Systematic Review of PPCP Models, Artificial Intelligence, and Optimization Applied to the Small-Scale Textile Industry

Gabriel R. B. da Silva(✉), Itamir de M. B. Filho, André M. Gurgel, Lhayana V. de Macedo, Débora N. de A. Valentim, Ramon S. Malaquias, Dinorah de F. Chagas, Yasmim A. Lopes, and Jean M. M. Lima

Digital Metropolis Institute (IMD), Federal University of Rio Grande do Norte (UFRN), Natal, Brazil
{gabriel.ribeiro.099,dinorah.farias.080,yasmim.araujo.709}@ufrn.edu.br, {itamir.filho,jean.lima}@imd.ufrn.br, andre.gurgel@ufrn.br, lhayana11@gmail.com, ramon@nutit.com.br
https://www.metropoledigital.ufrn.br/portal/

Abstract. The textile industry, vital to the global economy, is dominated by Micro and Small Enterprises (MSEs) struggling with digitalization and resource limitations in volatile markets. The adoption of Production Planning, Scheduling, and Control (PPCP) models enhanced by Artificial Intelligence (AI) and optimization is a key strategy for improving their operational efficiency. This paper presents a Systematic Literature Review (SLR) investigating the application of these advanced solutions in textile MSEs. The findings show that hybrid models, such as Genetic Algorithms combined with other heuristics, and process optimization frameworks like Lean Six Sigma, are highly effective, leading to significant gains such as productivity increases of up to 55%. However, a clear gap was identified in the literature regarding the use of Large Language Models (LLMs), presenting a clear opportunity for future research. Integrating specialized AI and optimization techniques is crucial for the digital transformation of textile MSEs, enabling flexible and robust production management.

Keywords: PPCP · textile industry · micro and small enterprises · workload balancing · optimization algorithms · artificial intelligence

1 Introduction

The textile industry is projected to reach a market size of US$295.87 billion by 2025 [28]. Despite this significant volume, the sector relies heavily on Micro and Small Enterprises (MSEs) for both raw material production and apparel manufacturing. This pattern is global: in the European Union (EU), the Organization

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2027
O. Gervasi et al. (Eds.): ICCSA 2026, LNCS 16768, pp. 89–106, 2027.
https://doi.org/10.1007/978-3-032-30488-9_6

for Economic Co-operation and Development (OECD) [23] classifies the textile industry as reliant on MSEs, which account for 77% of its workforce. In Asia, according to SEED [25], this predominance is even more pronounced, with 99.6% of the firms in the sector qualifying as MSEs.

Industrial MSEs struggle to adapt to digitalization and modern manufacturing methods. According to Hulla et al. [15], key challenges include inefficient production processes, the need for agility to respond to a volatile market, and difficulties in maintaining a competitive edge. This gap is particularly evident in Asia, where two-thirds of the sector's large corporations report investing in innovation, whereas this figure drops to just 40% for small companies, highlighting the challenge they face in keeping pace with the competition.

Thus, the implementation of Production Planning and Control Processes (PPCP) is crucial. PPCP is a management system that translates market demands into operational plans by organizing materials, labor and capacity. Integrating Artificial Intelligence (AI) and Optimization into PPCP is a promising path for textile MSEs to boost productivity, reduce idle time, and lower costs, enhancing their competitiveness by improving existing processes.

However, according to the authors' analysis, the volume of scientific publications on AI between 2000 and 2024 has not kept pace with the growth of academic output involving PPCP. This finding is based on searches conducted on the Scopus platform, using the following strings:

- **AI:**

```
    ALL("optimization algorithm*" OR "deep learning" OR "
genetic algorithm*" OR "metaheuristic*" OR "machine learning"
OR "LLM" OR "large language model*" OR "generative AI" )
```

- **AI e PPCP**

```
    ALL(("production planning" OR "PPCP" OR "PCP" OR "
scheduling" OR "job shop scheduling") AND ("workload balancing"
 OR "line balancing" OR "resource allocation" OR "production
optimization") AND ("small enterprise*" OR "small business*" OR
 "small companies" OR "SME") AND ("optimization algorithm*" OR
"deep learning" OR "genetic algorithm*" OR "metaheuristic*" OR
"machine learning" OR "LLM" OR "large language model*" OR "
generative AI"))
```

- **PPCP**

```
    ALL(("production planning" OR "PPCP" OR "PCP" OR "
scheduling" OR "job shop scheduling") AND ("workload balancing"
 OR "line balancing" OR "resource allocation" OR "production
optimization") AND ("small enterprise*" OR "small business*" OR
 "small companies" OR "SME"))
```

The results were then normalized using the formula $\frac{\text{CurrentYear}}{\text{BaseYear}}/100$, with 2000 as the base year, which produced the graph shown in Figure 1:

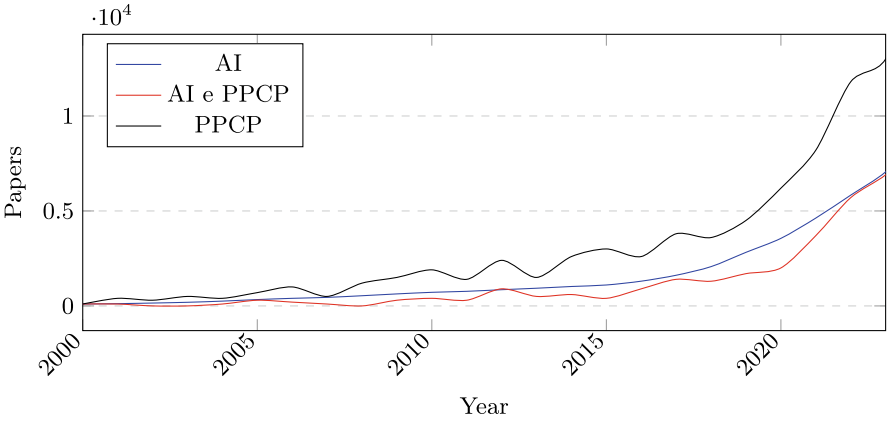

Fig. 1. Normalized growth in the volume of publications for AI, AI and PPCP, and PPCP between 2000 and 2024.

Analysis of the graph reveals that despite the sharp increase in the volume of publications addressing PPCP, the number of publications involving both PPCP and AI has not mirrored this growth. This indicates a gap between the volume of scientific publications on the intersection of PPCP and AI and those focusing solely on PPCP. Such a discrepancy suggests a clear research opportunity to explore these two fields by applying advances from one to the domain of the other.

Ultimately, this work aims to analyze, through a systematic review, the application of models that integrate Artificial Intelligence (AI) and Optimization in textile MSEs—covering both raw material production and apparel manufacturing—to identify the research opportunities the field presents.

Previous reviews, such as Giri et al. [13] and Bi et al. [9], discuss specific technologies within the textile industry. However, the key differentiator of this systematic review lies in its evaluation of diverse technologies within the context of PPCP applied to the textile and similar sectors. The authors begin from an agnostic standpoint and identify which approaches emerge as most promising. This heterogeneous lens reduces bias and strengthens confidence in the findings.

The article is organized as follows: Methodology (planning, objectives, and research questions); Results (selected studies); Discussion (interpretation against the research questions); and Conclusion (key insights and future work).

2 Methodology

The methodology adopted in this Systematic Literature Review (SLR) follows the guidelines proposed by Kitchenham et al. [16], aiming to identify, evaluate, and synthesize scientific evidence on models and techniques for workload balancing applicable to textile Micro and Small Enterprises (MSEs). The methodological process was structured into three main phases: review planning, execution

of the search and selection protocol, and data extraction and synthesis. Each of these phases was conducted rigorously, using explicit inclusion, exclusion, and quality assessment criteria for the studies to ensure reproducibility and reduce bias in the analysis.

2.1 Research Planning

The Systematic Literature Review begins with a methodological planning phase to reduce errors and bias in the selection and analysis of studies. This planning defines the research objective, the research questions, the search string, and the inclusion and exclusion criteria. These elements are essential for the subsequent conduction phase.

Research Objective and Research Questions

- **Research Objectives**:
  - To identify existing models and algorithms for workload balancing in the textile sector or similar industrial contexts, aiming to optimize the utilization of available human resources;
  - To analyze optimization approaches applied to PPCP problems in similar industries, with the goal of mitigating the impact of these challenges;
  - To evaluate modern artificial intelligence techniques (e.g., deep learning, genetic algorithms, LLMs) for solving NP-Hard problems—which are difficult to solve but easy to verify—in industrial contexts;
  - To identify strategies for simplifying order entry and allocation processes within production systems;
  - To map stochastic demand forecasting solutions that address the challenges of the textile industry, such as high volatility and short product lifecycles.

To ensure all established objectives are addressed, the research questions were formulated to guide the investigation. These are divided into a primary question and secondary questions. The primary question (PQ) is: "**What are the most effective models and techniques for workload balancing in textile Micro and Small Enterprises (MSEs) or companies in similar contexts?**". The secondary questions are as follows:

- **Secondary Questions (SQ)**:
  - SQ1: Which optimization algorithms perform best regarding computational time and solution quality for PPCP problems within the textile context or similar companies?
  - SQ2: How have deep learning, genetic algorithm, and LLM approaches been applied to solve job shop scheduling problems in industries with characteristics similar to the textile sector?
  - SQ3: What strategies for data entry simplification and process automation have been utilized in PPCP systems for MSEs?

- SQ4: Which demand forecasting models are most suitable for the context of order variability in the textile sector or companies in similar contexts?
- SQ5: What are the key factors affecting production line balancing in textile companies?
- SQ6: What are the types of applications and scenarios utilized in the reviewed models?

Search Engine, Inclusion and Exclusion Criteria. The search strategy was designed to identify studies involving production planning, optimization techniques, and artificial intelligence, with a focus on the textile industry and Micro and Small Enterprises (MSEs).

The initial string was developed for the Scopus database [5] and adapted for other databases, such as: IEEE Xplore [3], ACM Digital Library [1], Web of Science [7], Science Direct [4], Springer Link [6], and arXiv [2]. The primary search string is as follows:

```
 ALL(("production planning" OR "PPCP" OR "PCP" OR "scheduling" OR
"job shop scheduling") AND
("workload balancing" OR "line balancing" OR "resource allocation"
OR "production optimization") AND
("small enterprise*" OR "small business*" OR "small companies" OR
"SME") AND
("optimization algorithm*" OR "deep learning" OR "genetic
algorithm*" OR "metaheuristic*" OR
"machine learning" OR "LLM" OR "large language model*" OR
"generative AI"))
```

The inclusion and exclusion criteria, which determine which studies are to be included in or excluded from the systematic review, were established as follows:

– **Inclusion Criteria**:
  - Studies that address workload balancing techniques in the textile sector or in similar contexts;
  - Studies that apply optimization algorithms to PPCP problems;
  - Studies that utilize deep learning, genetic algorithms, or large language models (LLMs) for PPCP;
  - Studies that propose demand forecasting models applicable to the textile industry or to sectors with similar characteristics;
  - Studies that discuss process simplification in PPCP systems;
  - Studies published in English;
  - Full papers published in peer-reviewed scientific journals or conference proceedings;
  - Studies published from 2019 onwards.

– **Exclusion Criteria**:

- Studies lacking practical application or empirical validation;
- Studies focused exclusively on large enterprises, without applicability to MSEs;
- Studies that do not detail the methodology or the algorithms used;
- Literature reviews, editorials, conference abstracts, and other types of gray literature;
- Duplicate studies (with only the most complete version being considered);
- Studies with unavailable full text;
- Studies published before 2019.

2.2 Execution

The review's execution followed a protocol structured into two main phases: preliminary selection and final selection. Table 1 presents the number of studies included and excluded in each phase.

Table 1. Works included and excluded at each phase

	Input	Removed	Remaining
Initial Screening	379	353	26
Final Selection	26	3	23

During the preliminary selection phase, a search was conducted across the previously selected databases using the search strings defined in the methodology. After retrieving the results, duplicates were removed. Subsequently, the titles and abstracts of the remaining studies were screened against the established inclusion and exclusion criteria.



Fig. 2. Review steps

As illustrated in Fig. 2, preliminary screening excluded 353 out of 379 studies that did not meet the inclusion criteria or met the exclusion criteria. The remaining 26 studies were deemed relevant and thus advanced to the full-text review stage.

In the final selection, the articles underwent a complete reading, with strict application of the inclusion and exclusion criteria, resulting in the exclusion of 3 of the 26 articles, ensuring the final set aligned with the research objectives and questions.

In cases of disagreement between reviewers, decisions were reached through consensus.

3 Results

3.1 Overview of the Papers

Table 2 lists all the articles remaining after the final selection.

Table 2. Overview of all papers

Id	Authors	Year	Document Type
[27]	Singh et al.	2025	Article
[19]	Li et al.	2025	Article
[18]	Le et al.	2024	Article
[26]	Shahin et al.	2024	Article
[33]	Wang	2024	Conference paper
[24]	Qaffas et al.	2023	Article
[21]	Marín et al.	2023	Article
[29]	Stavropoulos et al.	2023	Review
[20]	Li et al.	2023	Article
[11]	De Oliveira et al.	2023	Article
[22]	Nedra et al.	2022	Article
[10]	Darmian et al.	2022	Article
[17]	Kulka et al.	2022	Article
[31]	Wan et al.	2022	Article
[37]	Zhang et al.	2021	Article
[14]	Guo et al.	2021	Article
[32]	Wang et al.	2021	Article
[30]	Teerasoponpong et al.	2021	Article
[8]	Bai et al.	2021	Article
[35]	Wang et al.	2021	Article
[36]	Zennaro et al.	2020	Article
[34]	Wang et al.	2020	Article
[12]	Eccher et al.	2020	Review

Most of the selected studies were published in 2021 (n = 6) and 2023 (n = 5). The remainder of the publications were from 2022 (n = 4), 2020 (n = 3),

2024 (n = 3), and 2025 (n = 2). No studies from 2019 were selected. Figure 3 shows a chart with the distribution of the studies by year.

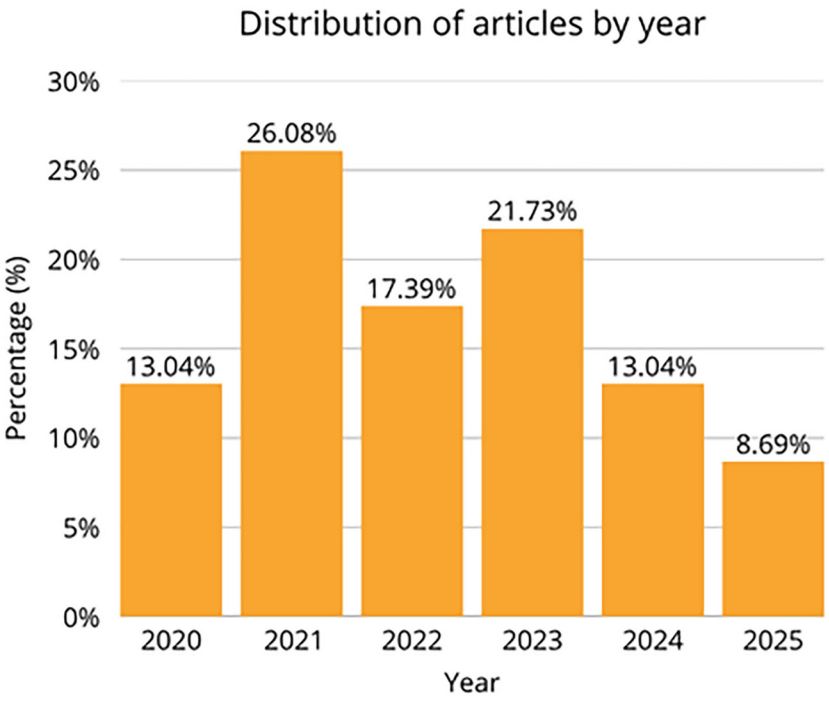

Fig. 3. Distribution of articles by year.

Furthermore, to aid in the thematic analysis, a word cloud was generated from the abstracts of the articles approved in the final phase (Fig. 4). To prevent visual clutter, numbers and common stop words were excluded.



Fig. 4. Word cloud of the abstracts of the selected articles

4 Discussion

This section addresses the primary research question (PQ) and the secondary questions (SQ).

4.1 PQ: What Are the Most Effective Models and Techniques for Workload Balancing in Textile Micro and Small Enterprises (MSEs) or Companies in Similar Contexts?

Several studies indicate that the most effective models and techniques for workload balancing in textile Micro and Small Enterprises (MSEs), or in similar industrial contexts, are those that combine hybrid and adaptive approaches capable of handling the production variability and resource constraints characteristic of these organizations [14,19,22,27,30,33,35,37]. Notable among these are models that integrate Lean Six Sigma with discrete-event simulation [22], providing significant gains in operational efficiency; hybrid genetic algorithms applied to the optimized allocation of human resources and production tasks [33]; and approaches based on Dynamic Takt Time (dTT), which adjust the production pace in real-time, reducing idle time by up to 46% [37]. Other relevant strategies include the use of Intelligent Machine Monitoring System (IMMS) [27], digital twins combined with GRAFCET [14], flexible cellular manufacturing, and models that logically separate assembly and line-feeding tasks to optimize labor utilization [19]. Techniques such as Shojinka [35] and models based on neural networks combined with evolutionary algorithms [30] also prove effective, especially in environments with highly variable demand.

Table 3. Models

Model	Refs
Lean Six Sigma	[22]
Hybrid Genetic Algorithms	[33]
Semi-Supervised Explainable k-means	[24]
Digital Maturity Level	[21]
Iterative Two-step heuristic based on Local Search	[10]
XGBoost Stacked Model	[31]
Analytic Hierarchy Process	[11]
Smart Machine Monitoring System	[27]
AC-Ptr	[19]
Convolutional Neural Network	[26]
Monte Carlo Tree Search	[34]
Bee Colony	[37]
Artificial Neural Network	[30]
Recommended Cleaning Scheduling	[12]

4.2 SQ1: Which Optimization Algorithms Exhibit the Best Performance in Terms of Computational Time and Solution Quality for PPCP Problems in the Textile Sector or Similar Industrial Settings?

Analysis of the literature reveals a divergence of opinion among various authors regarding which optimization algorithm exhibits the best performance [10,11, 19,22,27,30,33–35].

Nedra et al. [22] propose the use of Lean Six Sigma (LSS), which resulted in a 5% reduction in process time compared to the original baseline. It is worth noting that Lean methods combined with a cellular layout can be highly effective in terms of solution quality and implementation simplicity, especially when computational resources are constrained [35].

Similarly, Wang [33] and Teerasoponpong et al. [30] address the use of genetic algorithms (GA). While Teerasoponpong et al. [30] highlight the robust and effective search capabilities of GA, Wang [33] utilizes a combination of GA with tabu search, a type of Hybrid GA, aiming to increase calculation accuracy. The proposed algorithm demonstrates better performance in human resource allocation, resulting in an optimized utilization of at least 92%, whereas other algorithms, such as Ant Colony and cyclic neural network, could not exceed 80% utilization. Furthermore, the Hybrid GA required 40 iterations, compared to 240 for the other algorithms, demonstrating faster convergence.

Finally, some authors propose their own custom models. Darmin et al. [10] developed a two-stage iterative heuristic based on local search (ITbLS), which showed superior performance to CPLEX with a gap of less than 2.4%. Singh et al. [27] propose an algorithm named Intelligent Machine Monitoring System

(IMMS), which increased productivity by 55% compared to a conventional ERP. The AC-Ptr algorithm, proposed by Li et al. [19], has a worse computational time compared to Actor-Critic, Proximal Policy Optimization, and Approximation algorithms; however, in terms of revenue, it results in an increase of 7.23% to 37.44% compared to the other algorithms. Wang et al. [34] compare Monte Carlo Tree Search (MCTS) with the value iteration (VI) algorithm, concluding that MCTS provides an optimal solution with a 0 to 1% gap and a lower computational time than VI, thus being a solution with better overall performance. In contrast, De Oliveira et al. [11] propose algorithms but do not present performance metrics or comparisons with other algorithms.

In conclusion, different optimization approaches perform well on PPCP problems, highlighting the trade-off between computational time and solution quality. Methods such as the Hybrid Genetic Algorithm (GA), Monte Carlo Tree Search (MCTS), and Lean Six Sigma (LSS) achieved satisfactory results along with a reduction in computational time.

4.3 SQ2: How Have Deep Learning, Genetic Algorithm, and LLM Approaches Been Applied to Solve Job Shop Scheduling Problems in Industries with Characteristics Similar to the Textile Sector?

Job Shop Scheduling (JSS) is the process of determining the sequence in which different tasks must be performed on each machine, with the objective of minimizing the total production time (makespan). In this context, Teerasoponpong et al. [30] propose the use of Artificial Neural Networks (ANN) and Genetic Algorithms (GA), where the ANN is trained to simulate the production process, and the GA utilizes the ANN to evaluate each proposed solution in search of the optimal one. However, the paper in question does not use a Job Shop model, but rather a Flow Shop model, as there is a predefined flow of tasks, which is not the case in JSS. Nevertheless, the way the simulation/optimization methods are employed is noteworthy due to its flexibility.

Ultimately, only Eccher et al. [12] mentions JSS. In it, the authors advocate for their own solution, called Recommended Cleaning Scheduling (RCS). The solution uses mathematical operations and concepts, such as summations and objective functions, to determine the decision-making process. However, despite discussing the disadvantages of other solutions, no concrete metrics are presented comparing other algorithms, such as genetic algorithms, with RCS.

Therefore, after analyzing the articles, it is not possible to specify how the application of technologies like deep learning, genetic algorithms, and LLMs can directly affect Job Shop Scheduling. This becomes problematic, since JSS is NP-Hard and MSEs don't have the computational capacity for exhaustive search (brute force and back tracking) of solutions, so the question of performance under such circumstances becomes interesting for them. It can be stated, however, that GA, ANN, and Deep Learning can be used for simulation and optimization within the industrial context [30].

4.4 SQ3: What Strategies for Data Entry Simplification and Process Automation Have Been Utilized in PPCP Systems for Micro and Small Enterprises (MSEs)?

Analysis of the reviewed literature indicates that to simplify data entry and system setup, object-oriented modeling is utilized to create virtual factory models, often in conjunction with direct data importation from ERP and MES systems. This approach reduces the manual workload of data entry and maintenance for planners [32]. The same study notes that the use of package diagrams also enhances modeling efficiency and data stability. Additionally, for MSEs with fragmented data, observational and empirical data are employed as an alternative, which minimizes collection costs and operational disruptions without the need for complex ERPs [30].

In the context of process automation, prominent solutions include Cloud-based Advanced Planning and Scheduling (C-APS) systems, which provide cost-effective, practical solutions featuring 'on-demand self-service' and rapid adaptation to new products or processes [32]. Additionally, Digital Twins (DTs) enable continuous simulation and optimization of production lines, allowing for fast adjustments to layout and processes [14]. They also support micro smart factories in intelligent data collection, control, and maintenance, including blockchain integration for authenticity and traceability [8]. For specific task automation, RFID is used for material tracking, AGVs for flexible movement, and MES for scheduling and resource optimization logic [8].

In terms of operations, the active and idle assembly islands (AII) strategy optimizes operator time and parts feeding for large, customized products by allowing for parallel preparation and avoiding non-value-added activities. Finally, modeling and simulation using Lean Six Sigma (LSS) and BPMN help to identify waste and bottlenecks, thereby facilitating future automations [22].

4.5 SQ4: Which Demand Forecasting Models Are Most Suitable for the Context of Order Variability in the Textile Sector or Companies in Similar Contexts?

A review of the literature indicates that to manage the typical order variability in micro and small enterprises (MSEs) in the textile sector, the most suitable models are those that capture non-stationary and stochastic demand. This characteristic is common in products with short life cycles and production variable demand patterns [30,34].

Models based on Markov Decision Processes (MDP), combined with algorithms such as Monte Carlo Tree Search (MCTS), demonstrate efficiency in considering demand dynamics and lead times, while also offering good computational scalability [34].

Furthermore, simulation-optimization approaches are recommended for environments with incomplete data and uncertainty, which are typical of MSEs [30]. The integration of Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) into simulation frameworks allows for learning patterns from observational

data, thereby overcoming collection limitations and producing optimal solutions for various production targets [30].

4.6 SQ5: What Are the Key Factors Affecting Production Line Balancing in Textile Companies?

Based on the analysis of the reviewed studies, the key factors affecting production line balancing in textile companies involve both operational and structural aspects. Among the operational factors, notable issues include: demand variability [30,32,35]; the sequencing of operations and sequence-dependent setup times [32]; and labor variability, along with the need for flexibility to handle different product types and volumes [30].

Regarding structural aspects, Guo et al. [14] highlights elements such as inadequate layouts and unbalanced process capacity, while task precedence constraints and finite machine capacity directly influence line efficiency, as evidenced by Eccher et al. [12]. Other critical factors include: bottlenecks at specific workstations, noted by Nedra et al. [22]; the use of buffers, according to Bai et al. [8]; as well as Cleaning-In-Place (CIP) times, equipment failures (MTBF), and imprecise logistics, which are also pointed out by Guo et al. [14].

Additionally, the digital maturity of companies, as discussed by Stavropoulos et al. [29], as well as technological integration and human-machine collaboration, are crucial for achieving an efficient balance. This is especially true when these are combined with intelligent systems like Manufacturing Execution Systems (MES) and real-time control technologies such as RFID. When not managed in an integrated manner, these factors can compromise the production flow and make it difficult to achieve a consistent work pace (takt time) [37].

4.7 SQ6: What Are the Types of Applications and Scenarios Utilized in the Reviewed Models?

The models examined in the literature have been applied across a broad spectrum of industrial scenarios and operational contexts. There is a notable emphasis on micro, small, and medium-sized enterprises (MMSEs) in diverse sectors, including textile, automotive, electronics, and chemicals. These applications also extend to custom assembly and high-mix production industries [37].

Applications range from production line balancing [14]; dynamic worker allocation [19,33]; adaptive production capacity planning [30,34]; and multi-criteria inventory classification [24]; to more specific scenarios such as predictive maintenance [26]; quality control; industrial cybersecurity; and logistics during health crises [10].

Studies featuring simulations of real production lines were identified, with applications including trouser manufacturing in the textile sector [22], and the production of air conditioners, printed circuit boards and automotive seals [8, 32]. The tools utilized in these simulations include digital twins, reinforcement learning models (e.g., MDP and MCTS), and discrete-event simulation [35].

The models have also been applied to companies in emerging economies [18]. These applications focus on areas such as supply chain resilience; digital transformation [20,21]; and operational flexibility. This demonstrates the versatility and adaptability of these solutions across different industrial environments.

4.8 Comparative Analysis

Due to space constraints, a comprehensive comparison of the models detailing their respective inputs, evaluation metrics, datasets, and limitations is provided as external supplementary material[1]. An analysis of the data presented in this comparison reveals a pattern: the proposed models operate on a large input space comprising multiple variables, yet their performance is evaluated against a narrow, set of metrics. This suggests that problem complexity resides not in the outputs, but in the intricate relationships between the various inputs.

Furthermore, no pattern emerges regarding dataset usage, as the reviewed studies utilize a wide variety of real-world, synthetic, public, and private datasets of varying sizes.

Finally, the identified limitations can be categorized into two groups: low external validity and low practical applicability. For models with low external validity, the most recurrent limitations were the assumption that dynamic factors are constant and the failure to consider influential process factors. As for models with low applicability, the primary limitations revolved around a lack of flexibility, high cost, and significant operational time.

4.9 Broader Implications

The findings of these studies can benefit Micro and Small Enterprises (MSEs) in several ways. Notably human resource optimization [19,33], and increased operational efficiency, whether through faster process execution or cost reduction [12,22,30].

From an organizational perspective, the evaluated models not only simplify routine tasks but also aids in the holistic assessment of processes. Implementing these models enables an organization to optimize staff allocation, forecast demand, and minimize idle time. For instance, a manager can utilize these models to assign an employee to tasks where they excel and for which demand is forecasted, thereby optimizing the production process.

From a theoretical perspective, this review identifies a clear trend in PPCP: a shift from monolithic models to more flexible approaches. Recent literature shows growth in hybrid algorithms [30,33], and of models with well-defined functionalities [14,27]. Accordingly, modern PPCP system should not be confined to a single algorithm but should integrate the complementary strengths across models. The feasibility of collaboration between these models, observed in the analysis, reinforces the potential for the development of modular, multi-model PPCP systems.

[1] The complete comparison table is available at: https://drive.google.com/file/d/1X02QxtRvIZ0ZDHm8HyWUja9duyOdSKSN/view?usp=sharing.

4.10 Limitations of the Review

The review process revealed several limitations. Notably, identifying studies that met the inclusion criteria was difficult, especially those demonstrating practical applications of PPCP algorithms. A further limitation was finding multiple articles covering the same technologies. As demonstrated in Table 3, each paper proposes a different model, making it more complex to compare the various lines of thought and impeding a straightforward interpretation.

Another limitation concerns the differences within the final set of studies. We searched for studies that offered solutions for textile SMEs or other sectors with similar characteristics (e.g. high demand variability, labour-intensive, limited resources). Consequently, the last group of studies includes various industries. The findings may not be very generalizable to textiles are in line with the intent of identifying approaches that may be transferable.

5 Conclusion and Future Work

The studies reveal a pattern in the use of genetic algorithms (GAs) combined with other technologies, such as Tabu Search or Artificial Neural Networks (ANNs). These combinations aim to enhance the GA's performance, which is notable for its capabilities in load balancing, as well as the optimization and simulation of resources and environments.

Solutions involving Lean Six Sigma (LSS) are effective for load optimization and balancing by their ability to identify waste and bottlenecks. Other approaches, such as Monte Carlo Tree Search (MCTS), focus on load balancing and demand forecasting, while Intelligent Machine Monitoring Systems (IMMS) focus on load balancing and resource optimization.

No study included in this review has explicitly addressed the use of LLMs within PPCP systems, which indicates a clear gap in the current literature. This lack of research makes itself apparent when considering that SMEs usually lack structured data and generally run on undocumented knowledge. LLMs might address this shortage of structured data by providing a human - like interface that allows for easy order submission or decision-making support, thus bypassing the need for extensive computer knowledge from those running the business. Moreover, while Eccher et al. [12] covers Job Shop Scheduling (JSS), the paper does not provide concrete metrics to demonstrate the proposed algorithm's performance against genetic and deep learning algorithms.

For future work, the authors plan to investigate the application of JSS to process planning within MSEs, with the goal of enhancing productivity and lowering costs. Additionally, a PPCP system focused on the textile industry's MSEs will be developed. Furthermore, the potential of applying intelligent models optimized for this specific context will be explored to increase productivity, reduce costs, and shorten idle periods. The proposed model will be designed to understand natural language, generate context-aware responses, and support decision-making processes.

Acknowledgments. This study was supported by the CNPq, National Council for Scientific and Technological Development - Brazil (grant number 443723/2024-9).

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Acm digital library (2025). https://dl.acm.org/. Accessed 4 July 2025
2. arxiv e-print archive (2025). https://arxiv.org/. Accessed 4 July 2025
3. Ieee xplore digital library (2025). https://ieeexplore.ieee.org/. Accessed 4 July 2025
4. Sciencedirect (2025). https://www.sciencedirect.com/. Accessed 4 July 2025
5. Scopus (2025). https://www.scopus.com/. Accessed 4 July 2025
6. Springer link (2025). https://link.springer.com/. Accessed 4 July 2025
7. Web of science (2025). https://www.webofscience.com/. Accessed 4 July 2025
8. Bai, Y., You, J.B., Lee, I.K.: Design and optimization of smart factory control system based on digital twin system model. Math. Probl. Eng. **2021**(1), 2596946 (2021)
9. Bi, Y., Pan, L., Cao, L.: Research status and development trends of digital twin technology in apparelproduction: a review. J. Text. Inst. (2025)
10. Darmian, S.M., Farughi, H.: An optimization-based approach for managing downstream logistic operations: a real application in pandemic outbreak conditions. Comput. Ind. Eng. **171**, 108495 (2022)
11. De Oliveira, U.R., de Souza, H.A.D., Menezes, C.A.G., Rocha, H.M.: Straightening machine preventive maintenance intervention plan based on ahp: a case study in a steel company in brazil. Oper. Manag. Res. **16**, 1577–1593 (2023)
12. Eccher, C., Geraghty, J.: Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process: a dairy case study. J. Manuf. Syst. **55**, 159–170 (2020)
13. Giri, C., Jain, S., Zeng, X., Bruniaux, P.: A detailed review of artificial intelligence applied in the fashion and apparel industry. IEEE Access **7**, 95376–95396 (2019)
14. Guo, H., Chen, M., Mohamed, K., Qu, T., Wang, S., Li, J.: A digital twin-based flexible cellular manufacturing for optimization of air conditioner line. J. Manuf. Syst. **58**, 65–78 (2021)
15. Hulla, M., Herstätter, P., Wolf, M., Ramsauer, C.: Towards digitalization in production in smes – a qualitative study of challenges, competencies and requirements for trainings. Procedia CIRP **104**(1), 887–892 (2021)
16. Kitchenham, B., Brereton, O.P., Budgen, D., Turner, M., Bailey, J., Linkman, S.: Systematic literature reviews in software engineering-a systematic literature review. Inf. Softw. Technol. **51**(1), 7–15 (2009)
17. Kulka, J., Mantic, M., Onofrejova, D., Siman, M.: Case study of production optimization using the enumerative method. MM Sci. J. **June | 2022**, 5656–5661 (2022)
18. Le, T.T., Behl, A.: Linking artificial intelligence and supply chain resilience: roles of dynamic capabilities mediator and open innovation moderator. IEEE Trans. Eng. Manag. **71**, 8577–8590 (2023)

19. Li, D., Jin, H., Zhang, Y.: Dynamic worker allocation in seru production systems with actor-critic and pointer networks. Eur. J. Oper. Res. **324**(1), 62–74 (2025)
20. Li, L., Xu, S.X., Ning, Y., Liu, Y., Yang, S.: How should companies deploy their digital supply chain platforms to gain competitive advantages? An asset orchestration perspective. Inf. Manag. **60**(6), 103842 (2023)
21. Marín Díaz, G., Galdón Salvador, J.L.: Group decision-making model based on 2-tuple fuzzy linguistic model and ahp applied to measuring digital maturity level of organizations. Systems **11**(7), 341 (2023)
22. Nedra, A., Néjib, S., Boubaker, J., Morched, C.: An integrated lean six sigma approach to modeling and simulation: a case study from clothing sme. Autex Res. J. **22**(3), 305–311 (2022)
23. OECD: Introductory paper on smes and responsible business conduct in the garment and footwear sector. Website (2018). https://mneguidelines.oecd.org/Introductory-paper-on-smes-and-responsible-business-conduct-in-the-garment-and-footwear-sector.pdf. Accessed 5 July 2025
24. Qaffas, A.A., Hajkacem, M.A.B., Ncir, C.E.B., Nasraoui, O.: Interpretable multi-criteria abc analysis based on semi-supervised clustering and explainable artificial intelligence. IEEE Access **11**, 43778–43792 (2023)
25. SEED: Asia future lab for innovation and policy background note: Textile and fashion in asia. Website (2022). https://www.switch-asia.eu/site/assets/files/3488/asia_future_lab_background_note.pdf. Accessed 5 July 2025
26. Shahin, M., Maghanaki, M., Hosseinzadeh, A., Chen, F.F.: Improving operations through a lean ai paradigm: a view to an ai-aided lean manufacturing via versatile convolutional neural network. Int. J. Adv. Manuf. Technol. **133**(11), 5343–5419 (2024)
27. Singh, J., Singh, A., Singh, H., Doyon-Poulin, P.: Implementation and evaluation of a smart machine monitoring system under industry 4.0 concept. J. Ind. Inf. Integr. **43**, 100746 (2025)
28. Statista: Textiles - worldwide. Website (2025). https://www.statista.com/outlook/io/manufacturing/material-products/textiles/worldwide. Accessed 5 July 2025
29. Stavropoulos, P., Papacharalampopoulos, A., Sabatakakis, K., Mourtzis, D.: Metamodelling of manufacturing processes and automation workflows towards designing and operating digital twins. Appl. Sci. **13**(3), 1945 (2023)
30. Teerasoponpong, S., Sopadang, A.: A simulation-optimization approach for adaptive manufacturing capacity planning in small and medium-sized enterprises. Expert Syst. Appl. **168**, 114451 (2021)
31. Wan, J.: Demand prediction and optimization of workshop manufacturing resources allocation: a new method and a case study. Adv. Prod. Eng. Manag. **17**(4), 413–424 (2022)
32. Wang, L.C., Chen, C.C., Liu, J.L., Chu, P.C.: Framework and deployment of a cloud-based advanced planning and scheduling system. Robot. Comput.-Integr. Manuf. **70**, 102088 (2021)
33. Wang, L.: Improved human resource allocation method based on genetic algorithm. In: Intelligent Computing Technology and Automation, pp. 97–104. IOS Press (2024)
34. Wang, L., Ai, W., Deng, T., Shen, Z.J.M., Hong, C.: Optimal production ramp-up in the smartphone manufacturing industry. Nav. Res. Logist. (NRL) **67**(8), 685–704 (2020)
35. Wang, P.S., Lin, C.C., Yang, T.: A study on shojinka design for automobile engine piston-rod manufacturing. Comput. Ind. Eng. **151**, 106974 (2021)

36. Zennaro, I., Finco, S., Calzavara, M., Battini, D., Persona, A.: A parts feeding model for big size products: the active and idle assembly islands strategy. Int. J. Adv. Oper. Manag. **12**(3), 211–236 (2020)
37. Zhang, W., Hou, L., Jiao, R.J.: Dynamic takt time decisions for paced assembly lines balancing and sequencing considering highly mixed-model production: an improved artificial bee colony optimization approach. Comput. Ind. Eng. **161**, 107616 (2021)