	1200		

Figure 43 – Gantt chart for the optimal solution of the illustrative example.

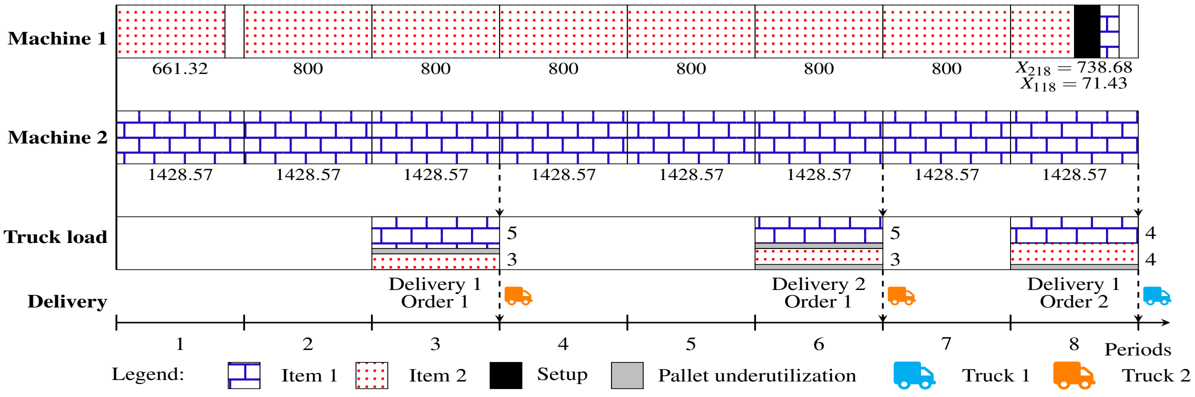


Table 12 – Amount (kg) of items held at the end of each period.

Item	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6	t = 7	t = 8
1	1428.57	2857.14	0.00	1428.57	2857.14	571.43	2000.00	0.00
2	661.32	1461.32	149.32	949.32	1749.32	661.32	1461.32	0.00

To meet the demand of order $k = 1$ two deliveries are planned using vehicle $v = 2$. The first delivery is made on the due date $t = 3$, but the order will only be considered complete at $t = 6$, when the entire amount demanded is fully delivered, so $BO_{13} = BO_{14} = BO_{15} = 1$ and $XO_{16} = 1$. For order $k = 2$, a single delivery with vehicle $v = 1$ is planned on the due date at $t = 8$, incurring no delay delivery cost, i.e. $XO_{28} = 1$ and $BO_{2t} = 0$ for all t.

In each delivery planned, the items are unitized on pallets. The pallets are arranged inside the trucks according to the values shown in Table 13. Variables A_{ikt} determine the number of pallets needed to transport the load W_{ikt} given in kilograms. For example, for order $k = 1$, $4285.71kg$ of item 1 must be delivered over 5 pallets. These 5 pallets are not complete, leaving empty $F_{113} = 0.13$ of the pallets. Also, 2112 kg of item 2 is transported in this same delivery on exactly $A_{123} = 3$ full pallets. The total cost of this example in the optimal solution is 47720.24 units.

It is common for companies to solve the production and distribution problems hierarchically. First, the amount produced on each machine and other production decisions are taken, and then the delivery loads are determined. In this sense, we analyzed the integrated model with three scenarios of non-integrated models. We use the classical capacitated lot-sizing problem (CLSP) and distribution problem (DP) models.

Table 13 – Amount of each item delivered to meet each order.

			Pallets	
		Weight (kg)	**Delivered**	**Not completed**
$k = 1$		(W_{ikt})	(A_{ikt})	(F_{ikt})
Delivery 1	Item 1	4285.71	5	0.13
	Item 2	2112.00	3	0.00
Delivery 2	Item 1	3714.29	5	0.78
	Item 2	1888.00	3	0.32
$k = 2$				
Delivery 1	Item 1	3500.00	4	0.02
	Item 2	2200.00	4	0.88

CLSP

$$min \sum_{i=1}^{N} \sum_{t}^{T} h_i I_{it} + h_i^- I_{it}^- + \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} c_{ijm} Y_{ijmt} \tag{5.25}$$

S.t:

$$I_{it-1} - I_{it-1}^- + \sum_m X_{imt} = dem_{it} + I_{it} - I_{it}^-$$

$$\forall i, \forall t \tag{5.26}$$

(5.3) – (5.8)

$$X_{imt}, I_{it}, V_{imt}, \geq 0, \tag{5.27}$$

$$Y_{ijmt}, Z_{imt} \in \{0, 1\} \tag{5.28}$$

DP

$$min \quad \sum_{v=1}^{V} \sum_{k=1}^{K} \sum_{t}^{T} tr_{vkt} B_{vkt} + \sum_{k=1}^{K} \sum_{t}^{T} dc_{kt} BO_{kt} \tag{5.29}$$

S.t:

$$\sum_k W_{ikt} \leq \sum_m X_{imt}, \forall i, \forall t \tag{5.30}$$

(5.10) – (5.16)

$$F_{ikt}, W_{ikt} \geq 0, \tag{5.31}$$

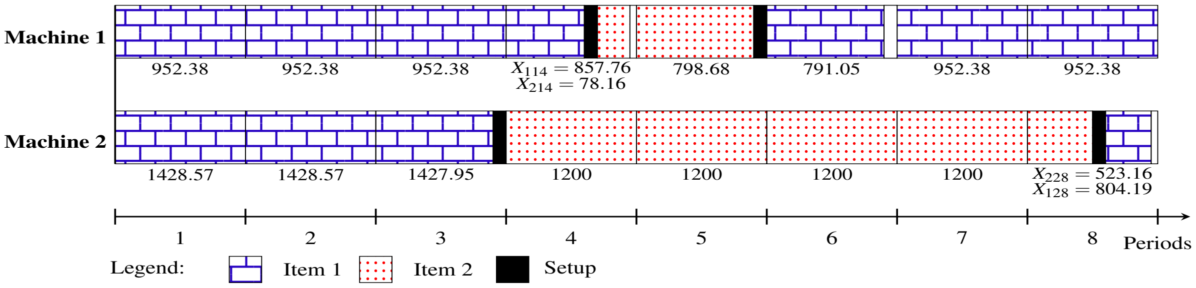
$$A_{ikt}, B_{vkt} \in \mathbb{Z}^+, \tag{5.32}$$

$$XO_{kt}, BO_{kt} \in \{0, 1\} \tag{5.33}$$

Considering that the model is no longer integrated with delivery decisions, constraint (5.2) is changed to a common inventory balance constraint represented in (5.26). The decision variable I_{it}^- counts the amount (kg) of item i that is delayed in period t. If there is insufficient capacity to meet all the planned demand for period t. Variables I_{it}^- suffer a penalty h_i^- in the objective function to avoid the model from delaying the production of the items. The term $\sum_k W_{ikt}$ is replaced by the parameter dem_{it} : demanded amount (kg) of i in period t. The value of dem_{it} : $\forall i, t$ is obtained by summing the quantity demanded of item i of all orders with a due date for period t, i.e., $dem_{it} = \sum_k d_{ik}, \forall t$.

The optimal solution to the CLSP is illustrated in Figure 44. The initial configuration of each machine at the beginning of period $t = 1, 2, 3$ is given by $Z_{11t} = 1$ and $Z_{12t} = 1$. There is a configuration changeover from item $i = 1$ to item $j = 2$ on machine $m = 1$ in period $t = 4$ ($Y_{1214} = 1$). Another changeover is made at the end of period $t = 5$ ($Y_{2115} = 1$) that remains the configuration in periods $t = 6$ to $t = 8$. On machine $m = 2$, there is a configuration changeover from $i = 1$ to $j = 2$ at the end of period $t = 3$ ($Y_{1223} = 1$), so the item $i = 2$ is produced on machine 2 in periods $t = 4$ to $t = 8$. In period $t = 8$, a changeover occurs ($Y_{2128} = 1$), and item $i = 1$ is produced on both production machines.

Figure 44 – Gant Chart for the optimal solution to the CLSP.



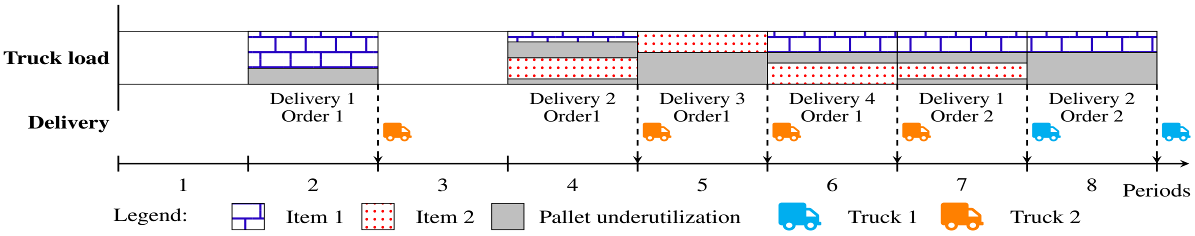
The results of the inventory variables are shown in Table 14. Comparing the results obtained in Table 12, we can see that fewer items are stored, reducing inventory costs. The non-integrated model cannot meet the entire order demand $k = 1$, in period $t = 3$, similar to the integrated model. Thus $I^-_{13} = 857.76$ kg, $I^-_{23} = 4000$ kg, $I^-_{24} = 2721.84$ kg and $I^-_{25} = 723.16$ kg represent the backlog items by the model.

Table 14 – Amount (kg) of items held at the end of each period for CLSP.

Item	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$	$t = 8$
1	2380.95	4761.90	0.00	0.00	0.00	791.05	1743.43	0.00
2	0.00	0.00	0.00	0.00	0.00	476.84	1676.84	0.00

After solving the CLSP, the values of the variables X_{imt} are input parameters for the amount that should be unitized on pallets and delivered to customers in the DP1 model. The optimal solution for DP1 is represented in Figure 45. It can be seen that more deliveries are necessary to fulfill the orders compared to the solution obtained by the integrated model. For example, for order $k = 1$, four deliveries were planned with vehicle $v = 2$, while the integrated model needed two deliveries with vehicle $v = 2$. In addition, for order $k = 2$, two deliveries were planned with vehicle $v = 1$, and the integrated model fulfilled this order with one delivery vehicle $v = 1$.

Figure 45 – Chat Gantt for the optimal solution to the DP.



Similar to integrated model order $k = 1$ is complete at $t = 6$, thus $XO_{16} = 1$, this order is delayed by $BO_{13} = BO_{14} = BO_{15} = 1$. Order $k = 2$ is complete at $t = 8$, on the expected due date, so $XO_{28} = 1$ and $BO_{2t} = 0$ for all t.

The objective function for the non-integrated transportation model is 50400.00 cost units, 5.61% higher than the value found by the integrated model, considering the costs related to the production and distribution of the items. Moreover, CLSP does not address order fulfillment and distribution decisions in the production stage. As a result, fewer items are stored, and we have less than the truckload cargo in the distribution stage. For this reason, more trips are needed to fulfill the same order compared to the results obtained by the integrated model.

5.3 Solution method based on adaptive large neighborhood search (ALNS)

The ALNS operates as follows: Given a starting solution, the meta-heuristic iteratively tries to improve the objective function by exploring different neighborhoods. Each neighborhood focuses on MIP model variables, such as customer orders in a transportation problem and items or setups in a lot-sizing problem (Muller et al., 2012).

These neighborhoods are divided into two types of operators: destroy operators and repair operators. Given a solution, the destroy operators change part of it, removing some stated decisions. A new neighborhood is created, and a repair operator searches for new solutions, inserting new choices based on keeping some parts of the solution fixed (Belo-Filho et al., 2015). (Belo-Filho et al., 2015). In the context of the ALNS heuristic discussed here, the repair operator utilizes a MIP solver.

5.3.1 Initial solution

We use the first feasible solution obtained from solving the integrated model (5.1) - (5.19) with Gurobi as the initial solution. To achieve this purpose, we limit Gurobi parameters to finding only one feasible solution.

5.3.2 Destroy operators

Destroy operators consist of implementations aiming to remove parts of a feasible solution to generate a new solution from a new rearrangement (Mara et al., 2022). Using an

ALNS heuristic, a set of these operators and a probability of choice are defined, determining the chance of executing that move to improve the incumbent solution.

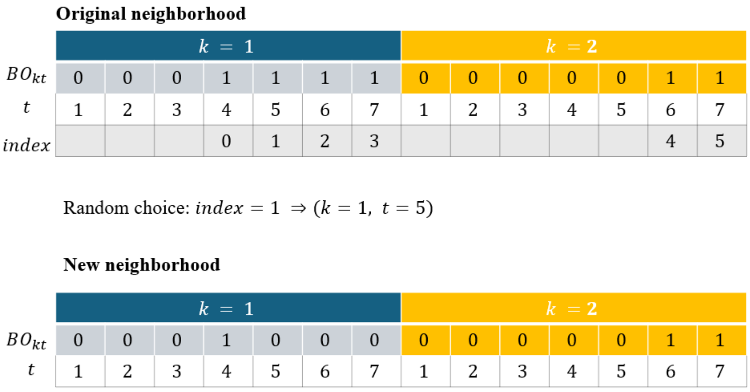
The destroy operators of the proposed solution method are based on each part present in the objective function. As the implementation of ALNS initially seeks to destroy operators, we chose to explore the variables described in minimization, as they directly impact the results obtained for the instances. Therefore, delays, inventory, setups, and transportation costs were mainly evaluated during design. In this context, we describe five destroy operators in the following sections.

5.3.2.1 No Delay, One Choice

This operator first identifies all the orders and periods in which delays occur and stores this information, mapping the number of days each order is delayed. Orders with longer delays are prioritized, making them more likely to be selected. Then, it selects a position from this list, where the selection probability is weighted based on the number of delayed days. Then, it randomly selects a position from this list, indicating a specific order k' and period t' to correct the delay. Thus, the selection is limited to orders already identified as delayed, implying that randomness applies only to choosing one of the previously mapped delay situations. Finally, the values of $BO_{k't+1}$ to $BO_{k'T}$ are updated.

Figure 46 exemplifies the *No Delay, One Choice* destroy operator. In this example, two orders ($k=1, k=2$) are unmet in a planning horizon of $T=7$ periods. The due date of order $k=1$ is $t=4$, and the due date of order $k=2$ is $t=6$. A new neighborhood is created by randomly selecting position 4, which means that we should modify the order $k=1$ and period $t=5$, and shifting the value from 1 to 0 for $BO_{15}=BO_{16}=BO_{17}=0$.

Figure 46 – Example “No delay, one choice” operator.



Original neighborhood

	$k = 1$							$k = 2$						
BO_{kt}	0	0	0	1	1	1	1	0	0	0	0	0	1	1
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7
$index$				0	1	2	3						4	5

Random choice: $index = 1 \Rightarrow (k = 1,\ t = 5)$

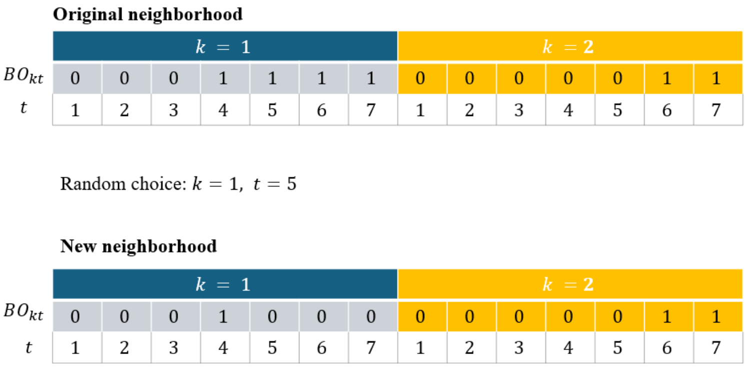
New neighborhood

	$k = 1$							$k = 2$						
BO_{kt}	0	0	0	1	0	0	0	0	0	0	0	0	1	1
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

5.3.2.2 No Delay, Random Choice

Although similar to the first operator, this operator differs in its approach by allowing double randomness in the selection. It randomly selects order k' and the period t' without first identifying and listing the delay situations. In this sense, any combination of order and delay period can be randomly chosen, introducing additional randomness into the selection process and potentially more significant variability in the decisions to correct delays. Figure 47 illustrates this operator.

Figure 47 – Example “No delay, random choice” operator.



Original neighborhood

	$k = 1$							$k = 2$						
BO_{kt}	0	0	0	1	1	1	1	0	0	0	0	0	1	1
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

Random choice: $k = 1, \ t = 5$

New neighborhood

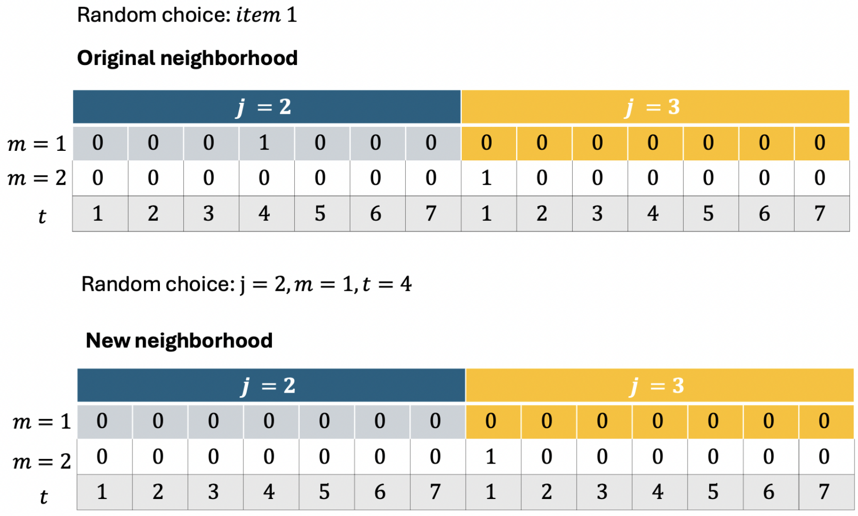
	$k = 1$							$k = 2$						
BO_{kt}	0	0	0	1	0	0	0	0	0	0	0	0	1	1
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

5.3.2.3 Minimize Changeovers

This destroy operator aims to reduce the number of setup changes using a mechanism similar to a roulette wheel. The variable Y_{ijmt} is initially run through to identify the combination of items, machines, and periods in which a changeover occurred. We compute the total number of changeovers and the relative frequency for each item.

The destroy operator then randomly selects an item i' based on a probability distribution derived from the relative frequency of changeovers. We create a set containing all the changeovers associated with i'. From this set, a combination (i', j', m', t') is randomly selected for which $Y_{i'j'm't'} = 0$, indicating no setup change for that configuration. This data, along with the cumulative number of setups performed, is appended to the instance set, which will be utilized later by the repair operator. Figure 48 exemplifies the *Minimize Changeovers* destroy operator. In this example, the item $i = 1$ was randomly selected. There is two changeovers from $i = 1$ to $j = 2$ in machine $m = 1$, period $t = 4$, and from $i = 1$ to $j = 3$ in machine $m = 2$, period $t = 1$. A new neighborhood is created by randomly selecting $j = 2$, $m = 1$, and $t = 4$ and shifting the value from 1 to 0 for $Y_{1214} = 0$.

Figure 48 – Example “Minimize changeovers” operator.



Random choice: *item* 1

Original neighborhood

	$j = 2$							$j = 3$						
$m = 1$	0	0	0	1	0	0	0	0	0	0	0	0	0	0
$m = 2$	0	0	0	0	0	0	0	1	0	0	0	0	0	0
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

Random choice: j $= 2, m = 1, t = 4$

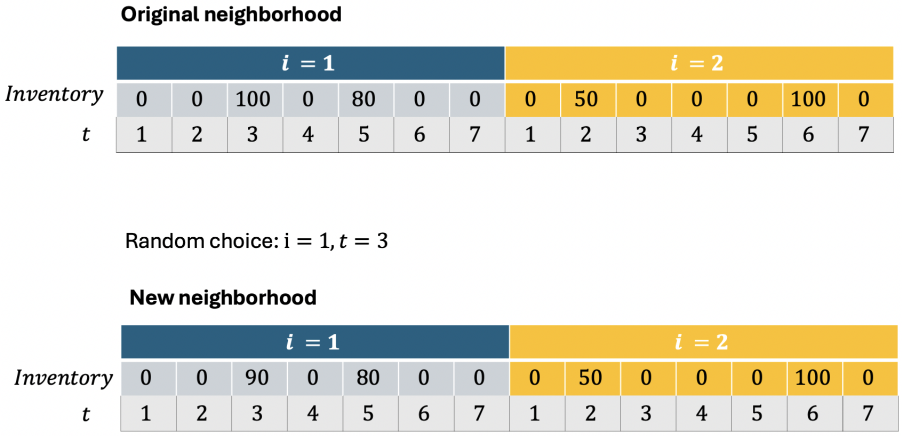
New neighborhood

	$j = 2$							$j = 3$						
$m = 1$	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$m = 2$	0	0	0	0	0	0	0	1	0	0	0	0	0	0
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

5.3.2.4 Minimize Inventory

This destroy operator aims to minimize inventory costs. It identifies items and periods with existing inventory and the total inventory amounts for all items. The relative frequency is calculated for each item. Next, the destroy operator randomly selects an item i' and a period t'. For $I_{i't'}$, the inventory level is reduced to $\delta = 0.9$ of the original value. Figure 49 illustrates this process.

Figure 49 – Example “Minimize inventory” operator.



Original neighborhood

	$i = 1$							$i = 2$						
Inventory	0	0	100	0	80	0	0	0	50	0	0	0	100	0
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

Random choice: i $= 1, t = 3$

New neighborhood

	$i = 1$							$i = 2$						
Inventory	0	0	90	0	80	0	0	0	50	0	0	0	100	0
t	1	2	3	4	5	6	7	1	2	3	4	5	6	7

5.3.2.5 Minimize Transport

This destroy operator focuses on reducing transportation costs. It starts by evaluating the F_{ikt} variable to determine the sum of incomplete orders and assessing the feasibility of reducing the total vehicle count. Next, the B_{vkt} variable calculates the number of vehicles assigned per order. Considering the vehicle types, the operator establishes the minimum number of pallets that can be loaded onto a vehicle for each order. Suppose the total of incomplete parts exceeds the maximum capacity of the smallest vehicle in the fleet, and additional trucks are available. In that case, the B_{vkt} value is set to zero for that instance. This adjustment decreases the number of vehicles employed, potentially lowering associated costs.

5.3.3 Repair operators

5.3.3.1 Fix by solution value

Let P represent the set created by applying one of the following destruction operators: *No Delay, One Choice or No Delay, Random Choice*. During the repair phase, we proceed similarly for each operator by formulating a sub-problem with minor adjustments.

If a variable BO_{kt} is not included in P (i.e., $BO_{kt} \notin P$), we set its value to $BO_{kt} = \overline{BO_{kt}}$, where $\overline{BO_{kt}}$ is the value of the current solution. However, if $BO_{kt} \in P$, we allow it to vary, meaning it is "free" in the optimization process. When employing this repair operator, the optimization problem (5.1) - (5.19) is extended with the following constraint:

$$BO_{kt} = \overline{BO_{kt}}, \quad \forall BO_{kt} \notin P \tag{5.34}$$

5.3.3.2 Bound by the sum of the solution value

Let Q be the set created by applying the destroy neighborhood operator *Minimize Changeovers*. We introduce two repair operators. The first repair operator introduces two constraints. The first constraint imposes that for item $i \in Q$, the total number of setups must not exceed the total setups of the current solution decreased by one.

For item $i \notin Q$, the second constraint ensures that the setup numbers do not exceed those of the total setups of the current solution. When employing this repair operator, the optimization problem (5.1) - (5.19) is extended with the following constraints:

$$\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} Y_{ijmt} \leq TS - 1, \quad \forall i \in Q \tag{5.35}$$

$$\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} Y_{ijmt} \leq TS, \quad \forall i \notin Q \tag{5.36}$$

where $TS = \sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} \overline{Y_{ijmt}}$ is the total number of setups in the current solution.

In the second repair operator for the destroy *Minimize Changeovers*, we maintain the constraint (5.35) for $i \in Q$. We propose a new constraint for $i \notin Q$ to produce more flexibility to the model. Then we have:

$$\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T} Y_{ijmt} \leq TS + 1, \quad \forall i \notin Q \tag{5.37}$$

A similar procedure is proposed to repair the destroy *Minimize Transport*. Let R be the set created by applying the destroy neighborhood operator *Minimize Transport*. The first constraint imposes that for order $k \in R$ the total number of vehicles must not exceed the total amount of vehicles in the current solution decreased by one. Conversely, for order $k \notin R$, the second constraint guarantees that their vehicle count remains within the bounds of the current solution's total vehicles. When employing this repair operator, the optimization problem (5.1) - (5.19) is extended with the following constraints:

$$\sum_{v=1}^{N}\sum_{t=1}^{T} B_{vkt} \leq TV - 1, \quad \forall k \in R \tag{5.38}$$

$$\sum_{v=1}^{N}\sum_{t=1}^{T} B_{vkt} \leq TV, \quad \forall k \notin R \tag{5.39}$$

where $TV = \sum_{v=1}^{N}\sum_{t=1}^{T} \overline{B_{vkt}}$ is the total number of vehicles in the current solution.

5.3.3.3 Bound by solution value

Let O be the set constructed by applying one of the destroy neighborhood: *Minimize Inventory*. The variables $I_{it} \in O$ are constrained to a fraction of their existing value, meaning if I_{it} is a variable in O, then $\sum_{t=1}^{T} I_{it} \leq \delta \overline{I_{it}}$, for some value of δ. $\overline{I_{it}}$ is the value of the current solution. For the problem under consideration, δ was set to 0.9. When employing this repair operator, the optimization problem (5.1) - (5.19) is extended with the following constraint:

$$\sum_{t=1}^{T} I_{it} \leq \delta \overline{I_{it}}, \quad \forall I_{it} \in O \tag{5.40}$$

If $I_{it} \notin O$, then limit them to the value of the current solution. In this case, the optimization problem (5.1) - (5.19) is extended with the following constraint:

$$\sum_{t=1}^{T} I_{it} \leq \overline{I_{it}} \quad \forall I_{it} \notin O \tag{5.41}$$

5.3.4 Stop criteria

The ALNS procedure employs multiple stopping criteria for efficient and effective solution improvement. The algorithm terminates if it reaches a maximum number of iterations, encounters an infeasible solution, fails to improve the objective function within a set time, or finds no feasible operator can further enhance the current solution. At the start of each iteration, the algorithm assesses the characteristics of the current solution —such as backlog orders, inventory, setups, and deliveries—to determine which operators are relevant. For instance, if positive inventory levels exist, the inventory-reduction operator may be applied to reduce holding costs. This approach ensures only applicable operators are used, optimizing the search process and preventing unnecessary computations.

Throughout each iteration, if an infeasible solution is generated during an operator application, the algorithm may discard it, backtrack, or interrupt the loop if other options are exhausted. After each re-optimization, it terminates early if no operator yields improvement or the algorithm reaches a convergence point with no further objective gains. Finally, at the end of each iteration, the algorithm checks whether it has reached the maximum iteration count. These stop conditions help manage the ALNS search process, balancing computational efficiency with solution quality.

5.3.5 ALNS parameters

We define parameters to guide the ALNS procedure and balance efficiency with solution quality. The first parameter is the number of iteration limits. Through experimentation, the values from 5 to 10 are chosen as the number of iterations, which results in different time executions. For this reason, we define a time limit of execution of 3,600s. We also define weights for destroy operators (w_i) as initial values determining the probability of selecting each operator. These weights adapt based on operator success rates to prioritize effective strategies. Table 15 shows the initial weights associated with each destroy operator.

Table 15 – Weights for the destroy operators (w_i).

	No Delay One Choice	No Delay Random Choice	Inventory	Changeover 1	Changeover 2	Transport
Weight	0.30	0.10	0.15	0.30	0.10	0.05

The initial weights are updated throughout the iterations. Empirically, when an operator produces a better solution, its weight increases by 0.01, increasing its selection probability. Conversely, weights decrease by 0.01 for operators that yield infeasible solutions, reducing their probability of selection. Due to the unique characteristics of each instance and the influence of randomness, results may vary with each iteration.

Let x be a feasible solution, $x^{'}$ be a newly obtained solution, x^{*} be the best-known solution, and $f(x)$ is the objective function value of the solution x. The set $\Omega^{-} = \{\Omega_1^{-}, \Omega_2^{-}, \cdots, \Omega_n^{-}\}$ is a set of destroy operators created from the characteristics of x as explained in the section 5.3.4. The set $\Omega^{+} = \{\Omega_1^{+}, \Omega_2^{+}, \cdots, \Omega_n^{+}\}$ is a set of repair operators based on the destroy operator previously selected. The weight associated with destroy operator i is w_i. Considering the destroy and repair operators described in this Section, Algorithm 2 presents a framework for the proposed ALNS.

5.4 Computational study

The computational tests aim to evaluate the performance of ALNS compared to a commercial solver and analyze the structure of the solution concerning the number of orders

Algorithm 2: Proposed ALNS

```
$x \leftarrow$ Solve the MIP model with $SolutionLimit$ = 1
Set initial solution: $x^* \leftarrow x$
repeat
    Based on the characteristics of $x^*$
    Create the set of destroy operators $\Omega^-$ and the set of repair operators $\Omega^+$
    if $\Omega^- = \varnothing$ then
        break
    else
        Initialize weights $w_i^-$ for each operator in $\Omega^-$
        Randomly select a destroy operator $\Omega_i^- \in \Omega^-$ based on weights $w_i^-$
        Apply destroy operator $\Omega_i^-$ and its corresponding repair $\Omega_i^+$ operator to $x$
        $x^{'} \leftarrow repair(\Omega_i^+, destroy(\Omega_i^-, x))$
        if $x^{'}$ is feasible then
            $x \leftarrow x^{'}$
            if $f(x) < f(x^*)$ then
                $x^* \leftarrow x$
                Increase weight $w_i$ for the successful operator $\Omega^-$
            else
                Decrease weight $w_i$ for the unsuccessful operator $\Omega^-$
        else
            Remove $\Omega_i^-$ from $\Omega^-$
until any of the stop criteria is reached;
return $x^*$
```

met and the factors affecting solution quality. For this purpose, a set of instances has been systematically generated with different parameters.

The models were coded using Python 3.8 language and the Gurobi 9.5.2 optimization software, with default settings and a time limit of 3,600s. The experiments were performed on an Intel Core i7 with 2.9 GHz and 32 GB of RAM on a Windows 10 operational system.

5.4.1 Data generation

The instance generator is based on works by (Amorim et al., 2013), (Molina et al., 2016), and real data collected from a textile company that presents characteristics analyzed in this work. There are $N = \{5,6,7\}$ items, $K = \{3,4,5\}$ orders, $M = \{2,3\}$ machines, $V = \{2,3\}$ vehicles and $T = 30$ periods. A total of $3 \cdot 3 \cdot 2 \cdot 2 = 36$ instances were generated (Table D1).

The fixed parameters are $h_{it} = 3$ and $r_v = 1$. The uniform distribution is used to generate the follow parameters: $b_i = U[200, 900]$, $p_{im} = U[6, 45]$, $q_v = U[4, 8]$. Demand for items is calculated by: 75% of the demand $d_{ik} = U[1000; 10000]$, and the remaining 25% is set to 0. The setup time and cost are computed as: $s_{ijm} = U[720, 3600]$ and $c_{ijm} = (66.67/2160) \cdot s_{ijm}$ for all $i \neq j$, , where 2160 is the average between 720 and 3600, and 66.67 is a fixed value based on

(Amorim et al., 2013).

The machine capacity is determined according to $cap_m = \frac{\sum_{ik} dem_{ik} p_{im}}{0.6T}$. We define the capacity utilization to be around 60% with this expression. For the computation of travel costs tr_{vk}, all customers are positioned randomly in a square of locations from $(0,0)$ to $(100,100)$, fixing the depot at the point (50,50). The Euclidean distance ($dist_k$) is then calculated between all pairs of customers. The fixed cost of using vehicle v is set to $f_v = U[200,250]$. Finally, the travel costs are computed by: $tr_{vk} = f_v \cdot dist_k$

To calculate the order delay costs, we first determine the due date for each order. For that, we determine the time needed to produce the order k: $OT_k = \frac{\sum_{im} p_{im} d_{ik}}{M} \forall k$. The time needed to deliver each order k is $DT_k = dist_k/vel$, where vel is the vehicle's speed set as $100km/h$. So the minimum due date is $t_1 = DT_k + OT_k$, and the due date is $dd_{kt} = U[t_1, T]$. The cost for delaying order k in period t is $dc_{kt} = OT_k \cdot \beta_k \cdot (t+1)$ where β_k is the initial delay of order k (in periods). If order k is not delayed, $dc_{kt} = 100000$ is a large number.

5.4.2 Numerical results

Table 16 presents a comparison of the solution upper bounds (UB) and times for the results obtained using the ALNS and the Gurobi solver with default settings. Due to randomness, each instance was executed 10 times with the ALNS, and Table 16 shows the average results from these runs. In the Time column for ALNS, the average duration required to find the best solution is indicated, whereas, for the Gurobi solver, the time reflects the duration to achieve the best solution within a 3600-second limit. The optimality gap for both methods was calculated using the lower bound (LB) provided by Gurobi. Regarding the objective function, Gurobi outperformed ALNS in most tested instances. However, ALNS demonstrated the capability to achieve similar solutions to Gurobi but with lower computation times.

Figure 50 exhibits the performance profile of ALNS and Gurobi. software for execution time and objective function. A performance profile refers to the distribution function of a performance metric. A plot of the performance profile reveals all major performance characteristics. If the set of instances is sufficiently large and representative of likely real-world applications, solvers with higher probabilities should be preferred (Dolan and Moré, 2002).

In Figure, the curve for ALNS is initially flatter but eventually reaches 100% probability for larger τ, meaning it handles more difficult instances effectively. In Figure 50b, the curve for ALNS is flatter, indicating that it struggles to match the best objective function values early but eventually achieves high probabilities at larger τ values. Gurobi has a steep curve that rises quickly, consistently producing best objective values across most instances.

Figure 51 further shows that, on average, the ALNS heuristic matches the order fulfillment rate achieved by the Gurobi solution.

The analysis underscores the significant influence of operational factors on the efficiency and cost-effectiveness of the integrated lot sizing and distribution model. Notably, the number of machines available emerges as a critical bottleneck. As the order volume increases, but the

Table 16 – Results for objective function and execution time for ALNS and Gurobi solver.

	ALNS			**Gurobi**			
Instance	**UB**	**Gap**	**Time (s)**	**UB**	**LB**	**Gap**	**Time (s)**
i1	208076.17	0.07%	363.74	207953.88	207933.08	0.01%	139.7
i2	179718.83	0.12%	614.45	179521.34	179503.38	0.01%	210.2
i3	315705.12	0.44%	870.87	314374.69	314316.48	0.02%	3606.55
i4	275205.55	0.32%	1070.43	274341.28	274317.39	0.01%	954.99
i5	387853.07	2.32%	1588.73	379055.06	378851.02	0.05%	3602.87
i6	340249.22	1.01%	1305.12	336869.56	336801.61	0.02%	3600.44
i7	207928.76	0.05%	361.46	207848.78	207828.01	0.01%	217.77
i8	179933.97	0.29%	218.92	179430.96	179413.03	0.01%	92.25
i9	315158.65	0.30%	520.84	314295.49	314211.60	0.03%	3607.33
i10	274454.70	7.07%	595.68	274376.04	255051.04	7.04%	3603.09
i11	387648.49	7.50%	701.95	378971.35	358556.94	5.39%	3603.26
i12	337056.26	9.73%	379.59	336807.36	304256.85	9.66%	3603.51
i13	238457.96	2.04%	573.81	233927.77	233592.11	0.14%	3603.40
i14	204489.80	1.95%	249.95	200714.80	200496.41	0.11%	3601.95
i15	354005.69	5.20%	1193.55	350842.46	335608.18	4.34%	3603.86
i16	306209.75	6.11%	1460.60	297412.72	287497.60	3.33%	3603.05
i17	434588.97	5.16%	2980.18	426615.08	412163.76	3.39%	3603.55
i18	373786.94	6.95%	2453.03	361330.99	347810.06	3.74%	3604.05
i19	238017.31	2.37%	267.19	233611.92	232382.75	0.53%	3604.54
i20	203283.89	1.42%	177.92	200452.66	200390.75	0.03%	3603.53
i21	352757.76	4.86%	1315.66	350507.44	335596.95	4.25%	3609.89
i22	298695.08	4.10%	931.42	297010.30	286443.75	3.56%	3606.20
i23	445815.45	7.52%	3072.04	426101.35	412299.62	3.24%	3611.35
i24	370168.76	6.05%	1811.16	360908.07	347789.85	3.63%	3617.72
i25	326335.19	3.60%	2074.65	323769.67	314571.88	2.84%	3603.60
i26	275420.14	1.38%	1577.51	271878.22	271607.98	0.10%	3601.57
i27	72731987.53	29.60%	3192.67	105360049.36	51203931.96	51.40%	3612.16
i28	424080.99	4.36%	3070.90	416435.85	405590.63	2.60%	3605.76
i29	290876751.36	58.31%	3089.09	191237501.01	121259441.71	36.59%	3607.42
i30	122123020.08	99.62%	2594.39	483194.49	469173.08	2.90%	3607.71
i31	327200.45	3.67%	1585.58	323303.41	315190.68	2.51%	3622.43
i32	277814.83	3.03%	794.79	271963.10	269404.29	0.94%	3621.66
i33	72953304.13	29.81%	2569.22	78015850.71	51203503.46	34.37%	3608.96
i34	422875.24	4.01%	1420.74	415915.05	405903.36	2.41%	3610.01
i35	208882674.88	49.76%	3266.27	175377759.12	104941663.25	40.16%	3606.21
i36	517640.62	9.37%	2006.14	483509.13	469134.32	2.97%	3609.03
Average	21593565.88	10.54%	1453.34	15558455.85	9402006.36	6.45%	3150.88

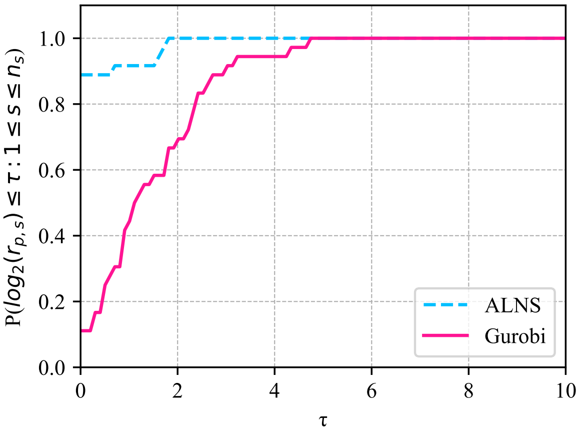
machine count remains static at two, the model tends to generate lower-quality solutions, as evidenced by higher gaps in instances like i27 and i33.

Similarly, the number of vehicles plays a crucial role in operational costs and the ability to meet delivery schedules. For example, instance i1, which operates with two vehicles, incurs higher total costs than instance i2, which uses three vehicles to meet the same orders. This cost reduction with an additional vehicle is also consistent across other instances. For instance, in i8, adding a vehicle enables the fulfillment of all orders, a significant improvement over i7, where some orders could not be fulfilled.

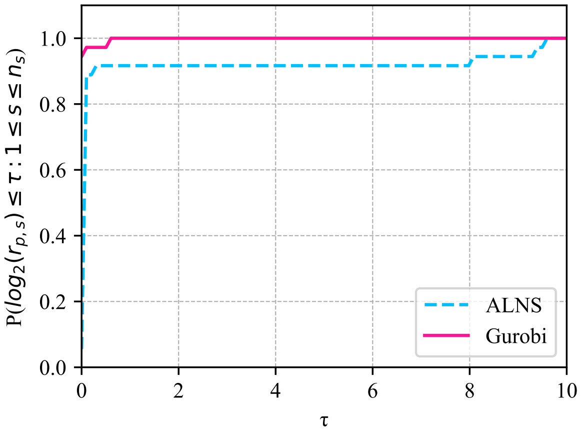
We evaluated the performance of the ALNS concerning inventory levels, the number of changeovers, and the volume of shipments, with the detailed results presented in Appendix D. Inventory levels exhibited two patterns: several instances displayed minimal variability, sug-

Figure 50 – Performance profile on tested instances.

(a) Execution Time



(b) Objective function

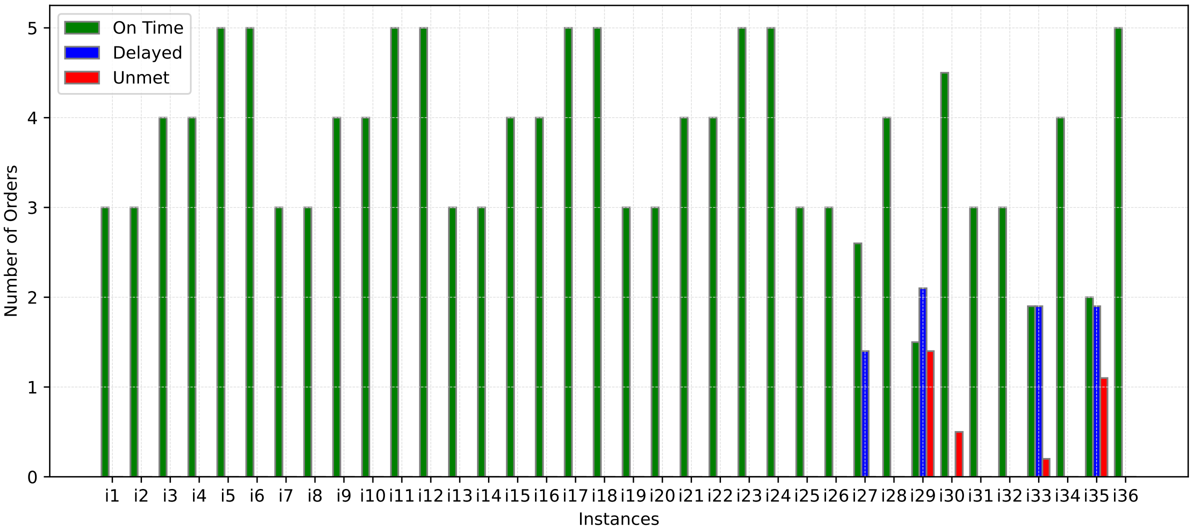


gesting a consistent use of inventory operators, while others showed high deviations, indicating significant fluctuations in inventory management strategies across different rounds. The general trend toward minimizing inventory demonstrates a deliberate effort to control this cost factor within the data set. Regarding changeovers, some instances maintained consistent setup averages with minimal variance, suggesting stable production schedules. However, instances characterized by limited capacity, particularly instance 27, experienced more significant fluctuation in setup frequency. As for shipments, most instances reported uniform values, except instances i29 and i30, which stood out due to the extensive variation in shipment volumes across multiple simulations.

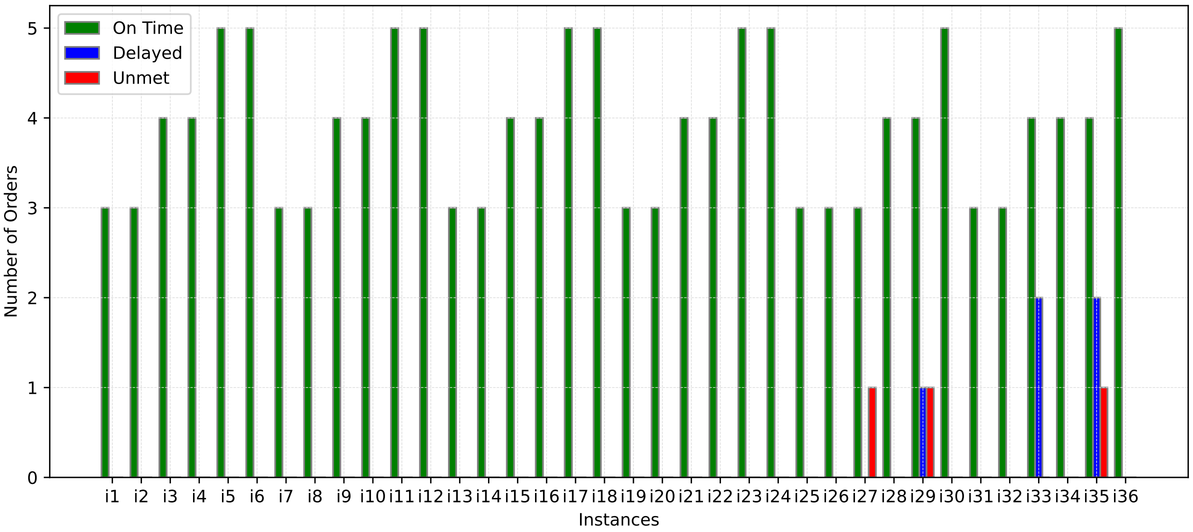
The analysis of execution times, presented in Table 17, points to a significant emphasis on restart processes within the computational model, indicating inefficiencies in the search algorithm. The preponderance of time dedicated to restart, often exceeding 90% for most instances, suggests that many computational resources are expended on activities that only sometimes yield feasible solutions or contribute to objective function improvements. This pattern of resource allocation

Figure 51 – Comparison of fulfilling orders for ALNS and Gurobi.

(a) ALNS



(b) Gurobi



highlights the potential for optimization within the proposed ALNS. By reducing the time spent on non-contributory restarts, we can enhance the heuristic efficiency, ultimately leading to faster achievement of feasible solutions and improving the overall effectiveness of the problem-solving process.

Figure 52 reports the average use by the operator in each tested instance. It is possible to notice that the operators *No Delay One Choice*, *Minimize Changeover 1*, and *Minimize Inventory* operators were predominantly employed during the restart phases. Given the increased probability assigned to inventory operators, their high involvement throughout the iterations was anticipated. On the other hand, the average of the Minimize transport operator is close to zero, showing that it was not selected. Changeover operators were more readily applied due to the routine necessity of item shifts within orders. However, the frequent restarts suggest that many

Table 17 – Execution time of the ALNS.

	Feasible solution search		**Restart**		**Relative frequency**	
Instance	**mean**	**std**	**mean**	**std**	**Feasible solution search**	**Restart**
i1	97.75	63.99	265.99	298.48	26.87%	73.13%
i2	61.28	2.31	553.17	416.82	9.97%	90.03%
i3	82.31	24.52	788.56	370.62	9.45%	90.55%
i4	87.86	67.88	982.57	920.05	8.21%	91.79%
i5	102.27	28.69	1486.46	464.91	6.44%	93.56%
i6	69.30	18.86	1235.82	823.99	5.31%	94.69%
i7	93.12	55.52	268.34	306.96	25.76%	74.24%
i8	66.24	13.39	152.68	44.38	30.26%	69.74%
i9	85.77	57.89	435.07	445.06	16.47%	83.53%
i10	61.74	3.29	533.94	472.30	10.36%	89.64%
i11	63.39	8.84	638.56	554.08	9.03%	90.97%
i12	65.10	11.53	314.49	353.20	17.15%	82.85%
i13	60.52	0.70	513.29	637.28	10.55%	89.45%
i14	62.02	2.35	187.93	367.49	24.81%	75.19%
i15	90.27	38.95	1103.29	409.74	7.56%	92.44%
i16	84.70	28.08	1375.90	812.61	5.80%	94.20%
i17	244.05	129.78	2736.14	567.81	8.19%	91.81%
i18	127.48	49.78	2325.54	910.86	5.20%	94.80%
i19	70.55	21.40	196.64	166.75	26.41%	73.59%
i20	83.00	35.28	94.92	145.42	46.65%	53.35%
i21	87.65	28.33	1228.01	623.44	6.66%	93.34%
i22	84.40	30.55	847.01	380.46	9.06%	90.94%
i23	310.23	120.47	2761.80	572.55	10.10%	89.90%
i24	127.89	43.42	1683.27	1116.03	7.06%	92.94%
i25	179.90	59.17	1894.75	745.47	8.67%	91.33%
i26	124.75	67.39	1452.76	957.82	7.91%	92.09%
i27	267.23	103.43	2925.45	777.10	8.37%	91.63%
i28	272.24	105.04	2798.66	1010.46	8.87%	91.13%
i29	307.05	155.77	2782.04	1026.75	9.94%	90.06%
i30	166.76	129.40	2427.63	1149.30	6.43%	93.57%
i31	148.21	120.51	1437.37	786.50	9.35%	90.65%
i32	76.60	25.76	718.19	556.07	9.64%	90.36%
i33	298.57	126.29	2270.66	897.41	11.62%	88.38%
i34	128.50	47.90	1292.25	1145.75	9.04%	90.96%
i35	341.49	83.65	2924.78	553.77	10.46%	89.54%
i36	149.36	151.21	1856.77	896.63	7.45%	92.55%

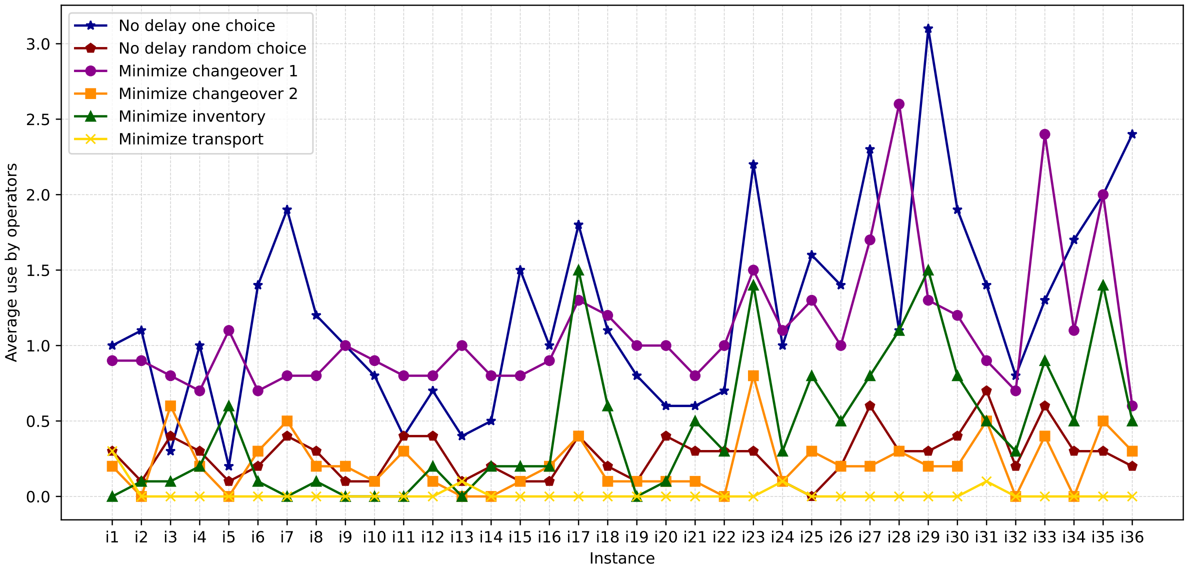
of these operations did not translate into improvements in the objective function.

5.5 Final remarks

In this study, we developed a MIP model for the integrated lot-sizing and distribution problem, focusing on customer orders and cargo arrangements. We consider setup carryover and sequence-dependent constraints alongside distribution decisions influenced by cargo unitization on pallets. This research is inspired by operational complexities observed in a spinning industry in the state of São Paulo, Brazil.

We started our investigation with a comparative analysis to evaluate the efficacy of the proposed integrated model against traditional hierarchical models. Our model consistently delivered superior performance, achieving lower-cost solutions compared to non-integrated

Figure 52 – Use of destroy operators in each instance.



approaches. Our findings highlight a crucial correlation between the number of vehicles and machines and the timeliness of fulfilling orders, providing critical insights for enhancing operational efficiency.

A set of instances was generated to evaluate the integrated model's behavior. Some optimal solutions were found for small instances, and good solutions were provided for a reasonable number of tested instances. However, Gurobi found it challenging to solve instances with increasing orders and items when the number of machines and vehicles remained low. Hence, we proposed an adaptative large neighborhood search (ALNS) solution procedure. Although Gurobi achieves better solution costs than ALNS, the proposed heuristic can find reasonable solutions with lower computational times.

Our approach included developing different destroy operators to address different objective function components. Analysis of the performance suggests that ALNS can quickly identify feasible solutions but often reallocates time to restart the process with alternative operators. Therefore, refining the strategy for generating initial solutions and setting limits on restart durations could improve the effectiveness of ALNS, making it a more viable option for solving complex distribution and lot-sizing problems.

In future research, we plan to explore new initial solution procedures and further refine the parameters of the ALNS to enrich the efficiency and quality of the solutions. Additionally, we intend to incorporate new constraints into the model to capture better the specific challenges faced by the textile industry, such as production flexibility, labor dynamics, and sustainability requirements.

6 Remarks and future research

6.1 Remarks

In the previous chapters, we have studied the integration of decisions in the context of the order fulfillment problem in the textile industry. In this section, we summarize the major findings and contributions of each chapter of this work. In Section 6.2, we conclude this work with the next steps and schedule of the activities.

In Chapter 2, we presented a comprehensive analysis of the textile production planning problems and the adoption of management information systems in São Paulo, Brazil. The study focuses on identifying production-related issues and evaluating the implementation of production management solutions within textile companies. Our results reveal that scheduling is the most critical production planning problem for the surveyed companies. Furthermore, the study highlights the importance of customer relationships, product quality, and quick response for competitive fulfillment of orders on time.

In Chapter 3, a detailed literature review of models and solution approaches for the textile supply chain was provided to identify the main problems in textile industries, their scope, integrated decisions, and solution methods. The chapter provides a detailed structure of production problems in the textile manufacturing process, from raw material processing to final goods production. The literature review and survey results point to scheduling as the most critical problem at the operational level for the textile industries. Also, we decided to focus on two gaps posted by the review: Operational performance metrics and integrated production and distribution planning at the operational level.

Based on the findings of Chapters 2 and 3, we proposed two MIP models for production planning problems based on the fulfillment of orders. In Chapter 4, we investigate service-level and capacity utilization constraints within capacitated lot-sizing problems, focusing on customer orders. We formulate γ service-level constraints to limit backlogging orders, μ service-level constraints to maximize the number of orders delivered during the planning horizon, and equipment utilization (θ) constraints to measure machine usage. The impact of service-level constraints is analyzed on solution structure and performance indicators such as average delay, maximum delay, throughput, lead time, work in process, and capacity utilization. We conducted an extensive computational test. Finally, we compared the different service-level constraints, suggesting in which context they are best applied, and show the contrast between high-capacity utilization in a make-to-order context.

In Chapter 5, we present a MIP model to support integrated production and distribution decisions at an operational level. We analyze order fulfillment, carryover setup sequence-dependent constraints, and cargo arrangement in lot-sizing and distribution decisions. A comparative analysis of the integrated model is performed with a hierarchical model, showing the relevance of the integrated model. We proposed an ALNS heuristic to solve this model.

6.2 Future research

There are several possible future research directions for the continuity of this study, some of them are described as follows:

- *Uncertainty:* Variability in order demand, lead time, and other parameters, as discussed in Chapter 3, introduces uncertainty that can significantly impact decision-making processes. Researching how to integrate this uncertainty into our models and extending the existing solution methods to accommodate these variations represents a valuable direction for further study.
- Solution methods: In Chapter 4, we employed a solution method based on Surrogate Relaxation, and in Chapter 5, we utilized an ALNS heuristic. We suggest an improvement phase to enhance these methods and find better solutions. Additionally, exploring other heuristics and metaheuristics could yield better outcomes with reduced computational times.
- Service-level analysis: Analyzing the impact on service levels and key performance indicators for the integrated model proposed in Chapter 5 is crucial. This analysis will help ascertain the practical benefits and limitations of our models under varying operational conditions.
- *Application in a real case:* Implementing the proposed approaches in a real-world case study is essential. This application will allow us to more effectively evaluate the practical advantages of these methods within an actual company setting, thus bridging the gap between theoretical research and practical implementation.

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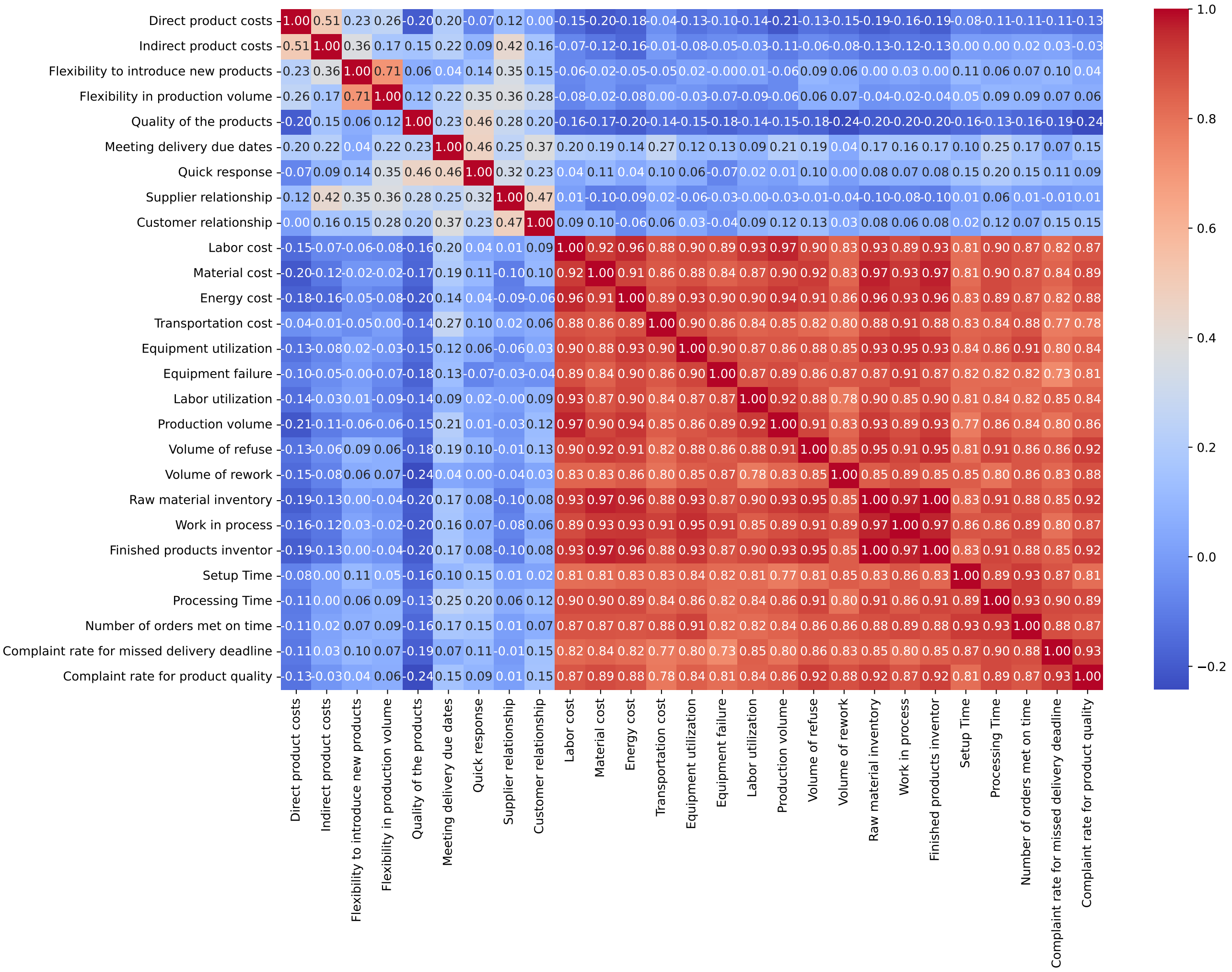
APPENDIX A – Supplementary material of Survey

To use the PCA analysis the original variables must be correlated. Figure 53 shows the correlation between the survey variables, in which the color blue is a negative correlation and the color red is a positive correlation.

Figure 53 – Correlation matrix between variables of the survey



	Direct product costs	Indirect product costs	Flexibility to introduce new products	Flexibility in production volume	Quality of the products	Meeting delivery due dates	Quick response	Supplier relationship	Customer relationship	Labor cost	Material cost	Energy cost	Transportation cost	Equipment utilization	Equipment failure	Labor utilization	Production volume	Volume of refuse	Volume of rework	Raw material inventory	Work in process	Finished products inventor	Setup Time	Processing Time	Number of orders met on time	Complaint rate for missed delivery deadline	Complaint rate for product quality
Direct product costs	1.00	0.51	0.23	0.26	-0.20	0.20	-0.07	0.12	0.00	-0.15	-0.20	-0.18	-0.04	-0.13	-0.10	-0.14	-0.21	-0.13	-0.15	-0.19	-0.16	-0.19	-0.08	-0.11	-0.11	-0.11	-0.13
Indirect product costs	0.51	1.00	0.36	0.17	0.15	0.22	0.09	0.42	0.16	-0.07	-0.12	-0.16	-0.01	-0.08	-0.05	-0.03	-0.11	-0.06	-0.08	-0.13	-0.12	-0.13	0.00	0.00	0.02	0.03	-0.03
Flexibility to introduce new products	0.23	0.36	1.00	0.71	0.06	0.04	0.14	0.35	0.15	-0.06	-0.02	-0.05	-0.05	0.02	-0.00	0.01	-0.06	0.09	0.06	0.00	0.03	0.00	0.11	0.06	0.07	0.10	0.04
Flexibility in production volume	0.26	0.17	0.71	1.00	0.12	0.22	0.35	0.36	0.28	-0.08	-0.02	-0.08	0.00	-0.03	-0.07	-0.09	-0.06	0.06	0.07	-0.04	-0.02	-0.04	0.05	0.09	0.09	0.07	0.06
Quality of the products	-0.20	0.15	0.06	0.12	1.00	0.23	0.46	0.28	0.20	-0.16	-0.17	-0.20	-0.14	-0.15	-0.18	-0.14	-0.15	-0.18	-0.24	-0.20	-0.20	-0.20	-0.16	-0.13	-0.16	-0.19	-0.24
Meeting delivery due dates	0.20	0.22	0.04	0.22	0.23	1.00	0.46	0.25	0.37	0.20	0.19	0.14	0.27	0.12	0.13	0.09	0.21	0.19	0.04	0.17	0.16	0.17	0.10	0.25	0.17	0.07	0.15
Quick response	-0.07	0.09	0.14	0.35	0.46	0.46	1.00	0.32	0.23	0.04	0.11	0.04	0.10	0.06	-0.07	0.02	0.01	0.10	0.00	0.08	0.07	0.08	0.15	0.20	0.15	0.11	0.09
Supplier relationship	0.12	0.42	0.35	0.36	0.28	0.25	0.32	1.00	0.47	0.01	-0.10	-0.09	0.02	-0.06	-0.03	-0.00	-0.03	-0.01	-0.04	-0.10	-0.08	-0.10	0.01	0.06	0.01	-0.01	0.01
Customer relationship	0.00	0.16	0.15	0.28	0.20	0.37	0.23	0.47	1.00	0.09	0.10	-0.06	0.06	0.03	-0.04	0.09	0.12	0.13	0.03	0.08	0.06	0.08	0.02	0.12	0.07	0.15	0.15
Labor cost	-0.15	-0.07	-0.06	-0.08	-0.16	0.20	0.04	0.01	0.09	1.00	0.92	0.96	0.88	0.90	0.89	0.93	0.97	0.90	0.83	0.93	0.89	0.93	0.81	0.90	0.87	0.82	0.87
Material cost	-0.20	-0.12	-0.02	-0.02	-0.17	0.19	0.11	-0.10	0.10	0.92	1.00	0.91	0.86	0.88	0.84	0.87	0.90	0.92	0.83	0.97	0.93	0.97	0.81	0.90	0.87	0.84	0.89
Energy cost	-0.18	-0.16	-0.05	-0.08	-0.20	0.14	0.04	-0.09	-0.06	0.96	0.91	1.00	0.89	0.93	0.90	0.90	0.94	0.91	0.86	0.96	0.93	0.96	0.83	0.89	0.87	0.82	0.88
Transportation cost	-0.04	-0.01	-0.05	0.00	-0.14	0.27	0.10	0.02	0.06	0.88	0.86	0.89	1.00	0.90	0.86	0.84	0.85	0.82	0.80	0.88	0.91	0.88	0.83	0.84	0.88	0.77	0.78
Equipment utilization	-0.13	-0.08	0.02	-0.03	-0.15	0.12	0.06	-0.06	0.03	0.90	0.88	0.93	0.90	1.00	0.90	0.87	0.86	0.88	0.85	0.93	0.95	0.93	0.84	0.86	0.91	0.80	0.84
Equipment failure	-0.10	-0.05	-0.00	-0.07	-0.18	0.13	-0.07	-0.03	-0.04	0.89	0.84	0.90	0.86	0.90	1.00	0.87	0.89	0.86	0.87	0.87	0.91	0.87	0.82	0.82	0.82	0.73	0.81
Labor utilization	-0.14	-0.03	0.01	-0.09	-0.14	0.09	0.02	-0.00	0.09	0.93	0.87	0.90	0.84	0.87	0.87	1.00	0.92	0.88	0.78	0.90	0.85	0.90	0.81	0.84	0.82	0.85	0.84
Production volume	-0.21	-0.11	-0.06	-0.06	-0.15	0.21	0.01	-0.03	0.12	0.97	0.90	0.94	0.85	0.86	0.89	0.92	1.00	0.91	0.83	0.93	0.89	0.93	0.77	0.86	0.84	0.80	0.86
Volume of refuse	-0.13	-0.06	0.09	0.06	-0.18	0.19	0.10	-0.01	0.13	0.90	0.92	0.91	0.82	0.88	0.86	0.88	0.91	1.00	0.85	0.95	0.91	0.95	0.81	0.91	0.86	0.86	0.92
Volume of rework	-0.15	-0.08	0.06	0.07	-0.24	0.04	0.00	-0.04	0.03	0.83	0.83	0.86	0.80	0.85	0.87	0.78	0.83	0.85	1.00	0.85	0.89	0.85	0.85	0.80	0.86	0.83	0.88
Raw material inventory	-0.19	-0.13	0.00	-0.04	-0.20	0.17	0.08	-0.10	0.08	0.93	0.97	0.96	0.88	0.93	0.87	0.90	0.93	0.95	0.85	1.00	0.97	1.00	0.83	0.91	0.88	0.85	0.92
Work in process	-0.16	-0.12	0.03	-0.02	-0.20	0.16	0.07	-0.08	0.06	0.89	0.93	0.93	0.91	0.95	0.91	0.85	0.89	0.91	0.89	0.97	1.00	0.97	0.86	0.86	0.89	0.80	0.87
Finished products inventor	-0.19	-0.13	0.00	-0.04	-0.20	0.17	0.08	-0.10	0.08	0.93	0.97	0.96	0.88	0.93	0.87	0.90	0.93	0.95	0.85	1.00	0.97	1.00	0.83	0.91	0.88	0.85	0.92
Setup Time	-0.08	0.00	0.11	0.05	-0.16	0.10	0.15	0.01	0.02	0.81	0.81	0.83	0.83	0.84	0.82	0.81	0.77	0.81	0.85	0.83	0.86	0.83	1.00	0.89	0.93	0.87	0.81
Processing Time	-0.11	0.00	0.06	0.09	-0.13	0.25	0.20	0.06	0.12	0.90	0.90	0.89	0.84	0.86	0.82	0.84	0.86	0.91	0.80	0.91	0.86	0.91	0.89	1.00	0.93	0.90	0.89
Number of orders met on time	-0.11	0.02	0.07	0.09	-0.16	0.17	0.15	0.01	0.07	0.87	0.87	0.87	0.88	0.91	0.82	0.82	0.84	0.86	0.86	0.88	0.89	0.88	0.93	0.93	1.00	0.88	0.87
Complaint rate for missed delivery deadline	-0.11	0.03	0.10	0.07	-0.19	0.07	0.11	-0.01	0.15	0.82	0.84	0.82	0.77	0.80	0.73	0.85	0.80	0.86	0.83	0.85	0.80	0.85	0.87	0.90	0.88	1.00	0.93
Complaint rate for product quality	-0.13	-0.03	0.04	0.06	-0.24	0.15	0.09	0.01	0.15	0.87	0.89	0.88	0.78	0.84	0.81	0.84	0.86	0.92	0.88	0.92	0.87	0.92	0.81	0.89	0.87	0.93	1.00

Table A1 – PCA Eigenvalues and Proportion of Variance Explained

Components	**PC1**	**PC2**	**PC3**	**PC4**
Eigenvalues	16.35	3.16	1.74	1.23
Proportion of Variance (%)	59.29	11.45	6.30	4.47

Questionário sobre pequenas e médias indústrias têxteis do interior de São Paulo

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Dados gerais

Nome da empresa:

Endereço completo:

Nome do responsável pelo preenchimento do questionário:

Cargo que ocupa na empresa:

Telefone: **E-mail:**

Ramo de atuação na indústria têxtil:

( ) Fiação **( ) Tecelagem** **( ) Malharia** **( ) Confecção**

1) Características da empresa:
1.1) Tipo da empresa:
☒ empresa limitada

☒ sociedade anônima
1.2) Tipo do capital da empresa:
☒ nacional

☒ internacional
1.3) Área de atuação da empresa:
☒ nacional

☒ multinacional

1.5) Número total de trabalhadores:

Número de trabalhadores na produção:

1.6) Faturamento durante 2022:
☒ menor que R$ 1 milhão ☒ entre R$ 1 e 5 milhões ☒ entre R$ 5 e 20 milhões

☒ entre R$ 20 e 50 milhões ☒ acima de R$ 50 milhões

1.7) Produção diária (toneladas): _______________

1.8) Existe alguma operação terceirizada? Se sim, qual(is)? _______________

Características dos produtos

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2) Defina as três principais linhas de produtos e o material utilizado na produção, como por exemplo: algodão, fibra sintética, couro, seda, lã etc.

LINHA A)

LINHA B)

LINHA C)

Para cada uma das linhas de produtos citadas anteriormente preencha o quadro abaixo:

Linha	**% do faturamento atual**	**Quantidade Produzida Por ano (em tonelada)**	**Produção Própria (P) ou Terceirizada (T)**	**Tamanho médio de lote (lista abaixo)**	**Nível de concorrência (lista abaixo)**	**Principal Mercado (lista abaixo)**	**Tendência dos negócios da linha (lista abaixo)**
A							
B							
C							

TAMANHO MÉDIO DE LOTE: 1) lotes unitários; 2) lotes pequenos (de 2 a 100 peças); 3)lotes médios (de 101 a 1000 peças); 4) lotes grandes (acima de 1000 peças).

NÍVEL DE CONCORRÊNCIA: 1) pouca concorrência; 2) muita concorrência.

PRINCIPAL MERCADO: 1) regional (raio de 100 Km); 2) estadual 3) nacional; 4) internacional.

TENDÊNCIA DOS NEGÓCIOS DA LINHA: 1) crescimento rápido; 2) em crescimento; 3) estável; 4) em declínio; 5) declínio rápido.

Fator de competitividade

3) Avalie cada fator de competitividade abaixo a respeito da importância do fator para a competitividade da empresa e a respeito da força atual da empresa em relação à importância do fator, para cada fator em questão (por exemplo: se o fator custos diretos é muito importante para a competitividade da empresa e a força atual para esse fator é média, a empresa precisa empreender esforços para reduzir ainda mais seus custos diretos de produção), preenchendo com um X o espaço escolhido:

Fator de competitividade	**Importância para a competitividade**					**Força atual da empresa**				
	1-Não importante	**2-Pouco importante**	**Média importância**	**Importante**	**Muito importante**	**Muito fraca**	**Fraca**	**Média**	**Forte**	**Muito forte**

Custos diretos de produção (adicionados diretamente aos produtos). Ex.: mão-de-obra direta e matéria-prima										
Custos indiretos de produção (imputados aos produtos por meio de rateio). Ex.: mão de obra indireta, energia, manutenção, transporte etc.										
Flexibilidade do processo para produzir novos produtos										
Flexibilidade do processo para variar o volume de produção de cada produto										
Qualidade do produto segundo as necessidades do cliente										
Atendimento dos prazos de entrega estipulados pelo cliente										
Rápido atendimento de pedidos urgentes										
Parcerias com fornecedores										
Parcerias com clientes										
Parcerias com empresas do mesmo ramo										
Outros (especificar):										

Medição de desempenho

4) Principais medidas de acompanhamento do desempenho do sistema de produção:

			Qual é o grau de importância de manter registros formais dessas medidas de acompanhamento? Marque um X no espaço escolhido.

Medida de desempenho	São mantidos registros formais desta medida? (sim; não)	Está informatizado? (sim; não)	**Não importante**	**Pouco importante**	**Média importância**	**Importante**	**Muito importante**
Custo de mão de obra direta							
Custo de materiais							
Custo de energia							
Custo de transporte							
Utilização de equipamentos							
Quebra de equipamento							
Utilização da mão-de-obra							
Volume de produção							
Volume de refugo							
Volume de retrabalho							
Estoques de matérias primas							
Estoques em processo							
Estoques de produtos acabados							
Tempo de preparação de máquinas							
Tempo de processamento							

Número de atendimentos dos prazos de entrega							
Índice de reclamações por não atendimento dos prazos de entrega							
Índice de reclamações referente à qualidade do produto							
Outra:							

5) Identifique para cada um dos problemas abaixo a relevância para a sua empresa e o nível de solução atual:

	Importância para a empresa					**Nível da solução atual praticada pela empresa**				
Problemas	**Não importante**	**Pouco importante**	**Média importância**	**Importante**	**Muito importante**	**Péssima**	**Ruim**	**Média**	**Boa**	**Ótima**
Programação da produção										
Programação da distribuição (transporte)										
Estoque de matéria-prima										
Estoque de produtos acabados										
Estoque em processo										
Número de atrasos nas entregas para os consumidores										
Tempo dos maiores atrasos										
Tempo de preparação de máquinas										
Layout de produção										
Tempos inativos de máquina (parada p/ esperar operário ou matéria-prima)										
Tempos inativos de operário (parado p/ esperar máquina ou matéria-prima)										
Qualificação da mão-de-obra										
Cumprimento dos prazos pelos fornecedores de matéria-prima										
Produtividade da mão-de-obra										
Tempo de preparação de máquinas										
Tempo de processamento										

% de atendimento dos prazos de entrega										
Índice de reclamações por não atendimento dos prazos de entrega										
Índice de reclamações referente à qualidade do produto										
Outra:										

7) Identifique para cada um dos projetos de melhoria abaixo como é realizado pela empresa a relevância de implementar o projeto nos próximos 3 anos.

*** Apoio técnico = (Empresa de consultoria, Universidade, Instituto de Pesquisa, SEBRAE ou SENAI)**

	Realizado pela empresa			**A ser implementado pela empresa nos próximos 3 anos**			**Importância de implantar esse projeto de melhoria**					**Necessitará de apoio técnico?* (sim ; não)**
Projeto de melhoria	**Ferramenta Computadorizada**	**Manualmente**	**Não se aplica**	**Ferramenta Computadorizada**	**Manualmente**	**Não se aplica**	**Não importante**	**Pouco importante**	**Média importância**	**Importante**	**Muito importante**	
Projeto do produto												
Previsão de vendas de longo prazo (acima de 1 ano)												
Planejamento da capacidade de produção de longo prazo												
Implantação de sistema de emissão de ordens de produção												
Implantação de sistema de emissão de ordens de compra de materiais												
Previsão de vendas de curto prazo (menos de 4 meses)												
Planejamento da capacidade de produção de curto prazo												

Programação da produção para maximizar o volume de produção sujeito a restrições de espaço disponível												
Programação da produção visando melhor utilização dos equipamentos para aumentar a produção												
Programação da produção visando redução de refugos												
Programação da produção visando redução de consumo de energia												
Programação da produção visando melhor cumprimento de prazos												
Programação da produção visando o atendimento de pedidos												
Implantação de codificação de materiais												
Redução do número de fornecedores												
Aumento do número de fornecedores												
Redução de estoques de matérias primas												
Redução de estoques em processo												
Redução de estoques de produtos finais												
Redução das taxas de refugo ou retrabalho para redução de custos												
Equipamentos automatizados controlados por computador												
Software que defina as quantidades das matérias-primas para atingir a composição do produto a um mínimo custo												
Melhoria da qualidade dos produtos entregues aos clientes												
Sistema de gestão da qualidade (Ex.: ISO 9000)												

Implantação da Gestão de Processos[1] (que visa gerenciar os processos que extrapolam os domínios funcionais (produção, marketing, finanças etc.) para obter melhorias graduais)												
Implantação de Reengenharia de Processos de Negócios (remodelar totalmente os processos da empresa, geralmente usando Tecnologia da Informação[2])												

Existe o interesse em automação industrial?
☒ Sim ☒ Não.
E em sistemas informatizados para gestão da produção?
☒ Sim ☒ Não.

Caso não em ambas as perguntas acima, não há necessidade de responder a próxima Pergunta

7) Seus investimentos em automação industrial e em sistemas informatizados para gestão da produção dependem de quais fatores? Assinale os três principais.

☒ da disponibilidade de recursos financeiros na empresa.

☒ da perspectiva de crescimento da economia.

☒ do volume de produção.

☒ nível tecnológico do mercado concorrencial.
Atualmente esse nível é baixo, médio ou alto?
☒ Baixo ☒ médio ☒ alto

☒ da qualidade da mão de obra.

☒ necessidade de mais informações sobre automação industrial.

☒ necessidade de mais informações sobre sistemas informatizados de gestão da produção.

8) Qual o grau de instrução média da mão de obra direta?

___ Analfabetos

___ Ensino Fundamental Incompleto

___ Ensino Fundamental Completo

___ Ensino Médio Incompleto

___ Ensino Médio Completo

___ Ensino Superior Incompleto

___ Ensino Superior Completo

___ Pós-graduação

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[1] Por processo entende-se um conjunto de atividades que, tomadas conjuntamente, produzem um resultado de valor para o cliente: o desenvolvimento de um novo produto, por exemplo

[2] Tecnologia da Informação compreende todos os avanços da informática/comunicação: banco de dados, redes locais de interligação, internet, intranet, sistemas CAD/CAM, sistemas de gestão integrada etc.

Qual o grau de instrução média da mão de obra indireta (diretoria, gerência, chefia, supervisão, encarregados de produção, pessoal de escritório)?

___ Analfabetos

___ Ensino Fundamental Incompleto

___ Ensino Fundamental Completo

___ Ensino Médio Incompleto

___ Ensino Médio Completo

___ Ensino Superior Incompleto

___ Ensino Superior Completo

___ Pós-graduação

Existe rede local no escritório? ☒ Sim ☒ Não.
Existe rede local no chão de fábrica? ☒ Sim ☒ Não.

A empresa está ligada a fornecedores por meio de rede (p. ex. Internet)? ☒ Sim ☒ Não.
A empresa está ligada aos clientes por meio de rede (p. ex. Internet)? ☒ Sim ☒ Não.

10) Por gentileza, liste os seus três principais problemas e necessidades relativos à Produção.

Table A2 – Principal Component Analysis (PCA).

Original variables	**PC1**	**PC2**	**PC3**	**PC4**
Direct product costs	−0.040	−0.196	−0.496	−0.429
Indirect product costs	−0.019	−0.329	−0.304	−0.352
Flexibility to introduce new products	0.004	−0.353	−0.347	0.444
Flexibility in production volume	0.000	−0.403	−0.181	0.446
Quality of the products	−0.048	−0.235	0.465	0.022
Meeting delivery due dates	0.044	−0.315	0.240	0.286
Quick response	0.021	−0.334	0.396	−0.085
Supplier relationship	−0.008	−0.413	0.043	0.008
Customer relationship	0.020	−0.324	0.205	−0.063
Labor cost	0.239	0.015	0.038	−0.098
Material cost	0.239	0.016	0.059	0.095
Energy cost	0.241	0.064	0.017	0.111
Transportation cost	0.229	−0.026	0.006	−0.141
Equipment utilization	0.237	0.018	−0.010	−0.078
Equipment failure	0.229	0.043	−0.063	−0.067
Labor utilization	0.231	0.017	−0.004	0.087
Production volume	0.236	0.024	0.062	−0.066
Volume of refuse	0.238	−0.034	−0.010	0.114
Volume of rework	0.226	0.020	−0.085	0.044
Raw material inventory	0.244	0.027	0.031	−0.014
Work in process	0.241	0.023	0.001	0.032
Finished products inventory	0.244	0.027	0.031	−0.014
Setup Time	0.224	−0.039	−0.067	0.030
Processing Time	0.235	−0.077	0.014	−0.002
Number of orders met on time	0.234	−0.053	−0.039	0.066
Complaint rate for missed delivery deadline	0.224	−0.046	−0.063	0.082
Complaint rate for product quality	0.233	−0.029	−0.036	0.037

APPENDIX B – Results of Systematic Literature Review

Table B1 – List of references and corresponding textile and apparel manufacturing stages.

Reference	Manufacturing stage	Reference	Manufacturing stage
Duran et al. (2024)	Yarn	Hu et al. (2015)	Apparel
Demir (2024)	Yarn	Khalili-Damghani et al. (2015)	Fiber
Wang and Zhang (2023)	Fabric	Zhang et al. (2014)	Yarn
Salem et al. (2023)	Fabric; Apparel	Camargo et al. (2014)	Yarn
Demir (2023)	Fabric	Eroglu and Ozmutlu (2014)	Fabric
Berthier et al. (2022)	Fabric	Hung et al. (2014)	Apparel
Wang et al. (2022)	Apparel	Salassi et al. (2013)	Fiber
Srinath et al. (2022)	Fabric	Ghosh et al. (2013)	Yarn
Demir (2022)	Yarn	Huang and Yu (2013)	Apparel
Demir and Inan (2022)	Yarn	Gürsoy (2012)	Apparel
Kousar et al. (2022)	Yarn; Fabric	Pimentel et al. (2011)	Fabric
Wei et al. (2022)	Yarn	Sumihartati et al. (2011)	Fabric
He et al. (2022)	Fabric	Azadeh et al. (2010)	Fabric
Malik et al. (2022)	Apparel	Ünal and Koç (2010)	Fabric; Apparel
Camargo et al. (2021)	Yarn	Hadi-Vencheh and Aghajani (2010)	Yarn
Eliguzel et al. (2021)	Apparel	Hsu et al. (2009)	Yarn; Fabric
Li et al. (2021a)	Fabric	Peric et al. (2009)	Fabric
Mourtos et al. (2021)	Fabric	Beraldi et al. (2008)	Yarn
Sumathy and Amirthalingam (2021)	Apparel	Jungwattanakit et al. (2008)	Yarn
Croft et al. (2021)	Fabric; Apparel	Karabuk (2008)	Yarn
Zhou et al. (2020)	Fabric	Bhattacharyya et al. (2008)	Yarn
Biadgligne et al. (2020)	Yarn	Pimentel et al. (2008)	Fabric
Ghosh et al. (2020)	Apparel	de Armas et al. (2008)	Apparel
Tayyab et al. (2020)	Fabric	Ballestero (2006)	Fiber
Tsao et al. (2020)	Apparel	Beraldi et al. (2006)	Yarn
Ünal and Yüksel (2020)	Apparel	Silva and Magalhaes (2006)	Yarn
Xu et al. (2020)	Apparel	Guo et al. (2006)	Apparel
Hu et al. (2020)	Fabric	Min and Cheng (2006)	Fabric
Hong et al. (2019)	Fiber	Cooper and Saydam (2003)	Fabric
Sánchez-Herrera et al. (2019)	Fabric; Apparel	Wu and Chang (2003a)	Fabric
Zhang and Chen (2019)	Apparel	Wu and Chang (2003b)	Fabric

Reference	Manufacturing stage	Reference	Manufacturing stage
Zhang et al. (2019)	Apparel	Saydam and Cooper (2002)	Fabric
Tsai and Jhong (2019)	Apparel	Qiu et al. (2002)	Yarn
Ke et al. (2019)	Fabric	Wong et al. (2001)	Fabric
Shang et al. (2019)	Fabric; Apparel	Maldonado et al. (2000)	Fabric
Efe et al. (2018)	Yarn; Fabric; Apparel	Wong et al. (2000)	Fabric; Apparel
Chakraborty and Diyaley (2018)	Yarn	Ozdamar (2000)	Fabric; Apparel
El Hachemi et al. (2018)	Fabric	Dumoulin and Vercellis (2000)	Fabric
Tsai (2018)	Yarn; Fabric	Heckmann and Lengauer (1998)	Apparel
Pereira (2018)	Apparel	Degraeve and Vandebroek (1998)	Apparel
Wuttke and Heese (2018)	Fabric	Puigjaner et al. (1996)	Fabric
Du et al. (2018)	Fiber	Serafini (1996)	Fabric
Campo et al. (2018)	Fabric	Tomastik et al. (1996)	Apparel
Elmehanny et al. (2018)	Apparel	Morales et al. (1996)	Fabric
Wineman and Crawford (2017)	Fiber	Duffy et al. (1994)	Fiber
Zhang et al. (2017)	Fabric	Akinc (1993)	Fabric
Zaharie et al. (2017)	Apparel	Gunasekaran et al. (1993)	Yarn
Majumdar et al. (2017)	Fabric	Richter (1992)	Fabric
Celikbilek et al. (2016)	Apparel	Serafini and Speranza (1992)	Fabric
Rabbani et al. (2016)	Yarn	El Mogahzy (1992)	Yarn
Wang et al. (2016)	Apparel	Guinet (1991)	Fabric
Lin et al. (2016)	Fabric	Farley (1990)	Fabric
Gürsoy and Gürsoy (2015)	Apparel	Stern and Avivi (1990)	Fabric; Apparel
Gonçalves (2015)	Fabric	Frendewey and Sumichrast (1988)	Yarn
Silva et al. (2015)	Fabric; Apparel	Bhatnagar (1981)	Fabric
		Smirnov et al. (1976)	Yarn

Table B2 – Problems characteristics related to textile and apparel manufacturing.

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Duran et al. (2024)	Batch-processing machine Scheduling	MOMIP	✓	✓	CPLEX; Adaptive Large Neighborhood Search

Continued on next page

Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Demir (2024)	Batch-processing machine Scheduling	MOMIP	✓	✓	Gurobi; Iterated Greedy Algorithm
Wang and Zhang (2023)	Batch-processing machine Scheduling	MIP		✓	Tabu Search
Salem et al. (2023)	Cutting	MIP/MOMIP	✓		Gurobi
Demir (2023)	Batch-processing machine Scheduling	MOMIP	✓	✓	Gurbo; Genetic Algorithm
Berthier et al. (2022)	Scheduling	MIP	✓	✓	CPLEX; Genetic Algorithm
Wang et al. (2022)	Batch-processing machine Scheduling	MIP	✓	✓	CPLEX; Iterative heuristic; Variable neighborhood search procedure
Srinath et al. (2022)	Scheduling	MIP/MOMIP		✓	Constructive heuristics
Demir (2022)	Batch-processing machine Scheduling	MOMIP	✓	✓	Gurobi; Iterative greedy search algorithm; D-LexMOMIP; Constructive heuristic
Demir and Inan (2022)	Batch-processing machine Scheduling	IP		✓	Iterative greedy search algorithm
Kousar et al. (2022)	Resource planning	FLP	✓		Commercial solver
Wei et al. (2022)	Scheduling	MOMIP	✓		SCIP solver
He et al. (2022)	Product quality	MONLP		✓	Deep Q-networks
Malik et al. (2022)	Lot-sizing	GP	✓		LINGO
Camargo et al. (2021)	Lot-sizing and scheduling	MIP/MINLP	✓		CPLEX
Eliguzel et al. (2021)	Transportation	MIP	✓		Gurobi
Li et al. (2021a)	Batch-processing machine Scheduling	IP		✓	Hybrid differential evolution with chaos theory; Local search algorithms
Mourtos et al. (2021)	Scheduling	MIP		✓	Assignment heuristics
Sumathy and Amirthalingam (2021)	Scheduling	LP	✓		Commercial Solver

Continued on next page

Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Croft et al. (2021)	Scheduling	MIP/NLP	✓	✓	Bridging Algorithm; GAMS; CPLEX; BARON
Zhou et al. (2020)	Scheduling	MOLP		✓	Genetic Algorithm; Variable neighborhood search
Biadgligne et al. (2020)	Blending	IP	✓		Excel Solver
Ghosh et al. (2020)	Lot-sizing	LP	✓		Excel Solver
Tayyab et al. (2020)	Lot-sizing	MINLP		✓	Genetic Algorithm
Tsao et al. (2020)	Cutting	MIP		✓	Constructive heuristics; Genetic Algorithm; Simulated annealing; Tabu search
Ünal and Yüksel (2020)	Cutting	MINLP	✓		LINGO
Xu et al. (2020)	Cutting	IP		✓	Genetic Algorithm
Hu et al. (2020)	Cutting	MIP		✓	Greedy adaptive search algorithm
Hong et al. (2019)	Cotton production	LP	✓		Commercial solver
Sánchez-Herrera et al. (2019)	Scheduling	MIP		✓	Sequence heuristic; Iterated local search; Greedy randomized adaptive search
Zhang and Chen (2019)	Assembly line balance	MONLP		✓	Genetic Algorithm
Zhang et al. (2019)	Assembly line balance	MOLP		✓	Genetic Algorithm
Tsai and Jhong (2019)	Lot-sizing	MIP	✓		LINGO
Ke et al. (2019)	Product quality	MINLP		✓	Monte Carlo Simulation
Shang et al. (2019)	Cutting	MIP		✓	Iterated greedy algorithm
Efe et al. (2018)	Assembly line balance	IP	✓		GAMS

Continued on next page

Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	**Problem**	**Model**	**Solution Approach**		
			Exact	**Approximate**	**Method/Tool**
Chakraborty and Diyaley (2018)	Product quality	MONLP		✓	Artificial bee colony algorithm; Ant colony optimization; Particle swarm optimization algorithm; Genetic Algorithm
El Hachemi et al. (2018)	Scheduling	MIP	✓		CPLEX; Branch-and-price
Tsai (2018)	Lot-sizing	MIP	✓		LINGO
Pereira (2018)	Assembly line balance	IP	✓	✓	CPLEX; Constructive heuristic; Estimation of Distribution Algorithm
Wuttke and Heese (2018)	Cutting	MIP	✓	✓	CPLEX; Sequential heuristic with feedback loop; Gilmore and Gomory approach
Du et al. (2018)	Scheduling	MORP		✓	Multiobjective evolutionary algorithm
Campo et al. (2018)	Lot-sizing	LP	✓		GAMS
Elmehanny et al. (2018)	Lot-sizing	MIP	✓		CPLEX
Wineman and Crawford (2017)	Cotton production	LP	✓		Simplex
Zhang et al. (2017)	Batch-processing machine Scheduling	MIP/MOLP	✓	✓	CPLEX; Artificial bee colony algorithm
Zaharie et al. (2017)	Scheduling	IP	✓		Commercial Solver
Majumdar et al. (2017)	Product quality	MONLP		✓	Genetic Algorithm
Celikbilek et al. (2016)	Scheduling	MIP/MOLP		✓	Genetic Algorithm
Rabbani et al. (2016)	Cotton production	MIP	✓		GAMS
Wang et al. (2016)	Cutting schedule	MIP	✓		Gurobi
Lin et al. (2016)	Cutting	QP		✓	Global optimization algorithm
Gürsoy and Gürsoy (2015)	Assembly line balance	IP		✓	Genetic Algorithm

Continued on next page

Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	Problem	Model	Solution Approach		
			Exact	**Approximate**	**Method/Tool**
Gonçalves (2015)	Cutting	IP		✓	Biased random-key Genetic Algorithm
Silva et al. (2015)	Cutting	MIP	✓		CPLEX; Column generation
Hu et al. (2015)	Transportation	MIP/MISP	✓		Evolutionary algorithm
Khalili-Damghani et al. (2015)	Cotton production	LP	✓		Commercial Solver
Zhang et al. (2014)	Blending	MINLP		✓	Lagrange multiplier; Genetic Algorithm
Camargo et al. (2014)	Lot-sizing and scheduling	MIP	✓	✓	CPLEX; Branch-and-bound incorporate into fix-and-optimize improvement method
Eroglu and Ozmutlu (2014)	Scheduling	MIP	✓	✓	CPLEX; Genetic Algorithm
Hung et al. (2014)	Cutting schedule	MIP	✓	✓	Gurobi; Construtive heuristic
Salassi et al. (2013)	Cotton production	LP	✓		Commercial Solver
Ghosh et al. (2013)	Product quality	MONLP		✓	Genetic Algorithm
Huang and Yu (2013)	Scheduling	MIP		✓	Ant colony optimization
Gürsoy (2012)	Assembly line balance	IP		✓	Constructive heuristic
Pimentel et al. (2011)	Lot-sizing and scheduling	MIP	✓	✓	CPLEX; Network flow heuristic
Sumihartati et al. (2011)	Scheduling	MIP	✓	✓	CPLEX; Neighborhood search algorithm
Azadeh et al. (2010)	Scheduling	GP	✓	✓	LINGO; Computer simulation; Design of experiment
Ünal and Koç (2010)	Product quality	NLP/MONLP	✓		LINGO
Hadi-Vencheh and Aghajani (2010)	Lot-sizing	GP	✓		LINDO
Hsu et al. (2009)	Scheduling	MIP		✓	Genetic Algorithm
Peric et al. (2009)	Cutting	MIP/GP		✓	Weight Coefficients Method; Satisfactory goals method

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Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Beraldi et al. (2008)	Lot-sizing and scheduling	MIP	✓	✓	CPLEX; Rolling-horizon and fix-and-relax heuristics
Jungwattanakit et al. (2008)	Scheduling	MIP		✓	Construtive heuristic; Genetic Algorithm
Karabuk (2008)	Lot-sizing and scheduling	MISP	✓	✓	CPLEX; Two stage preprocessing; LP relaxation
Bhattacharyya et al. (2008)	Blending	LP	✓		Simplex
Pimentel et al. (2008)	Lot-sizing and scheduling	MIP	✓	✓	CPLEX; Network flow heuristic
de Armas et al. (2008)	Cutting	MIP	✓		Viswanathan-Bagchi algorithm
Ballestero (2006)	Blending	SLP	✓		LINGO
Beraldi et al. (2006)	Lot-sizing and scheduling	MISP	✓	✓	CPLEX; Fix-and-relax heuristic
Silva and Magalhaes (2006)	Lot-sizing and scheduling	MIP		✓	Constructive heuristics
Guo et al. (2006)	Scheduling	MIP		✓	Genetic Algorithm
Min and Cheng (2006)	Scheduling	MIP		✓	Genetic Algorithm
Cooper and Saydam (2003)	Scheduling	LP/MIP	✓	✓	LINDO; Fabric roll sequencing heuristic
Wu and Chang (2003a)	Lot-sizing	MINLP		✓	Genetic Algorithm
Wu and Chang (2003b)	Lot-sizing	MINLP		✓	Genetic Algorithm
Saydam and Cooper (2002)	Scheduling	LP		✓	3-phase general solution approach
Qiu et al. (2002)	Scheduling	MIP		✓	Constraint management heuristic
Wong et al. (2001)	Resource planning	MINLP	✓		Queuing theory models
Maldonado et al. (2000)	Scheduling	MIP		✓	Asymmetric travelling salesman problem heuristic
Wong et al. (2000)	Scheduling	MIP		✓	Genetic Algorithm
Ozdamar (2000)	Cutting	MIP		✓	Simulated annealing
Dumoulin and Vercellis (2000)	Lot-sizing and scheduling	MIP		✓	Lagrangean relaxation

Continued on next page

Table B2 – Problems characteristics related to textile and apparel manufacturing. (continued)

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Heckmann and Lengauer (1998)	Cutting	MIP	✓	✓	Greedy strategies; Simulated annealing; Branch-and-bound
Degraeve and Vandebroek (1998)	Cutting	MIP		✓	Enumerative search procedure
Puigjaner et al. (1996)	Batch-processing machine Scheduling	MIP		✓	Constructive heuristics
Serafini (1996)	Scheduling	MIP		✓	Max flow algorithm
Tomastik et al. (1996)	Scheduling	IP		✓	Lagrangian relaxation
Morales et al. (1996)	Scheduling	IP	✓		Branch-and-bound
Duffy et al. (1994)	Cotton production	MIP	✓		Commercial solver
Akinc (1993)	Lot-sizing and scheduling	MIP		✓	Fix-and-optimize
Gunasekaran et al. (1993)	Lot-sizing and scheduling	MIP		✓	Direct pattern search method
Richter (1992)	Cutting	MIP	✓		Dynamic programming
Serafini and Speranza (1992)	Scheduling	MIP		✓	Sweeping algorithm; LP-based heuristic
El Mogahzy (1992)	Blending	LP	✓		Simplex
Guinet (1991)	Scheduling	MIP		✓	Hungarian method; Assignment with a re-employment algorithm; Transportation algorithm; Sequential assignment algorithm
Farley (1990)	Cutting	MIP	✓		Three-stage Gilmore-Gomory algorithm
Stern and Avivi (1990)	Scheduling	IP		✓	Early due date sequence; Greedy heuristic
Frendewey and Sumichrast (1988)	Lot-sizing and scheduling	IP		✓	LP relaxation
Bhatnagar (1981)	Lot-sizing	LP	✓		CPLEX
Smirnov et al. (1976)	Transportation	LP	✓		Commercial solver

Table B3 – Major features of the models on yarn manufacturing reviewed papers.

Reference	Item		Period		Machine		Setup		Parameters		Uncertain data	Function
	M	S	M	S	M	S	C	T	D	U		
Duran et al. (2024)	✓		✓		✓			✓	✓			
Demir (2024)	✓			✓	✓				✓			
Demir (2022)	✓			✓	✓				✓			
Demir and Inan (2022)	✓			✓	✓			✓	✓			
Wei et al. (2022)	✓			✓	✓				✓			
Camargo et al. (2021)	✓		✓		✓		✓	✓	✓			
Biadgligne et al. (2020)	✓			✓		✓			✓			
Chakraborty and Diyaley (2018)	✓				✓				✓			
Efe et al. (2018)	✓			✓					✓			
Rabbani et al. (2016)	✓		✓		✓			✓	✓			
Camargo et al. (2014)	✓		✓		✓		✓	✓	✓			
Zhang et al. (2014)	✓			✓		✓			✓			
Ghosh et al. (2013)	✓			✓					✓			
Hadi-Vencheh and Aghajani (2010)	✓			✓	✓				✓			
Hsu et al. (2009)	✓			✓	✓			✓	✓			
Beraldi et al. (2008)	✓		✓		✓		✓		✓			
Jungwattanakit et al. (2008)	✓		✓		✓			✓	✓			
Karabuk (2008)	✓		✓		✓		✓			✓	Demand	Scenario based
Bhattacharyya et al. (2008)	✓			✓		✓			✓			
Beraldi et al. (2006)	✓		✓		✓		✓			✓	Demand, processing times	Scenario based
Silva and Magalhaes (2006)	✓		✓		✓		✓		✓			
Qiu et al. (2002)	✓		✓		✓							
Gunasekaran et al. (1993)	✓			✓	✓		✓	✓	✓			
El Mogahzy (1992)	✓			✓		✓			✓			

Frendewey and Sumichrast (1988)	✓	✓	✓	✓	✓
Smirnov et al. (1976)	✓	✓	✓		✓

Caption: M: Multiple S: Single, C: Costs, T: Times, D: Deterministic, U: Uncertain

Table B4 – Objective functions and other considerations on the yarn manufacturing reviewed papers.

Reference	Objective function			Real Data	Others
	Min costs	Max profits	Others		
Duran et al. (2024)			max processed jobs and min capacity usage	✓	Sustainability factors like water and chemical usage
Demir (2024)	✓		min over-capacity usage	✓	Optimization of boiler loading for yarn-dyeing
Demir (2022)	✓		min over-capacity usage	✓	Minimizing the number of batches for ground and pile-type yarn groups
Demir and Inan (2022)			min tardiness and number of boiler washing	✓	Special family group
Camargo et al. (2021)	✓			✓	Allow the decision maker to assign different priorities. Make-to-stock and for make-to-order decisions
Wei et al. (2022)			max production volume and min idle spindles	✓	Optimizing equipment allocation and for make-to-order decisions
Biadgligne et al. (2020)	✓			✓	Measurement of the diameter or linear density of an individual fiber
Chakraborty and Diyaley (2018)			min unevenness, hairiness, and imperfections, max yarn strength		Weight values are assigned to prioritize yarn characteristics
Efe et al. (2018)			min workstations		Age and gender-based workload constraint
Rabbani et al. (2016)		✓		✓	Make-to-order and water consumption constraints
Camargo et al. (2014)	✓			✓	Setup carry-over and micro-periods overlapping constraints

Zhang et al. (2014)			min distance between sample classes	✓	Image processing techniques for blending fibers
Ghosh et al. (2013)			max yarn strength, min cotton fiber quality	✓	Artificial neural network and regression equation to create objective functions
Hadi-Vencheh and Aghajani (2010)		✓	max demand fulfillment, max capacity utilization, and max material efficiency	✓	Workforce availability
Hsu et al. (2009)			min tardiness	✓	Job assignment and predecessor-successor constraints
Beraldi et al. (2008)	✓				Sequence-dependent setup costs, machine assignments and production rates constraints
Jungwattanakit et al. (2008)			min makespan		Constraints for partial schedule on each machine at each stage
Karabuk (2008)	✓			✓	Availability and changes in the number of machines and blends
Bhattacharyya et al. (2008)	✓			✓	Interfiber cohesion
Beraldi et al. (2006)	✓				Non-anticipative constraints
Silva and Magalhaes (2006)	✓			✓	Spinnerets have a limited lifetime
Qiu et al. (2002)		✓		✓	Constraint management
Gunasekaran et al. (1993)	✓			✓	Probability that are determined number of batches at each stage
El Mogahzy (1992)	✓				Fiber quality index constraints
Frendewey and Sumichrast (1988)	✓				Overtime production
Smirnov et al. (1976)			max total output	✓	Multi-stage process

Table B5 – Major features of the models on fabric manufacturing reviewed papers.

Reference	Item		Period		Machine		Setup		Parameters		Uncertain	Function
	M	S	M	S	M	S	C	T	D	U	data	
Wang and Zhang (2023)	✓			✓	✓			✓	✓			
Demir (2023)	✓			✓	✓		✓		✓			

Reference	Item		Period		Machine		Setup		Parameters		Uncertain	Function
	M	S	M	S	M	S	C	T	D	U	data	
Salem et al. (2023)	✓			✓		✓			✓			
Berthier et al. (2022)	✓		✓		✓			✓	✓			
Li et al. (2022)	✓			✓	✓				✓			
Srinath et al. (2022)	✓			✓	✓			✓	✓			
He et al. (2022)	✓									✓	Variables on the process performance	Random forest
Kousar et al. (2022)	✓			✓		✓				✓	Demand, supply parameters,and energy cos	Spherical fuzzy number
Li et al. (2021a)	✓			✓	✓			✓	✓			
Mourtos et al. (2021)	✓			✓	✓			✓	✓			
Croft et al. (2021)	✓		✓		✓				✓			
Zhou et al. (2020)	✓			✓	✓		✓		✓			
Tayyab et al. (2020)	✓			✓		✓	✓			✓	Random defective rate	
Hu et al. (2020)	✓			✓		✓			✓			
Ke et al. (2019)	✓			✓		✓			✓			
El Hachemi et al. (2018)	✓			✓	✓		✓	✓	✓			
Tsai (2018)	✓			✓	✓		✓					
Wuttke and Heese (2018)	✓			✓	✓			✓	✓			
Campo et al. (2018)	✓		✓		✓				✓			
Zhang et al. (2017)	✓			✓	✓				✓			
Majumdar et al. (2017)	✓			✓		✓			✓			
Lin et al. (2016)	✓			✓		✓			✓			
Gonçalves (2015)	✓			✓		✓			✓			
Silva et al. (2015)	✓			✓	✓				✓			
Eroglu and Ozmutlu (2014)	✓			✓	✓			✓	✓			
Pimentel et al. (2011)	✓		✓		✓				✓			

Reference	**Item**		**Period**		**Machine**		**Setup**		**Parameters**		**Uncertain**	**Function**
	M	**S**	**M**	**S**	**M**	**S**	**C**	**T**	**D**	**U**	**data**	
Sumihartati et al. (2011)	✓			✓		✓		✓	✓			
Azadeh et al. (2010)	✓			✓	✓				✓			
Peric et al. (2009)	✓			✓		✓			✓			
Pimentel et al. (2008)	✓		✓		✓			✓	✓			
Min and Cheng (2006)	✓				✓	✓			✓			
Cooper and Saydam (2003)	✓			✓	✓				✓			
Wu and Chang (2003a)	✓		✓		✓				✓			
Wu and Chang (2003b)	✓			✓		✓			✓			
Saydam and Cooper (2002)	✓			✓	✓				✓			
Wong et al. (2001)	✓			✓					✓			
Maldonado et al. (2000)	✓			✓	✓		✓		✓			
Wong et al. (2000)	✓		✓	✓				✓	✓			
Ozdamar (2000)	✓			✓	✓				✓			
Dumoulin and Vercellis (2000)	✓		✓		✓		✓	✓	✓			
Puigjaner et al. (1996)	✓				✓	✓			✓			
Serafini (1996)	✓			✓	✓				✓			
Morales et al. (1996)	✓			✓		✓	✓		✓			
Akinc (1993)	✓			✓	✓		✓		✓			
Richter (1992)	✓			✓		✓			✓			
Serafini and Speranza (1992)	✓			✓	✓				✓			
Guinet (1991)	✓			✓	✓		✓	✓	✓			
Farley (1990)	✓			✓		✓			✓			
Stern and Avivi (1990)	✓			✓		✓			✓			
Bhatnagar (1981)	✓			✓	✓				✓			

Caption: M: Multiple S: Single, C: Costs, T: Times, D: Deterministic, U: Uncertain

Table B6 – Objective functions and other considerations on the fabric manufacturing reviewed papers.

Reference	**Objective function**			**Real Data**	**Others**
	Min costs	**Max profits**	**Others**		
Wang and Zhang (2023)			min makespan		Hybrid flowshop scheduling with batch processing for textile packing
Demir (2023)	✓		min total tardiness, min number of washes		Sequence-dependent setups
Salem et al. (2023)			min of the total fabric area, min total number of cuts		Precedence between cutting pattern and strips
Berthier et al. (2022)			min makespan		Sequence-dependent setup times and precedence constraints
Li et al. (2022)	✓		min lateness		Pollution costs
Srinath et al. (2022)			min makespan, min lateness, min total setup time, max scheduling preferences, min shade inconsistencies		Job-machine eligibility and shade consistency and transitions
He et al. (2022)	✓		max quality, max productivity		Multi-agent aspects
Kousar et al. (2022)	✓			✓	Availability of total working time and production rate
Li et al. (2021a)			min tardiness	✓	Sequence-dependent setup times
Mourtos et al. (2021)			min makespan	✓	Job splitting and sequence-dependent setup times
Croft et al. (2021)			min makespan, min net freshwater consumption	✓	Water Network Constraints
Zhou et al. (2020)	✓			✓	Sequence-dependent setup times
Tayyab et al. (2020)	✓			✓	Sequence-dependent setup costs and defective proportion
Hu et al. (2020)			min length	✓	Optimal sheet utilization without part overlap
Ke et al. (2019)	✓				Concentration of the hydrogen peroxide, temperature and treatment time
El Hachemi et al. (2018)	✓		min total cleaning time, min waiting time	✓	Maximum waiting time
Tsai (2018)		✓		✓	Batch-level activity constraints and carbon tax function

Reference	**Objective function**			**Real Data**	**Others**
	Min costs	**Max profits**	**Others**		
Wuttke and Heese (2018)			min total time	✓	Sequence-dependent setup times and permissible tolerances
Campo et al. (2018)	✓			✓	Employee training requirements
Zhang et al. (2017)	✓		max machine utilization		Incapable machines for jobs
Majumdar et al. (2017)			max air permeability, max thermal conductivity		Loop length, carriage speed, yarn input tension, and yarn count
Lin et al. (2016)			min material waste		Stock utility
Gonçalves (2015)			min total area of fabric		Customer-specified small fabric rectangle with specified width and length
Silva et al. (2015)			min waste		Minimum length for each cutting pattern
Eroglu and Ozmutlu (2014)			min makespan		Precedence between jobs on the same machine
Pimentel et al. (2011)			min tardiness		Deviations between product completion time and component completion time
Sumihartati et al. (2011)			min setup time		Sequence-dependent setup times
Azadeh et al. (2010)			min tardiness, min makespan		Required number of controller workers
Peric et al. (2009)			min waste, min production time		Selection of the criteria for optimization of fabric cutting
Pimentel et al. (2008)	✓				Deviations between product completion time and component completion time
Min and Cheng (2006)	✓			✓	Undetermined common due date
Cooper and Saydam (2003)			max machine utilization	✓	Fabric handling constraint
Wu and Chang (2003a)		✓		✓	Water balance constraint
Wu and Chang (2003b)		✓		✓	Grey input-output
Saydam and Cooper (2002)			max machine utilization, min delays	✓	Regulate the allowable differences in strand lengths
Maldonado et al. (2000)	✓				Sequence-dependent setup costs

Reference	Objective function			Real Data	Others
	Min costs	Max profits	Others		
Wong et al. (2000)			min makespan and idle time	✓	Feasible schedules between fabric lays
Ozdamar (2000)		✓		✓	Allocation of pieces to quality levels and rolls
Dumoulin and Vercellis (2000)	✓			✓	Resource absorption limitations
Puigjaner et al. (1996)	✓				Mixed intermediate storage
Serafini (1996)			min tardiness		Job preemption and job splitting
Morales et al. (1996)	✓				Photocolorimetric differences
Akinc (1993)		✓		✓	Shift hours are adjusted for efficiency, utilization, and schedule non-production activities
Richter (1992)		✓	min unusable rest		Profit parameters for units of single pieces
Serafini and Speranza (1992)			min tardiness		Job preemption and job splitting
Guinet (1991)	✓		min sum of job completion dates min processing time		Sequence-dependent setup times
Farley (1990)			min waste on each strip	✓	Total length of roll required to produce unit
Stern and Avivi (1990)		✓			Job preemption and job splitting
Bhatnagar (1981)	✓			✓	Machine shift count for pre weaving centers

Table B7 – Major features of the models on apparel manufacturing reviewed papers.

Reference	Item		Period		Machine		Setup		Parameters		Uncertain data	Function
	M	S	M	S	M	S	Costs	Time	D	U		
Malik et al. (2022)	✓			✓	✓				✓			
Wang et al. (2022)	✓			✓	✓				✓			
Eliguzel et al. (2021)	✓				✓				✓			
Sumathy and Amirthalingam (2021)	✓			✓					✓			

Reference	Item		Period		Machine		Setup		Parameters		Uncertain	Function
	M	S	M	S	M	S	Costs	Time	D	U	data	
Ghosh et al. (2020)		✓		✓	✓				✓			
Tsao et al. (2020)	✓			✓		✓	✓		✓			
Ünal and Yüksel (2020)	✓			✓		✓			✓			
Xu et al. (2020)	✓			✓		✓			✓			
Sánchez-Herrera et al. (2019)	✓			✓		✓			✓			
Zhang and Chen (2019)	✓			✓	✓				✓			
Zhang et al. (2019)	✓			✓	✓				✓			
Tsai and Jhong (2019)	✓			✓	✓				✓			
Shang et al. (2019)	✓			✓		✓			✓			
Pereira (2018)	✓			✓	✓		✓		✓			
Elmehanny et al. (2018)	✓		✓						✓			
Du et al. (2018)	✓			✓	✓					✓	Daily production quantity	
Zaharie et al. (2017)	✓		✓		✓				✓			
Celikbilek et al. (2016)	✓			✓		✓			✓			
Wang et al. (2016)	✓			✓	✓				✓			
Gürsoy and Gürsoy (2015)	✓			✓	✓				✓			
Hu et al. (2015)		✓		✓		✓				✓	Try on times	Randomly generated
Hung et al. (2014)	✓			✓		✓			✓			
Gürsoy (2012)	✓			✓	✓				✓			
Ünal and Koç (2010)	✓			✓		✓			✓			
de Armas et al. (2008)	✓			✓		✓			✓			
Guo et al. (2006)	✓			✓	✓				✓			

Reference	Item		Period		Machine		Setup		Parameters		Uncertain	Function
	M	S	M	S	M	S	Costs	Time	D	U	data	
Ghiani et al. (2003)	✓		✓		✓		✓			✓	Worker productivity	Triangular fuzzy numbers
Heckmann and Lengauer (1998)	✓			✓		✓			✓			
Degraeve and Vandebroek (1998)	✓			✓		✓			✓			
Tomastik et al. (1996)	✓			✓	✓			✓	✓			

Caption: M: Multiple S: Single, D: Deterministic, U: Uncertain

Table B8 – Objective functions and other considerations on the apparel manufacturing reviewed papers.

Reference	Objective function			Real Data	Others
	Min costs	Max profits	Others		
Malik et al. (2022)			min the sum of undesired relative deviations, min the maximum relative deviation, min the range of unachieved goals	✓	Maximum limit of unsatisfied goals
Wang et al. (2022)			min total energy consumption		Lower and upper bounds on the makespan
Eliguzel et al. (2021)			min distance	✓	P-median and K-means models
Sumathy and Amirthalingam (2021)			min the number of staff	✓	One type of shift
Ghosh et al. (2020)		✓		✓	Manufacturing lead time constraints
Tsao et al. (2020)	✓				Layers in each section must fall within the specified range
Ünal and Yüksel (2020)			min total usage of fabric	✓	Maximum number of plies per spreading
Xu et al. (2020)	✓			✓	Mass customization
Sánchez-Herrera et al. (2019)			min tardiness	✓	Processing times are affected by the deteriorating effect
Zhang and Chen (2019)			min time loss rate, min smoothness index	✓	Material consumption, energy consumption, carbon emission and labor consumption.

Reference	Objective function			Real Data	Others
	Min costs	Max profits	Others		
Zhang et al. (2019)			min transfer distance of the semi-finished products, min the area occupied by the assembly line	✓	Three assembly line layotus
Tsai and Jhong (2019)		✓		✓	Batch-level activity constraints and carbon tax function
Shang et al. (2019)			min number of total used lays		Maximum allowed fabric length and layer number of the cutting bed
Pereira (2018)	✓			✓	Cycle time and precedence constraints
Elmehanny et al. (2018)		✓		✓	Make-to-order and mak-to-stock products
Du et al. (2018)			min tardiness, min total preproduction event clashes	✓	Preproduction events
Zaharie et al. (2017)	✓		min total earliness	✓	Order can be accepted, adjusted or rejected
Celikbilek et al. (2016)			min tardiness, min the number of tardy jobs	✓	Waiting times
Wang et al. (2016)			min makespan		Specific scenarios of fabric lay overlay
Gürsoy and Gürsoy (2015)			min idle time		Flexible operations
Hu et al. (2015)			min traveling time	✓	Try on services
Hung et al. (2014)			min cut piece WIP		Epoch break points
Gürsoy (2012)			min idle time		Flexible and non-flexible operations
Ünal and Koç (2010)	✓		min softness, max weft breaking strength, min hydrophility		Physical and performance properties
de Armas et al. (2008)		✓		✓	Reduce waste
Guo et al. (2006)	✓			✓	Operation precedence
Ghiani et al. (2003)			min the reduction of orders, min the average setups, max overall goods quality	✓	Throughput and quality of finished goods
Heckmann and Lengauer (1998)			min the the length of of the surface	✓	Computing cutting images and lower bounds on waste
Degraeve and Vandebroek (1998)	✓			✓	Maximum length and high of the stack
Tomastik et al. (1996)			min tardiness and earliness	✓	Flexible manufacturing system

Reference	**Objective function**				
	Min costs	**Max profits**	**Others**	**Real Data**	**Others**

Table B9 – Problem characteristics related to supply chain textile manufacturing.

Reference	**Problem**	**Model**	**Solution Approach**		
			Exact	**Approximate**	**Method/Tool**
Kian et al. (2024)	Green Product Processes	MOMIP	✓	✓	GAMS; Genetic Algortithm
Shefa et al. (2024)	Location allocation	MIP	✓	✓	Commercial solver
Ali and Zhang (2023)	Supplier selection	FMOLP	✓		LINGO
Mezatio et al. (2023a)	Sustainable SC Network designn	MINLP	✓		CPLEX
Mezatio et al. (2023b)	Sustainable SC Network design	MINLP	✓		CPLEX
Ghasemy Yaghin and Sarlak (2022)	Tactical production planning	FMOLP		✓	Credibility chance constraint programming
Ghasemy Yaghin and Darvishi (2022)	Integrated textile material and production management	FMOMINLP		✓	Three-stage hybrid algorithm
Mas'ud and Wahid (2022)	Resilient supply chain	LP	✓		LINGO
Mezatio et al. (2022)	Sustainable SC Network design and supplier selection	MIP	✓		CPLEX
Abbas et al. (2021)	Sustainable energy supply	LP	✓		AIMMS
Sarma et al. (2021)	Resilient retail supply chain	GP		✓	Theory of constraints and business secnario
Paydar et al. (2021)	SC Network design	MOSLP	✓		LINGO; Downside risk management
Safra et al. (2021)	Production and distribution planning	IP	✓		CPLEX
Tayyab and Sarkar (2021)	Supplier Selection	FMOMIP	✓		LINGO
Wang et al. (2021)	Production and distribution planning	MOMISP	✓		CPLEX

Reference	**Problem**	**Model**	**Solution Approach**		
			Exact	**Approximate**	**Method/Tool**
Ghasemy Yaghin et al. (2020)	Aggregate production and transportation planning	FSMINLP	✓		Generalized geometric programming; GAMS; IPOPT/MINOS solver
Darvishi et al. (2020)	Aggregate production and transportation planning	FSMINLP	✓		Linearization; Robust optimization; GAMS
Ghasemy Yaghin (2020)	Aggregate production planning	FMINLP	✓	✓	Scenario-based two-stage stochastic programming; Fuzzy credibility-based chance constraints; GAMS and BARON solver; Hybrid solution algorithm
Karami et al. (2020)	Supplier Selection	LP		✓	Integrated DEA-PCA-VIKOR approach
Berthier et al. (2020)	SC Network design	MIP	✓		CPLEX
Moreno-Camacho et al. (2020)	Sustainable SC Network design	MIP	✓		GAMS/CPLEX
Ghasemy Yaghin and Darvishi (2019)	Order allocation and procurement transport planning	FMOMIP	✓	✓	Fuzzy multi-choice goal programming; Isolating the non-convexities; GAMS and BARON solver; Hybrid solution algorithm
Safra et al. (2019)	Production and distribution planning	IP	✓		CPLEX
Ghasemy Yaghin and Sarlak (2019)	Supplier selection, order allocation, transportation planning	FMOMINLP	✓		CPLEX
Zheng and Song (2019)	Capacity allocation	MIP	✓		CPLEX
Khannan et al. (2018)	Warehouse allocation	LP	✓		LINGO
Kayvanfar et al. (2018)	Supply distribution	FMOGP	✓		CPLEX

Reference	Problem	Model	Solution Approach		
			Exact	Approximate	Method/Tool
Jatuphatwarodom et al. (2018)	Supplier selection and inventory optimization	MOGP	✓		LINGO
Felfel et al. (2018)	Production and distribution planning	MISP/ MOMISP	✓		Conditional-value-at-Risk; Downside risk management; Pareto optimal solutions; LINGO
Demirel et al. (2018)	Aggregate production planning	MIP	✓		CPLEX
Masoudipour et al. (2017)	Closed-loop supply chain	MOMINLP	✓		Linearization; CPLEX
Hashim et al. (2017)	Supplier Selection	FMOMIP		✓	Genetic algorithm
Jafari et al. (2017)	Sustainable SC Network design	MOMIP		✓	Pareto-based approach
Li et al. (2017)	Location allocation	MIP		✓	Bee colony algorithm
Felfel et al. (2016a)	Production and distribution planning	MOMIS	✓	✓	Epsilon-constraint method; Minimax method 3. LINGO
Felfel et al. (2016b)	Production and distribution planning	MOMISP	✓	✓	Pareto optimal robust solutions
Felfel et al. (2015)	Production and distribution planning	MISP		✓	LINGO
Jakhar (2015)	Performance evaluation and allocation decisions	FMOLP		✓	Fuzzy-AHP; LINDO
Saghaei et al. (2014)	Supplier selection	MINLP		✓	LINGO
Ait-Alla et al. (2014)	Production planning	MIRP		✓	Conditional-value-at-Risk; Frontline risk solver
Oh and Jeong (2014)	Closed-loop supply chain	MOMIP		✓	CPLEX
Bouzembrak et al. (2013)	SC Network design	FMIP		✓	Equivalent crisp model; CPLEX
Shaw et al. (2013)	Sustainable SC Network design	GP		✓	LINGO
Ying-Hua (2010)	SC Network design	MIP	✓	✓	LINGO; Genetic algorithm
Caro and Gallien (2010)	Distribution and inventory planning	MISP/MIP		✓	Aproximation heuristic
Karabuk (2007)	Transportation planning	IP	✓		CPLEX; Column generation

Reference	**Problem**	**Model**	**Solution Approach**		
			Exact	**Approximate**	**Method/Tool**
Araz et al. (2007)	Supplier selection	FGP	✓		Integrated multicriteria decision-making method
Leung et al. (2007)	Aggregate production planning	RP		✓	LINDO
Leung et al. (2006)	Aggregate production planning	MISP		✓	LINDO
Leung et al. (2003)	Aggregate production planning	GP		✓	LINDO; Analytical hierarchy process
De Toni and Meneghetti (2000)	Production planning	MIP	✓	✓	CPLEX; Constructive heuristic
Guan et al. (2000)	Aggregate production planning	FMIP	✓		Equivalent crisp model; CPLEX

Table B10 – Major features of the models on the textile supply chain in reviewed papers.

Reference	**Site**		**Item**		**Period**		**Supplier**		**Customer**		**Distri-bution**	**Parameters**		**Uncertain data**	**Function**
	M	**S**	**M**	**S**	**M**	**S**	**M**	**S**	**M**	**S**		**D**	**U**		
Kian et al. (2024)	✓		✓		✓		✓		✓		✓	✓			
Shefa et al. (2024)	✓		✓			✓	✓		✓		✓	✓			
Ali and Zhang (2023)	✓		✓			✓	✓			✓			✓	Transportation risks, supplier performance, exchange rates	Fuzzy (triangular fuzzy numbers)
Mezatio et al. (2023a)	✓		✓			✓	✓		✓		✓	✓			
Mezatio et al. (2023b)	✓		✓			✓	✓		✓		✓	✓			

Reference	**Site**		**Item**		**Period**		**Supplier**		**Customer**		**Distri-bution**	**Parameters**		**Uncertain data**	**Function**
	M	**S**	**M**	**S**	**M**	**S**	**M**	**S**	**M**	**S**		**D**	**U**		
Ghasemy Yaghin and Sarlak (2022)	✓		✓		✓		✓				✓		✓	purchasing prices, costs, carbon emission levels, demand, capacities, and labor levels	Fuzzy (trapezoidal possibility distribution)
Ghasemy Yaghin and Darvishi (2022)	✓		✓		✓		✓				✓		✓	purchasing prices, supplier scores, late deliveries, exchange rate, costs, and capacities	Fuzzy (triangular possibility distribution)
Mas'ud and Wahid (2022)	✓		✓			✓					✓	✓			
Mezatio et al. (2022)	✓		✓			✓	✓		✓		✓	✓			
Abbas et al. (2021)	✓		✓		✓		✓			✓	✓	✓			
Sarma et al. (2021)	✓		✓			✓						✓			
Paydar et al. (2021)	✓		✓		✓		✓				✓		✓	demand and price	Scenario based generation
Safra et al. (2021)	✓		✓		✓		✓				✓	✓			

Reference	Site		Item		Period		Supplier		Customer		Distribution	Parameters		Uncertain data	Function
	M	S	M	S	M	S	M	S	M	S		D	U		
Tayyab and Sarkar (2021)	✓		✓		✓		✓				✓		✓	Customer complaints	Fuzzy (triangular fuzzy numbers)
Wang et al. (2021)	✓		✓		✓		✓		✓		✓		✓	Demand	Scenario based generation
Ghasemy Yaghin et al. (2020)	✓		✓		✓		✓				✓		✓	selling prices,costs, production time and safety stock	Scenario based generation and Fuzzy trapezoidal possibility distribution
Darvishi et al. (2020)	✓		✓		✓		✓				✓		✓	Demand, Inventory cost, exchange rate, volume of fabric rolls, production capacity, inventory capacity, labor costs, and transportation variable cost	Fuzzy (symmetric triangular fuzzy numbers)

Reference	Site		Item		Period		Supplier		Customer		Distribution	Parameters		Uncertain data	Function
	M	S	M	S	M	S	M	S	M	S		D	U		
Ghasemy Yaghin (2020)	✓		✓		✓		✓								
Karami et al. (2020)		✓	✓			✓						✓			
Berthier et al. (2020)	✓		✓			✓	✓					✓			
Moreno-Camacho et al. (2020)	✓		✓			✓	✓		✓		✓	✓			
Ghasemy Yaghin and Darvishi (2019)		✓	✓			✓	✓				✓		✓	maximum transportation cost, purchasing price, percentage of late deliveries, suppliers capacity, total purchase of fabrics, percentage discounts, number of hole per fabric roll and preferential weight	Fuzzy (symmetric triangular fuzzy numbers)

Reference	Site		Item		Period		Supplier		Customer		Distribution	Parameters		Uncertain data	Function
	M	S	M	S	M	S	M	S	M	S		D	U		
Safra et al. (2019)	✓		✓		✓		✓				✓	✓			
Ghasemy Yaghin and Sarlak (2019)	✓		✓			✓	✓				✓		✓	transportation cost, purchasing cost, demand, transportation pollution, water pollution, energy consumption and lead time	Fuzzy (trapezoidal possibility distribution)
Zheng and Song (2019)	✓		✓		✓		✓		✓		✓	✓			
Khannan et al. (2018)	✓		✓			✓	✓		✓		✓	✓			
Kayvanfar et al. (2018)	✓		✓		✓		✓		✓		✓		✓	demand	Fuzzy (triangular fuzzy numbers)
Jatuphatwarodom et al. (2018)							✓								
Felfel et al. (2018)	✓		✓		✓		✓				✓		✓	demand and price	Scenario based generation
Demirel et al. (2018)		✓	✓		✓							✓			

Reference	Site		Item		Period		Supplier		Customer		Distri-	Parameters		Uncertain	Function
	M	S	M	S	M	S	M	S	M	S	bution	D	U	data	
Masoudipour et al. (2017)	✓			✓		✓	✓		✓			✓			
Hashim et al. (2017)		✓	✓		✓		✓							cost, demand, and quality	Fuzzy (triangular fuzzy numbers)
Jafari et al. (2017)	✓		✓			✓			✓		✓	✓			
Li et al. (2017)	✓				✓				✓			✓			
Felfel et al. (2016a)	✓		✓		✓				✓		✓	✓			
Felfel et al. (2016b)	✓		✓		✓				✓		✓	✓		demand	Scenario based generation
Felfel et al. (2015)	✓		✓		✓				✓		✓		✓	demand	Scenario based generation
Jakhar (2015)	✓			✓	✓		✓				✓		✓	parameters of the five objective functions	Fuzzy (triangular fuzzy numbers)
Saghaei et al. (2014)	✓		✓			✓		✓							
Ait-Alla et al. (2014)	✓		✓		✓						✓		✓	demand	Scenario based generation
Oh and Jeong (2014)	✓			✓	✓		✓		✓		✓	✓			

Reference	**Site**		**Item**		**Period**		**Supplier**		**Customer**		**Distri-bution**	**Parameters**		**Uncertain data**	**Function**
	M	**S**	**M**	**S**	**M**	**S**	**M**	**S**	**M**	**S**		**D**	**U**		
Bouzembrak et al. (2013)	✓			✓		✓	✓				✓		✓	demand, opening costs, transportation costs, treatment costs, and storage costs	Fuzzy (triangular fuzzy numbers)
Shaw et al. (2013)	✓			✓		✓	✓		✓		✓	✓			
Ying-Hua (2010)	✓		✓			✓	✓		✓		✓	✓			
Caro and Gallien (2010)	✓		✓			✓					✓		✓	Demand	Function of demand forecasts
Karabuk (2007)	✓			✓		✓			✓		✓	✓			
Araz et al. (2007)		✓	✓		✓		✓						✓	objective function	Fuzzy goals membership function
Leung et al. (2007)	✓		✓		✓								✓	Demand, labor hiring and lay-offs	

Reference	Site		Item		Period		Supplier		Customer		Distri-bution	Parameters		Uncertain data	Function
	M	S	M	S	M	S	M	S	M	S		D	U		
Leung et al. (2006)	✓		✓		✓								✓	Demand, production time and costs, inventory costs, shortage costs	
Leung et al. (2003)	✓		✓		✓										
Guan et al. (2000)		✓		✓	✓								✓	Capacity levels	
De Toni and Meneghetti (2000)	✓		✓			✓						✓		capacity plants	Fuzzy (Verdegay's non-symmetric approach)

Table B11 – Objective functions and other considerations on the textile supply chain in reviewed papers.

References	Objective function					Real Data	Other considerations
	Number		Min costs	Max profits	Others		
	S	M					
Kian et al. (2024)		✓	✓		min production time, min environmental impact	✓	Green suppliers and purifiers stages
Shefa et al. (2024)	✓		✓			✓	Wastewater management
Ali and Zhang (2023)		✓	✓		min delivery late, min transportation risks, min defect rate	✓	Carbon emission, rejection rate, quality assurance
Mezatio et al. (2023a)	✓		✓				Several sources of energy, fuel consumption and travel speeds

Mezatio et al. (2023b)	✓		✓				Carbon emission, life cycle assessment
Ghasemy Yaghin and Sarlak (2022)		✓	✓	✓	max total social value of purchasing min late deliveries min carbon emission tax	✓	Carbon emission and social responsibility
Ghasemy Yaghin and Darvishi (2022)		✓	✓		max total value of purchasing, min late deliveries	✓	Supplier selection, order allocation, inbound transportation
Mas'ud and Wahid (2022)	✓		✓			✓	COVID-19 impact on supply chain,Digital disruption
Mezatio et al. (2022)	✓		✓				Carbon emission
Sarma et al. (2021)		✓			max performance from the stores	✓	COVID-19 impact on supply chain
Paydar et al. (2021)	✓	✓		✓	min risk of having a low net profit	✓	Downside risk (DRisk) to manage uncertainty
Abbas et al. (2021)	✓		✓			✓	Sustainable energy supply using cotton crop waste
Safra et al. (2021)	✓		✓			✓	Tactical and operational decisions
Ghasemy Yaghin et al. (2020)	✓			✓		✓	Procurement and social responsibility plannings
Darvishi et al. (2020)	✓		✓			✓	Suppliers election, order allocation, inbound transportation logistics with cross-docking
Ghasemy Yaghin (2020)	✓			✓		✓	Marketing/retailing planning
Karami et al. (2020)	✓				min sum of dual variables	✓	Quantitative and qualitative decision-making criteria
Berthier et al. (2020)	✓		✓			✓	
Moreno-Camacho et al. (2020)	✓		✓			✓	Carbon emission
Ghasemy Yaghin and Darvishi (2019)		✓	✓	✓	max total social value of purchasing min delivery lead time min air and water pollution min energy consumption	✓	Social responsibility
Safra et al. (2019)	✓		✓			✓	Tactical and operational decisions

Ghasemy Yaghin and Sarlak (2019)		✓	✓	✓	min late deliveries	✓	Social responsibility
Zheng and Song (2019)	✓				max utilization of shared resources	✓	Entropy maximization
Khannan et al. (2018)	✓		✓			✓	Cross-docking, reserve, and forward areas
Kayvanfar et al. (2018)		✓	✓		max rate of demand satisfaction max delivery quality	✓	Using Third-party logistics (3PL)
Jatuphatwarodom et al. (2018)	✓				min sum of deviations from the similarity goals and consistency goals	✓	Quantitative and qualitative decision-making criteria
Felfel et al. (2018)				✓		✓	Risk aversion
Demirel et al. (2018)	✓		✓			✓	Flexible Requirements Profile
Masoudipour et al. (2017)	✓			✓		✓	Quality of returns
Hashim et al. (2017)		✓	✓		max suppliers environment friendly product quality	✓	Green raw materials
Jafari et al. (2017)		✓	✓		min water consumption, max number of employment opportunities		Water consumption, Justice-oriented employment
Li et al. (2017)	✓		✓			✓	Reverse logistics network system
Felfel et al. (2016a)		✓	✓		max product quality	✓	Multi stage problem and product quality
Felfel et al. (2016b)		✓	✓		min lost demand level	✓	Multi stage problem and semi-finished products
Felfel et al. (2015)	✓			✓		✓	Semi-finished products
Jakhar (2015)		✓	✓		max total value of sustainable performances; min carbon emission	✓	Sustainable supply chain
Saghaei et al. (2014)	✓			✓		✓	Quality improvement of the supply chain
Ait-Alla et al. (2014)	✓			✓		✓	Conditional value at risk
Oh and Jeong (2014)	✓			✓		✓	Carbon emission
Bouzembrak et al. (2013)	✓		✓			✓	
Shaw et al. (2013)		✓	✓		min carbon emission max trade credit	✓	Carbon emission
Ying-Hua (2010)	✓		✓			✓	
Caro and Gallien (2010)	✓				max overall predicted sales	✓	

Karabuk (2007)	✓				Model LTL1: min the total of trailer imbalances Model LTL2 min distance Model TL min empty travel distance	✓	Full truckload (TL) and less than full truckload (LTL) shipments
Araz et al. (2007)		✓	✓		max ordered quantities to the highest performing suppliers; max number of accepted units max quantities ordered from each supplier		Evaluation criteria for the suppliers and the objectives of the company
Leung et al. (2007)	✓		✓			✓	Warehouse to storage products
Leung et al. (2006)	✓		✓			✓	Regular-time production, overtime production and subcontracting cost
Leung et al. (2003)		✓	✓	✓		✓	Hiring and layoff goal, hierarchy priority for objective functions
De Toni and Meneghetti (2000)	✓				max capacity loading of the knitting firms	✓	Time-based competition
Guan et al. (2000)	✓		✓			✓	Seasonal demand
Caption:	M: Multiple		S: Single				

APPENDIX C – Additional results for Service-level and capacity utilization constraints for capacitated lot-sizing problem focus on customer orders

C.1 Surrogate relaxation for the Production Planning Problem of Orders (SRPO)

We use the solution method proposed by Alves et al. (2024) to solve the models in chapter 4. This solution is based on solving a surrogate relaxation model, which is given as follows:

Decision variables for the SRPO	
X_{jt}	Number of items j to be produced in period t;
I_{jt}	Number of items j held at the end of period t;
T_{kt}	Number of machine loads for family k in period t.

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{NP} b_{it}BO_{it} - \sum_{j=1}^{N} h_j I_{jT}$$

S.t:

(4.2), (4.9), (4.11),

$$I_{j,t-1} + X_{jt} = I_{jt} + \sum_{\substack{i=1,\\ j\in S(i)}}^{NP} a_{ji}\cdot XO_{it}, \qquad \forall j, \forall t \tag{C.1}$$

$$\sum_{j\in L(k)} p_j \cdot X_{jt} \leq cap \cdot T_{kt}, \qquad \forall k, \forall t \tag{C.2}$$

$$\sum_{t=1}^{T} X_{jt} \leq \sum_{i=1}^{NP} a_{ji}, \qquad \forall j \tag{C.3}$$

$$\sum_{k=1}^{K} T_{kt} \leq NS_t, \qquad \forall t \tag{C.4}$$

$$X_{jt} \in \mathbb{Z}^+ \qquad \forall j, \forall t \tag{C.5}$$

$$T_{kt} \in \mathbb{Z}^+ \qquad \forall k, \forall t \tag{C.6}$$

The objective function and constraints (4.2), (4.9), and (4.11) are the same as the original model. Constraints (C.1) determine the flow balance for the items. Constraints (C.2) determine the production limit per period, considering the number of equipment loads for each alloy. Constraints (C.3) limit production to the quantity demanded items. Constraints (C.4) ensure that the number of equipment loads does not exceed the limit in a working day. Finally, constraints (C.5) - (C.6) determine the variable domains.

To consider inventory and setup costs, we modify SRPO, including a variable and a constraint to control when a setup for a family of products k occurred in a period t. The new model is:

Decision variables for the SRPO	
Y_{kt}	Takes 1, if family k is prepared to produce at period t; 0 otherwise.

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{NP} b_{it}BO_{it} + \sum_{j=1}^{N}\sum_{t=1}^{T} h_j I_{jt} + \sum_{k=1}^{K}\sum_{t=1}^{T} sY_{kt} \tag{C.7}$$

(4.2), (4.9), (4.11),

(C.1) – (C.6),

$$T_{kt} \leq NS \cdot Y_{kt}, \qquad \forall k, \forall t \tag{C.8}$$

$$Y_{kt} \in \{0,1\}, \qquad \forall k, \forall t \tag{C.9}$$

C.2 Comparison of SUBH with a general lot-sizing problem

We conducted experiments to assess the effectiveness of SUBH and the conventional lot-sizing problem model in fulfilling orders. For this purpose, we used an instance with 43 orders, 165 items, 5 alloys, and 3 periods in the planning horizon. All orders have a due date for the period $t = 1$.

The traditional lot-sizing problem does not have variables XO_{it}, BO_{it} and constraints (4.2) and (4.3) related to order fulfillment. Thus, the backlogging item costs and the item demand are calculated as follows. Let $|S(i)|$ be the number of items in order i.

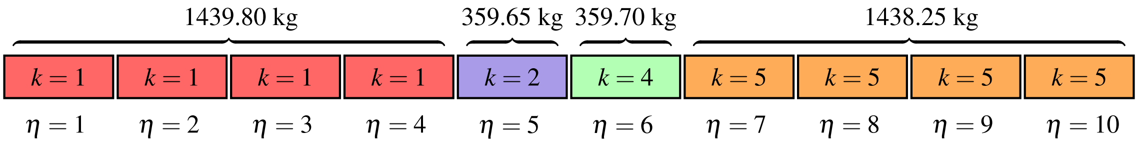
- The backlogging cost for item j in period t is: $b_{jt} = \frac{bo_{it}}{|S(i)| \cdot a_{ji}}$
- The total demand for item j in period t is: $dem_{jt} = \sum_{i=1,\, j \in S(i)}^{NP} a_{ji} \cdot d_{it}$

Figure 54 displays the alloy schedule and the amount produced using each alloy load in period $t = 1$. Using SUBH, it is possible to plan the production of $3597.4kg$ of alloys for the first period, while the traditional lot-sizing model results in the production of $3599.3kg$ of alloys. The difference in alloy planning between both approaches results in different items being produced and, consequently, in the number of orders fulfilled.

Figure 55 illustrates the results, revealing that SUBH successfully fulfills 42 orders, outperforming the best performance achieved by LSP, which fulfills a maximum of 33 orders. Moreover, SUBH achieves on-time completion for 26 orders, while LSP can only complete 22 orders on time. This contrast can be attributed to the fact that traditional LSP models do not prioritize the production of items based on the importance of the associated orders.

Figure 54 – Familiy schedule for SUBH and general lot-sizing problem models for $t = 1$.

(a) SUBH



(b) Traditional lot-sizing problem model

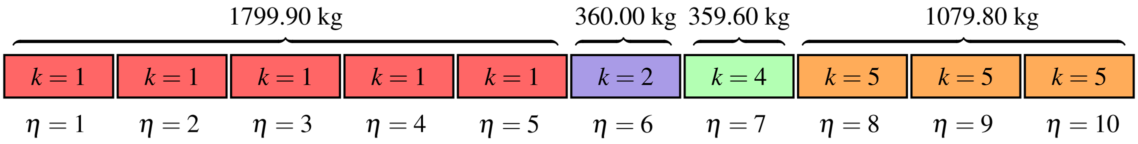
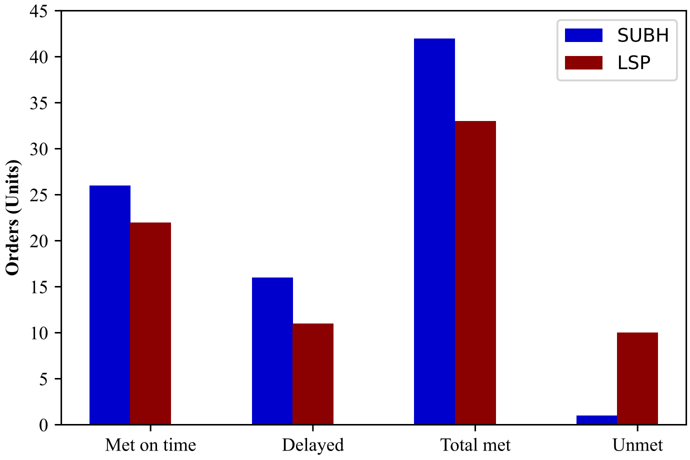


Figure 55 – Comparison of SUBH and lot-sizing problem models.



These findings highlight the superiority of the SUBH approach in achieving order fulfillment compared to the traditional LSP model. The ability to meet orders directly influences vital aspects such as customer satisfaction, business relationships, and competitiveness in the market. This example further emphasizes the importance of considering order fulfillment as a crucial aspect of production planning.

C.3 Computational results

Table C1 – Computational results for the PEBP in Scenario A.

Service-level			**Objective Function**		**Orders**			**KPIs**					
	γ	γ **orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0	-	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1055.28	91.72%
	0.1	9	143.02	0.01%	25	20	7	61.56	377	9.00	76.64	967.21	91.13%
	0.2	13	143.02	0.01%	25	20	7	61.56	377	9.00	76.64	967.25	91.13%
	0.3	18	143.02	0.00%	25	20	7	61.56	377	9.00	76.64	967.21	91.13%
	0.4	23	143.02	0.00%	25	20	7	61.56	377	9.00	76.64	967.89	91.13%
	0.5	28	143.25	0.00%	28	17	7	61.49	376	9.00	76.58	1029.81	91.13%
	0.5833	32	164.64	0.00%	32	12	8	62.73	376	8.80	77.43	991.76	92.17%
	r		0.79		0.88	-0.87	0.59	0.49	-0.79	-0.59	0.14	-0.14	0.23
M2	0	-	170.52	0.00%	54	83	80	42.04	376	27.40	60.76	302.99	93.05%
	0.1	22	171.01	0.00%	58	83	76	40.84	376	28.20	59.57	290.85	93.79%
	0.2	43	172.83	0.00%	63	88	66	38.17	376	30.20	56.81	289.63	93.79%
	0.3	65	175.30	0.00%	68	82	67	38.38	376	30.00	57.29	317.61	93.79%
	0.4	87	179.46	0.00%	89	68	60	36.60	376	31.40	55.54	327.69	95.05%
	0.5	109	200.25	0.01%	109	66	42	33.00	376	35.00	52.39	339.53	93.72%
	0.559	121	229.53	0.00%	123	57	37	31.98	376	36.00	51.43	348.28	93.72%
	r		0.82	-	0.95	-0.87	-0.96	-0.97	-	0.96	-0.97	0.90	0.43
M3	0	-	165.17	0.00%	88	143	152	35.26	376	46.20	54.20	83.52	93.03%
	0.1	38	165.52	0.00%	97	137	149	34.71	376	46.80	53.71	81.96	93.03%
	0.2	77	166.19	0.00%	108	138	137	33.05	376	49.20	52.33	86.12	93.03%
	0.3	115	167.49	0.00%	118	131	134	32.60	376	49.80	51.60	91.84	93.03%
	0.4	153	170.82	0.00%	155	109	119	30.62	376	52.80	49.79	102.88	93.76%
	0.5	192	190.86	0.01%	193	83	107	29.13	376	55.20	47.44	115.31	95.37%
	0.5818	223	231.02	0.00%	226	93	64	25.42	376	63.80	45.09	96.55	93.45%
	r		0.78	-	0.96	-0.92	-0.92	-0.96	-	0.92	-0.97	0.80	0.61

Table C2 – Computational results for the GEBP in Scenario A.

Service-level			**Objective Function**		**Orders**			**KPIs**					
	γ	γ **orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.1	5	110.58	0.01%	20	25	7	61.71	377	9.00	77.16	1055.20	91.72%
	0.2	10	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1068.56	91.72%
	0.3	15	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1072.65	91.72%
	0.4	20	110.76	0.00%	21	25	6	60.41	377	9.20	76.43	1011.37	91.72%
	0.5	26	114.34	0.00%	26	21	5	59.02	376	9.40	75.23	902.87	91.21%
	0.6	31	164.64	0.00%	32	12	8	62.73	376	8.80	77.43	980.87	92.16%
	0.6153	31	164.64	0.00%	32	12	8	62.73	376	8.80	77.43	980.87	92.16%
	r		0.78	-	0.90	-0.85	0.16	0.08	-0.87	-0.16	-0.11	-0.75	0.35
M2	0.1	21	170.52	0.00%	54	83	80	42.04	376	27.40	60.76	302.61	93.05%
	0.2	43	170.52	0.00%	54	83	80	42.04	376	27.40	60.76	302.91	93.05%
	0.3	65	170.72	0.00%	66	73	78	41.35	376	27.80	60.11	302.92	93.05%
	0.4	86	173.77	0.00%	87	68	62	37.04	376	31.00	56.11	321.39	93.78%
	0.5	108	183.74	0.30%	109	72	36	31.86	376	36.20	51.30	374.62	93.72%
	0.6	130	217.34	0.34%	131	58	28	30.39	376	37.80	50.02	391.34	93.61%
	0.6728	145	279.80	0.00%	146	40	31	30.77	376	37.20	49.83	407.42	94.49%
	r		0.80	-	0.98	-0.90	-0.94	-0.95	-	0.94	-0.96	0.94	0.87
M3	0.1	38	165.17	0.00%	88	143	152	35.26	376	46.20	54.18	79.5	93.03%
	0.2	76	165.17	0.00%	88	143	152	35.26	376	46.20	54.22	83.64	93.03%
	0.3	114	165.48	0.00%	115	123	145	34.09	376	47.60	53.21	86.8	93.03%
	0.4	153	167.90	0.00%	154	112	117	30.41	376	53.20	49.83	122.84	93.74%
	0.5	191	175.30	0.04%	192	125	66	25.72	376	63.40	45.53	91.14	93.69%
	0.6	229	204.05	0.26%	230	98	55	24.71	376	65.60	44.49	174.11	92.84%
	0.6997	267	283.38	0.00%	268	59	56	24.58	376	65.40	43.80	167.63	93.85%
	r		0.78		0.98	-0.89	-0.95	-0.96	-	0.95	-0.96	0.85	0.50

Table C3 – Computational results for the PEBP in Scenario B.

	Service-level		**Objective Function**		**Orders**			**KPIs**					
	γ	γ **orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0	-	19.25	0.01%	16	19	17	1.09	4	7.00	18.29	924.82	95.24%
	0.1	5	19.25	0.00%	16	19	17	1.09	4	7.00	18.29	930.60	95.24%
	0.2	11	19.26	0.00%	17	19	16	1.06	4	7.20	18.39	2694.42	95.23%
	0.3	15	19.57	0.00%	22	15	15	0.81	4	7.40	18.14	1021.22	95.49%
	0.4	21	19.75	0.00%	24	14	14	0.76	4	7.60	18.34	1131.56	95.49%
	0.5	26	20.10	0.00%	26	10	16	0.50	3	7.20	18.75	1162.86	94.57%
	0.6	31	20.86	0.34%	33	6	13	0.36	3	7.80	18.64	1473.83	95.83%
	0.7	37	21.54	0.00%	38	9	5	0.32	3	9.40	18.47	1180.38	91.23%
	0.75	40	22.03	0.00%	40	7	5	0.32	4	9.40	18.47	1301.17	91.24%
	r		0.93		0.97	-0.95	-0.84	-0.97	-0.58	0.84	0.59	0.00	-0.68
M2	0	-	21.00	0.03%	80	60	77	0.53	3	28.00	21.44	604.00	96.08%
	0.1	22	21.00	0.06%	83	61	73	0.53	3	28.80	21.41	601.28	96.68%
	0.2	44	21.01	0.06%	92	56	69	0.49	3	29.60	21.32	593.88	96.68%
	0.3	65	21.04	0.07%	97	55	65	0.50	3	30.40	21.47	601.11	96.68%
	0.4	86	21.12	0.07%	113	44	60	0.46	3	31.40	21.42	591.06	96.78%
	0.5	110	21.37	0.09%	126	38	53	0.37	3	32.80	21.10	634.90	97.64%
	0.6	131	21.73	0.49%	140	28	49	0.30	3	33.60	21.12	610.07	97.88%
	0.7	152	22.58	1.35%	155	20	42	0.26	4	35.00	21.21	679.66	97.97%
	0.8	173	25.48	3.92%	176	11	30	0.14	3	37.40	21.40	1011.23	97.55%
	0.8302	178	28.44	0.00%	184	7	26	0.09	3	38.20	21.54	1245.90	97.00%
	r		0.76		0.98	-0.98	-0.98	-0.95	0.31	0.98	-0.18	0.71	0.77
M3	0	-	21.17	0.00%	135	122	126	0.65	4	51.40	21.07	247.56	98.37%
	0.1	38	21.17	0.00%	146	117	120	0.63	4	52.60	21.08	247.65	98.37%
	0.2	76	21.37	0.01%	157	112	114	0.62	4	53.80	21.13	275.08	98.30%
	0.3	114	21.41	0.01%	180	98	105	0.50	4	55.60	20.99	265.78	98.31%
	0.4	153	21.50	0.01%	200	87	96	0.44	4	57.40	21.00	274.93	98.50%
	0.5	191	22.33	0.04%	219	73	91	0.37	4	58.40	21.07	377.83	98.94%
	0.6	229	21.87	0.00%	244	62	77	0.33	4	61.20	20.93	244.96	98.91%
	0.7	268	22.64	0.00%	276	37	70	0.20	4	62.60	20.83	335.43	99.13%
	0.8	306	24.02	0.00%	309	32	42	0.18	4	68.20	21.02	381.66	97.30%
	0.8641	330	27.50	0.01%	334	16	33	0.11	4	70.00	21.05	652.76	96.13%
	r		0.76		0.98	-0.98	-0.97	-0.99	-	0.97	-0.50	0.68	-0.39

Table C4 – Computational results for the GEBP in Scenario B.

Service-level			**Objective Function**		**Orders**			**KPIs**					
	γ	γ **orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.1	5	19.25	0.00%	16	19	17	1.09	4	7.00	18.29	886.04	95.24%
	0.2	10	19.25	0.00%	16	19	17	1.09	4	7.00	18.29	913.16	95.24%
	0.3	15	19.25	0.00%	16	19	17	1.09	4	7.00	18.29	947.46	95.25%
	0.4	21	19.47	0.00%	21	16	15	0.84	4	7.00	19.08	1026.02	94.57%
	0.5	26	19.86	0.01%	26	13	13	0.72	4	7.40	19.28	1093.49	94.57%
	0.6	31	20.43	1.25%	32	7	13	0.33	3	7.80	18.21	1254.25	95.83%
	0.7	36	21.14	0.00%	37	6	9	0.23	2	7.80	19.07	1141.36	94.58%
	0.8	42	21.96	0.00%	42	5	5	0.23	4	8.60	18.70	1262.79	91.94%
	0.88	46	25.12	0.00%	46	2	4	0.13	4	9.40	18.23	1614.90	91.24%
		r	0.82	-	0.96	-0.95	-0.93	-0.95	-0.36	9.60	0.28	0.89	-0.72
M2	0.1	22	21.00	0.05%	88	56	73	0.51	3	28.80	21.40	578.64	96.67%
	0.2	43	21.00	0.05%	83	60	74	0.52	3	28.60	21.40	606.55	96.68%
	0.3	65	21.00	0.05%	85	58	74	0.51	3	28.60	21.38	601.78	96.68%
	0.4	87	21.00	0.05%	87	58	72	0.52	3	29.00	21.39	587.13	96.69%
	0.5	109	21.03	0.09%	109	42	66	0.39	3	30.20	21.13	596.44	96.68%
	0.6	130	21.30	0.74%	131	25	61	0.27	3	31.20	21.17	602.71	96.78%
	0.7	152	22.01	1.32%	152	21	44	0.20	3	34.60	21.27	684.71	97.66%
	0.8	174	24.68	3.77%	174	15	28	0.16	3	37.80	21.52	752.57	97.19%
	0.88	191	29.84	2.14%	191	3	23	0.04	3	38.80	21.60	1242.55	97.16%
		r	0.70	-	0.92	-0.93	-0.89	-0.93	-	0.89	0.14	0.65	0.71
M3	0.1	38	21.17	0.00%	141	117	125	0.61	4	51.60	20.98	247.44	98.37%
	0.2	77	21.17	0.02%	143	117	123	0.62	4	52.00	21.14	239.18	98.37%
	0.3	115	21.19	0.07%	192	72	119	0.41	4	52.80	20.93	249.67	98.36%
	0.4	153	21.19	0.07%	192	72	119	0.41	4	52.80	20.93	249.67	98.36%
	0.5	192	21.19	0.07%	192	72	119	0.41	4	52.80	20.93	249.67	98.36%
	0.6	230	21.33	0.17%	230	51	102	0.28	4	56.20	20.84	246.58	98.70%
	0.7	268	21.83	0.47%	269	33	81	0.19	4	60.40	20.81	263.38	99.01%
	0.8	306	23.73	0.58%	307	31	45	0.18	4	67.60	20.98	397.17	97.75%
	0.86	329	26.34	0.71%	330	21	32	0.12	4	70.20	21.01	571.33	96.14%
		r	0.71		0.94	-0.94	-0.87	-0.94	-	0.87	-0.55	0.64	-0.44

Table C5 – Computational results for the PEBP in Scenario C.

Service-level			**Objective Function**		**Orders**			**KPIs**					
	γ	γ **orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0	-	1.22	0.00%	32	14	0	0.48	3	9.20	19.40	676.40	67.00%
	0.1 - 0.6	28	1.22	0.00%	32	14	0	0.48	3	9.20	19.41	653.11	67.00%
	0.7	32	2.14	0.00%	37	9	0	0.33	3	9.20	19.26	812.39	67.00%
	0.8	37	3.40	0.00%	41	5	0	0.13	2	9.20	19.07	1075.97	67.00%
	0.8461	39	3.40	0.00%	41	5	0	0.13	2	9.20	19.07	1075.97	67.00%
		r	0.83		0.87	-0.87	-	-0.83	-0.68	-	-0.82	0.83	0.88
M2	0	-	1.71	0.00%	146	14	0	0.11	2	32.00	21.94	988.45	67.03%
	0.1-0.5	80	1.71	0.00%	146	14	0	0.11	2	32.00	21.94	1127.25	67.03%
	0.6	96	2.44	0.00%	148	12	0	0.10	2	32.00	21.93	1191.41	67.03%
	0.7	112	2.95	0.00%	146	14	0	0.11	2	32.00	21.93	1283.58	67.03%
	0.705	113	2.95	0.00%	146	14	0	0.11	2	32.00	21.93	1283.58	67.03%
		r	0.81	0.00%	0.31	-0.31	-	-0.70	-	-	-0.70	0.21	-
M3	0	-	0.28	0.00%	201	8	0	0.04	1	41.80	21.52	1247.12	67.03%
	0.1-0.6	125	0.28	0.00%	201	8	0	0.04	1	41.80	21.52	1300.54	67.03%
	0.7	146	0.30	0.00%	202	7	0	0.03	1	41.80	21.52	1314.08	67.03%
	0.7692	161	0.42	0.00%	203	6	0	0.03	1	41.80	21.51	1382. 27	67.03%
		r	0.59		0.69	-0.69	-	-0.69	-	0.00	-0.69	0.12	-

Table C6 – Computational results for the GEBP in Scenario C.

Service-level			Objective Function		Orders			KPIs					
	γ	**γ orders**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.1-0.6	5	1.22	0.00%	32	14	0	0.48	3	9.20	19.41	685.44	67.00%
	0.7	32	1.32	0.00%	33	13	0	0.43	3	9.20	19.37	637.50	67.00%
	0.8	37	1.78	0.00%	37	9	0	0.41	4	9.20	19.35	827.04	67.00%
	0.9	41	3.29	0.00%	42	4	0	0.24	4	9.20	19.17	943,78	67.00%
	0.9347	43	5.77	0.00%	43	3	0	0.13	3	9.20	19.07	920.43	67.00%
	r		0.68		0.80	-0.80	-	-0.76	0.55	-	-0.76	0.76	-
M2	0.1-0.9	16	1.71	0.00%	146	14	0	0.11	2	32.00	21.94	1234.63	67.03%
	0.95	152	3.16	0.00%	152	8	0	0.08	2	32.00	21.91	1178.75	67.03%
	r		0.48		0.48	-0.48	-	-0.48	-	-	-0.48	0.13	-
M3	0.1-0.9	21	0.28	0.00%	201	8	0	0.04	1	41.80	21.52	1225.62	67.03%
	0.9712	203	0.42	0.00%	203	6	0	0.03	1	41.80	21.51	1325.82	67.03%
	r		0.50		0.50	-0.50	-	-0.50	-	-	-0.50	0.32	-

Table C7 – Computational results for the TMOP in Scenario A.

Service-level			Objective Function		Orders			KPIs					
	μ	**μ throughput**	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.5	5.20	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1068.72	91.72%
	0.6	6.24	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1044.78	91.72%
	0.7	7.28	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1004.48	91.72%
	0.8	8.32	110.58	0.00%	20	25	7	61.71	377	9.00	77.16	1029.89	91.72%
	0.9	9.36	111.70	0.00%	21	27	4	57.98	377	9.60	74.31	1048.72	90.35%
	0.923	9.60	111.70	0.00%	21	27	4	57.98	377	9.6	74.31	1030.14	90.35%
	r		0.80		0.80	0.80	-0.80	-0.80	-	0.80	-0.80	-0.39	-0.80
M2	0.5	21.70	170.52	0.00%	54	83	80	42.04	376	27.40	60.76	302.51	93.05%
	0.6	26.04	170.52	0.00%	54	83	80	42.07	376	27.40	60.78	301.45	93.05%
	0.7	30.38	171.21	0.00%	56	96	65	38.10	376	30.40	56.88	292.23	94.31%
	0.8	34.72	174.29	0.09%	64	110	43	33.63	376	34.80	52.79	296.70	92.08%
	0.9	39.06	193.15	3.24%	79	117	21	29.75	376	39.20	49.41	450.49	92.84%
	r		0.80		0.89	0.97	-0.96	-0.97	-	0.96	-0.97	0.67	-0.27
M3	0.5	38.30	165.17	0.00%	88	143	152	35.26	376	46.20	54.18	83.64	93.03%
	0.6	45.96	165.17	0.00%	88	143	152	35.26	376	46.20	54.18	79.2	93.03%
	0.7	53.62	166.81	0.05%	107	162	114	30.44	376	53.80	49.78	106.28	93.76%
	0.8	61.28	169.10	0.05%	109	198	76	27.14	376	61.40	46.55	87.22	93.65%
	0.9	68.94	177.23	0.91%	128	217	38	24.16	376	69.00	43.85	199.7	93.66%
	0.929	71.16	290.39	33.79%	141	215	27	23.21	376	71.20	42.10	133.9	94.97%
	r		0.62		0.95	0.97	-0.98	-0.98	-	0.98	-0.98	0.72	0.80

Table C8 – Computational results for the TMOP in Scenario B.

Service-level			Objective Function		Orders			KPIs					
	μ	μ throughput	**Cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.5	5.20	19.25	0.00%	16	19	17	1.09	4	7	18.29	898.99	95.25%
	0.6	6.24	19.25	0.00%	16	19	17	1.09	4	7	18.29	888.15	95.25%
	0.7	7.28	19.26	0.00%	17	20	15	1.05	4	7.4	18.38	886.57	95.25%
	0.8	8.32	20.32	1.05%	19	23	10	0.86	4	8.4	18.55	1066.17	95.13%
	0.9	9.36	20.71	0.00%	26	21	5	0.68	4	9.4	18.83	974.84	91.25%
	0.923	9.60	20.97	0.00%	28	20	4	0.65	4	9.6	19.06	1005.31	90.69%
		r	0.93	-	0.90	0.57	-0.96	-0.94	-	0.96	0.92	0.71	-0.81
M2	0.5	21.70	21.00	0.06%	83	60	74	0.52	3	28.60	21.40	603.25	96.68%
	0.6	26.04	21.00	0.06%	88	55	74	0.50	3	28.60	21.28	586.87	96.68%
	0.7	30.38	21.02	0.06%	95	57	65	0.48	3	30.40	21.32	584.28	96.68%
	0.8	34.72	21.52	0.77%	102	72	43	0.52	3	34.80	21.57	677.02	97.16%
	0.9	39.06	26.51	3.93%	158	38	21	0.27	4	39.20	21.62	823.97	95.75%
		r	0.76	-	0.85	-0.35	-0.94	-0.71	0.71	0.94	0.77	0.83	-0.42
M3	0.5	38.30	21.17	0.00%	139	123	121	0.64	4	52.20	21.06	238.29	98.37%
	0.6	45.96	21.17	0.00%	139	123	121	0.64	4	52.40	21.06	238.29	98.37%
	0.7	53.62	21.36	0.03%	139	130	114	0.64	4	53.80	20.97	238.74	98.37%
	0.8	61.28	22.61	0.00%	160	147	76	0.61	4	61.40	21.37	242.67	98.56%
	0.9	68.94	26.27	0.03%	207	138	38	0.51	4	69.00	21.37	290.61	96.64%
	0.9295	71.20	0.69	6.58%	292	64	27	0.28	4	71.20	21.23	480.33	94.96%
		r	0.77	-	0.79	-0.27	-0.94	-0.73	-	0.94	0.78	0.58	-0.74

Table C9 – Computational results for the ILUP in Scenario A.

		Objective Function		Orders			KPIs					
	θ	**Solution cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.5	131.77	0.01%	20	22	10	61.21	377	8.40	76.83	366.80	93.92%
	0.6	145.93	0.01%	21	19	12	62.30	377	8.00	77.98	448.40	97.44%
	0.7	149.49	0.02%	21	18	13	63.51	377	7.80	79.13	509.60	97.93%
	0.8	159.26	0.01%	22	14	16	67.64	377	7.20	83.31	501.80	99.47%
	0.9	159.28	0.02%	22	14	16	67.64	377	7.20	83.31	986.80	99.08%
	0.99	171.50	0.01%	22	13	17	69.11	377	7.00	84.86	903.60	99.91%
	r	0.97		0.92	-0.96	0.97	0.97	-	-0.97	0.97	0.89	0.89
M2	0.5	181.18	0.02%	51	102	64	36.10	376	30.60	55.33	127.20	95.97%
	0.6	186.21	0.20%	53	97	67	36.20	376	30.00	55.45	128.20	96.20%
	0.7	201.31	0.01%	56	98	63	34.39	376	30.80	53.98	248.40	97.31%
	0.8	209.44	0.02%	56	102	59	32.93	376	31.60	52.63	245.40	99.11%
	0.9	209.53	0.02%	57	100	60	33.13	376	31.40	52.84	249.20	99.14%
	0.99	216.54	0.02%	67	95	55	31.44	376	32.40	51.50	250.40	99.98%
	r	0.97		0.88	-0.41	-0.88	-0.96	-	0.88	-0.96	0.84	0.97
M3	0.5	165.95	0.01%	85	140	158	34.67	376	45.00	53.68	36.80	95.41%
	0.6	168.58	0.02%	86	143	154	33.84	376	45.80	52.88	36.40	96.34%
	0.7	173.83	0.01%	87	141	155	33.47	376	45.60	52.46	132.40	97.87%
	0.8	176.72	0.02%	84	139	160	33.75	376	44.60	52.64	23.40	98.87%
	0.9	176.72	0.02%	85	137	161	33.89	376	44.40	52.81	45.40	98.87%
	0.99	186.71	0.04%	85	165	133	29.82	376	50.00	48.64	28.60	99.93%
	r	0.95		-0.31	0.53	-0.49	-0.73	-	0.49	-0.74	-0.16	0.98

Table C10 – Computational results for the GLUP in Scenario A.

		Objective Function		**Orders**			**KPIs**					
	θ	**Solution cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
	0.5 - 0.9	110.58	0.01%	20	25	7	60.82	377	9.00	77.16	330.60	91.64%
M1	0.99	153.93	0.01%	22	16	14	65.03	377	7.60	80.66	566.20	99.06%
	r	0.64		0.64	-0.64	0.64	0.64	-	-0.64	0.64	0.56	0.64
	0.5 - 0.9	170.52	0.01%	52	85	80	41.52	376	27.40	60.74	160.20	93.05%
M2	0.99	197.82	0.03%	55	97	65	34.58	376	30.40	54.18	93.00	99.00%
	r	0.64		0.57	0.64	-0.64	-0.64	-	0.64	-0.64	-0.64	0.64
	0.5-0.9	165.17	0.02%	86	145	152	34.85	376	46.20	54.19	60.00	93.03%
M3	0.99	178.70	0.01%	84	139	160	33.59	376	44.60	52.54	34.60	99.15%
	r	0.64		-0.62	-0.53	0.64	-0.64	-	-0.64	-0.65	-0.56	0.64

Table C11 – Computational results for the ILUP in Scenario B.

		Objective Function		**Orders**			**KPIs**					
	θ	**Solution cost**	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
	0.5	21.86	0.98%	16	18	18	0.76	4.00	6.80	18.26	168.40	94.61%
	0.6	23.17	0.01%	26	14	12	0.55	4.00	8.00	18.35	220.00	97.51%
	0.7	23.85	0.04%	29	10	13	0.33	4.00	7.80	18.03	311.00	98.23%
M1	0.8	29.29	0.01%	36	0	16	0.00	0.00	7.20	17.81	4228.74	99.64%
	0.9	29.29	0.04%	36	0	16	0.00	0.00	7.20	17.81	4210.14	99.59%
	0.99	30.00	0.01%	35	0	17	0.00	0.00	7.00	17.86	4703.37	99.91%
	r	0.94		0.90	-0.94	0.22	-0.94	-0.88	-0.22	-0.87	0.91	0.91
	0.5	21.25	0.07%	75	64	78	0.65	4.00	27.80	21.62	71.60	96.39%
	0.6	21.31	0.16%	79	66	72	0.59	3.00	29.00	21.47	73.20	98.22%
	0.7	22.59	0.06%	106	56	55	0.36	3.00	32.40	21.71	96.00	98.23%
M2	0.8	23.00	0.02%	112	50	55	0.29	3.00	32.40	21.55	185.20	99.20%
	0.9	23.00	0.02%	113	46	58	0.27	3.00	31.80	21.72	200.60	99.20%
	0.99	23.35	0.02%	122	41	54	0.22	3.00	32.60	21.55	159.00	99.98%
	r	0.94		0.94	-0.97	-0.84	-0.95	-0.66	0.84	0.14	0.85	0.94
	0.5	21.17	0.01%	129	127	127	0.63	4.00	51.20	21.12	58.80	98.37%
	0.6	21.17	0.01%	129	131	123	0.66	4.00	52.00	21.06	25.80	98.37%
	0.7	21.19	0.01%	144	116	123	0.60	4.00	52.00	20.94	30.80	99.10%
M3	0.8	21.24	0.01%	129	128	126	0.60	3.00	51.40	21.07	23.60	99.62%
	0.9	21.42	0.84%	127	122	134	0.59	3.00	49.80	20.89	40.60	99.90%
	0.99	21.24	0.01%	135	118	130	0.58	3.00	50.60	20.92	44.80	99.96%
	r	0.67		0.07	-0.54	0.64	-0.79	-0.88	-0.64	-0.78	-0.14	0.96

Table C12 – Computational results for the GLUP in Scenario B.

θ		**Objective Function**		**Orders**			**KPIs**					
		Solution cost	**Gap**	**On time**	**Delayed**	**Unmet**	**Average delay**	**Maximum delay**	**Through put**	**Lead time**	**WIP (kg)**	**Capacity utilization**
M1	0.5 - 0.8	19.25	0.02 %	16	19	17	1.09	4.00	7.00	18.29	172.60	95.24%
	0.9	19.27	0.08%	15	19	18	1.12	4.00	6.80	18.53	199.80	95.23%
	0.99	24.12	0.01%	26	10	16	0.31	4.00	7.20	17.78	433.80	99.15%
	r	0.64		0.61	-0.65	-0.15	-0.62	-	0.15	-0.34	0.70	0.64
M2	0.5	21.05	0.45%	90	54	73	0.47	3.00	28.80	21.22	74.60	96.67%
	0.6	21.01	0.21%	86	60	71	0.49	3.00	29.20	21.25	101.40	96.68%
	0.7	21.00	0.12%	76	68	73	0.53	3.00	28.80	21.30	128.00	96.68%
	0.8	21.02	0.18%	80	63	74	0.56	3.00	28.60	21.27	104.40	96.67%
	0.9	21.02	0.17%	79	69	69	0.50	3.00	29.60	21.20	91.40	96.67%
	0.99	21.45	0.09%	88	57	72	0.45	3.00	29.00	21.57	85.20	99.03%
	r	0.61		-0.27	0.34	-0.30	-0.09	-	0.30	0.61	0.01	0.64
M3	0.5-0.9	21.17	0.02%	134	126	123	0.60	4.00	52.00	20.95	72.00	98.36%
	0.99	21.20	0.06%	141	113	129	0.59	4.00	50.80	21.11	233.87	99.06%
	r	0.61		0.47	-0.55	0.28	-0.15	-	-0.28	0.55	0.38	0.64

APPENDIX D – Additional results for Integrated production and distribution problem with order consideration and cargo arrangement

Table D1 – Instance parameters for the integrated model tests.

Instance	N	M	K	V
i1	5	2	3	2
i2	5	2	3	3
i3	5	2	4	2
i4	5	2	4	3
i5	5	2	5	2
i6	5	2	5	3
i7	5	3	3	2
i8	5	3	3	3
i9	5	3	4	2
i10	5	3	4	3
i11	5	3	5	2
i12	5	3	5	3
i13	6	2	3	2
i14	6	2	3	3
i15	6	2	4	2
i16	6	2	4	3
i17	6	2	5	2
i18	6	2	5	3
i19	6	3	3	2
i20	6	3	3	3
i21	6	3	4	2
i22	6	3	4	3
i23	6	3	5	2
i24	6	3	5	3
i25	7	2	3	2
i26	7	2	3	3
i27	7	2	4	2
i28	7	2	4	3
i29	7	2	5	2
i30	7	2	5	3
i31	7	3	3	2
i32	7	3	3	3
i33	7	3	4	2
i34	7	3	4	3
i35	7	3	5	2
i36	7	3	5	3

Table D2 – Results for total inventory, number of changeovers and number of shipments for ALNS.

Instance	Inventory (kg)		Number of changeovers		Number of shipments	
	mean	std	mean	std	mean	std
i1	2.60	8.22	4.80	1.40	26.00	0.00
i2	0.00	0.00	5.00	0.82	26.00	0.00
i3	184.80	222.03	6.30	4.16	36.20	0.42
i4	32.70	74.43	5.60	3.20	36.00	0.00
i5	1.294.90	1.726.02	16.00	10.38	44.00	0.67
i6	643.30	1.078.98	7.00	3.13	43.10	0.32
i7	0.00	0.00	2.60	0.70	26.00	0.00
i8	0.00	0.00	2.60	0.70	26.00	0.00
i9	0.00	0.00	3.00	1.15	36.40	0.52
i10	0.00	0.00	2.80	0.63	36.00	0.00
i11	32.00	101.19	3.40	1.58	44.10	0.32
i12	2.60	8.22	4.00	1.83	43.00	0.00
i13	512.10	780.33	6.40	0.84	30.50	0.53
i14	94.10	297.57	7.80	2.97	29.40	0.52
i15	602.20	1.084.70	12.80	6.96	42.00	0.00
i16	1.744.40	2.339.75	13.10	10.90	39.50	0.53
i17	1.701.60	2.891.59	33.40	12.23	50.00	0.00
i18	1.693.80	2.556.94	27.00	12.75	47.00	0.94
i19	0.00	0.00	6.00	1.33	30.50	0.53
i20	0.00	0.00	5.00	1.25	29.00	0.00
i21	206.30	652.38	14.70	8.78	41.90	0.32
i22	327.20	526.89	9.20	6.14	39.10	0.32
i23	874.11	1.688.29	41.50	18.22	50.00	0.00
i24	716.56	1.313.07	21.90	16.71	47.20	0.79
i25	178.90	438.00	23.80	15.62	43.00	0.00
i26	201.70	491.25	22.60	10.97	40.10	0.32
i27	14.849.76	9.378.53	48.30	14.05	58.90	0.57
i28	878.89	1.292.95	49.00	19.61	55.10	0.32
i29	6.924.17	11.922.27	30.60	13.78	45.50	15.99
i30	11.601.22	31.926.28	39.40	27.14	57.60	20.33
i31	453.10	1.284.11	22.10	20.40	43.10	0.32
i32	340.00	438.94	9.00	5.96	40.40	0.52
i33	25.591.01	61.566.76	36.80	21.48	55.50	6.62
i34	1.014.20	1.675.10	15.60	8.17	54.90	0.57
i35	14.355.73	18.016.72	33.90	18.61	48.60	4.79
i36	9.383.62	15.620.27	18.90	12.15	62.80	0.63