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Research Article

Including Labor Flexibility in the Integrated Suppliers' Selection and Aggregate Production Planning Problem Under Uncertainty

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Abstract: Uncertainty inherent to suppliers and customers must be effectively managed for planning decisions. The former directly affects production capacity, while the latter influences demand, both impacting production planning. To align production capacity with demand requirements, tactical production planning models serve as data-driven decision-support tools. However, uncertainty in key parameters can lead to impractical decisions and unfulfilled demand. To address these challenges, this paper presents an integrated approach that combines a multi-period tactical production planning model with the supplier selection problem, explicitly accounting for stochastic demand and supplier non-compliance by modeling a network that facilitates labor transfers between production lines. This approach mitigates the impact of uncertain demand and enhances workforce capacity utilization. The proposed framework is applied to a manufacturing company that processes a single raw material into multiple final products through multiple production lines. We extend the proposed deterministic formulation into a two-stage stochastic programming model, which incorporates labor flexibility, enabling workers to shift between production lines when needed. To enhance decision-makers' what-if analysis capabilities, a two-phase matheuristic is also proposed. In the first phase, a surrogate model is solved to reduce the search space of selected suppliers in time periods, while in the second phase, the reduced problem is optimized. The results demonstrate the matheuristic's advantages in terms of solution quality and computational efficiency. These findings indicate that the proposed approach holds significant value for practitioners. Furthermore, our computational experiments show that allowing workers to shift between production lines reduces overall production planning costs and improves supplier acquisition decisions. At lower levels of flexibility, however, the model recommends lower investment in supplier transactions, which results in higher initial installed labor capacity and greater inventory accumulation over time.

Keywords: supplier selection, production planning, labor flexibility, stochastic programming, matheuristics

MSC: 90B30, 90B70, 90C15

1. Introduction

Due to the complexity of modern supply chains, selecting suppliers is a challenging task in Supply Chain Management (SCM) because of the inherent uncertainty involved. Furthermore, another sources of uncertainty, such as customer

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demand, increase the complexity of the supplier selection process. An inadequate selection of suppliers can lead to increased lead times, disrupting production processes and, in some cases, reducing customer service levels, which may ultimately result in customer loss. This negative impact affects not only customers but also the organization itself. Supplier non-compliance can lead to underutilized labor capacity due to a lack of necessary raw materials for proper operation. The importance of addressing this uncertainty is evident. One approach is to incorporate labor flexibility, which enhances the operational efficiency of workforce capacity [1]. Labor flexibility enables the use of temporary workers or allows for the transfer of workers within a manufacturing network, enhancing productivity and mitigating the impact of uncertainties.

Since Supplier Selection (SS) is one of the most critical activities in SCM [2, 3], one of the main focuses is on increasing customer satisfaction and reducing lead times [4]. Particularly due to the growing adoption of total quality management and just-in-time concepts, the integration of SS with other SCM activities has attracted the attention of researchers and practitioners. [5] study the importance of partially integrating certain SCM functions, emphasizing the difficulty of achieving full integration. However, integrating some components helped avoid excessive inventory costs and shortages. According to the reviews of [6, 7], future directions of research related to production planning involve the integration of various SCM activities, promoting the efficient utilization of human, technological, and financial resources.

As noted in [8], production planning and control systems cannot be fully integrated into a single framework, such as Manufacturing Resource Planning II. However, addressing SCM activities independently is not efficient. Therefore, the integration of different SCM activities represents a promising research direction that deserves further attention. For example, [9] demonstrated the relevance and positive impact of integrating specific SCM activities. Furthermore, [10] not only highlighted the benefits of such integration but also quantified the impact of accounting for uncertainty in the process.

Specifically, integrating SS with Aggregate Production Planning (APP) activities enhances workforce utilization efficiency. As a result, production cost minimization and productivity maximization are achieved. This integration also enhances the responsiveness of the supply chain, leading to a more agile supply chain. For example, an adequate SS that meets demand requirements allows companies to estimate the correct production capacity levels, thereby enabling feasible scheduling and activity sequencing, as indicated in [11].

According to [7], oversimplifying production planning problems may result in short-term conflicts. On the other hand, [3] concluded that enhancing SCM is essential for increasing competitiveness. Therefore, it is crucial to integrate SS with other SCM activities at both the tactical and operational levels. Specifically, the gap we address in the literature concerns the integration of supplier selection, when raw materials are of fairly similar quality, with workforce estimation. To tackle this novel problem, we develop a two-phase matheuristic algorithm. This scheme first solves the supplier selection problem and then addresses workforce estimation alongside an APP problem. It leverages labor transfers between production lines as a flexibility mechanism to enhance labor capacity utilization without resorting to layoffs, which are undesirable due to new strict labor regulations [1].

Our study provides stochastic modeling approaches related to tactical decisions in SCM, focusing on supplier selection and the workforce capacity required in a manufacturing company, which can be used by decision-makers. Specifically, our contributions are listed as follows:

- We study the SS and APP problems for the first time by modeling a network that facilitates labor transfers between production lines. This approach mitigates the impact of uncertain demand and enhances workforce capacity utilization.
- We present a mixed-integer mathematical programming formulation for the SS and APP problem in a manufacturing company that processes a single raw material into multiple final products.
- We extend the proposed deterministic formulation into a two-stage stochastic programming model that accounts for stochastic demand and supplier compliance.
- We develop a two-phase matheuristic procedure. In the first phase, a surrogate model is solved to reduce the set of suppliers, while in the second phase, the reduced problem is optimized.
- The results of the proposed matheuristic demonstrate improved performance in both computational time and solution quality, enhancing decision-makers' ability to conduct more effective what-if analyses.

The key features of the problem proposed in this paper include the integration of SS and APP to determine the optimal suppliers and workforce capacity under uncertain demand. First, the problem is formulated, and its deterministic equivalent is solved using a general-purpose solver. Then, a two-phase matheuristic approach is developed. In the first phase, the SS problem is addressed. In the second phase, the APP problem is efficiently solved with the aid of valid inequalities. The novelty of this approach is twofold: first, the integration of both problems under stochastic demand, using labor transfers as an instrument of flexibility to mitigate the impact of uncertainty; and second, the development of a matheuristic algorithm that incorporates a surrogate model and solves a reduced-size problem.

The remainder of this paper is organized as follows: Section 2 presents the literature review, highlighting the importance of integrating production planning with other problems. Relevant studies related to APP under uncertainty and supplier selection problems are also reviewed. In Section 3, the problem under study is described. Section 4 details the proposed matheuristic algorithm. The computational results obtained from experimentation on a set of challenging instances are discussed in Section 5, along with interesting managerial insights. Finally, Section 6 presents the conclusions and outlines some promising future research directions.

2. Literature review

In this literature review, we first describe APP and discuss relevant studies, with an emphasis on problems that incorporate uncertainty. Next, we take the same approach for SS. Finally, we examine the integration of production planning models with other optimization problems within the supply chain.

APP is concerned with aligning production capacity and demand while minimizing costs related to production, inventory, and workforce levels [2, 12, 13]. Other approaches to production and inventory problems include joint inventory and pricing models [14], inventory models for multi-echelon supply chains [15], lot-sizing models with multi-level supply [16], and models focused on operational aspects such as inventory and transportation management, often studied as scheduling problems [17]. The main advantage of APP over these approaches lies in its hierarchical position within the supply chain, specifically in bridging strategic and tactical decisions, which are typically the responsibility of executives and operations managers.

A review of studies that apply APP across a wide range of industries, such as machinery, appliances, garments, food and beverages, wood, and chemicals, is presented in [6]. In particular, a goal programming approach for a multi-site APP in the textile industry is proposed in [18]. A hybrid discrete-event simulation combined with a system dynamics strategy for a soft drink company is studied in [19], while an APP with a flexible workforce in the automotive industry is analyzed in [20]. A multi-site APP with a case study in the wood and paper industry is solved in [21]. In addition, a multi-stage stochastic programming model for the sawmill industry is presented in [22]. More recently, an APP for biochar, a product obtained from biomass, is considered in [23].

As can be seen from the referenced studies, stochasticity has been considered in some of the parameters involved in APP problems. To address the inherent uncertainty in production systems, approaches involving fuzzy sets and stochastic programming frameworks are commonly used. In the review presented in [24], the importance of considering uncertainty in different production planning strategies, particularly in APP, is highlighted, while it is pointed out in [6] that APP with uncertainties has been consistently overlooked in recent research.

For solving APP problems under uncertainty, several exact methods have been proposed. In [25], a two-stage stochastic programming model is solved using a sample average approximation procedure. A piecewise linear approximation combined with a robust optimization scheme is considered in [26] to address an APP with stochastic demand, flexible lead times, and nonlinear cost functions. Similarly, a robust approximation approach that incorporates environmental constraints is employed in [27]. Furthermore, several studies propose exact methods for APP problems under uncertainty that focus on different factors, such as productivity [12, 26], multiple factories [26, 28–31], product quality [22, 25], workforce training [32], products with very limited expiration dates [33], and environmental factors [34], among others. Readers are encouraged to refer to the literature reviews presented in [12, 13] for further applications and solution strategies.

Building on the discussion of aggregate production planning, the SS problem similarly plays a critical role in supply chain efficiency. It involves determining the optimal number of suppliers for a company based on specific criteria. The importance of selecting the right supplier is highlighted in [35], which emphasizes that an effective supplier selection process contributes to cost minimization. Strategically selecting suppliers based on factors such as cost, quality, and reliability can have a positive impact on overall production costs.

Particularly, in [3] it is stated that the efficient selection of reliable suppliers, those that fulfill requested orders on time, enables smoother production processes, reduces costs associated with backlogs, and minimizes lead times. Then, in [36] it is highlighted that there is a lack of studies adopting a multi-methodological perspective in SS, particularly within fuzzy approaches.

Typically, the SS problem is treated as a deterministic model and solved using mathematical optimization techniques. However, few studies emphasize the importance of incorporating uncertainty. In [37], a minimal set of suppliers and optimal order quantities are determined while accounting for business volume discounts, and the advantages of the uncertainty-based approach over the deterministic one are highlighted. Additionally, in [38], a stochastic programming model for SS in the processed food industry is developed, considering procurement constraints on the required raw materials to adequately satisfy customer demands.

The integration of SS with carrier selection in the context of humanitarian relief operations is proposed in [39]. The problem is solved using a two-stage stochastic programming model that accounts for uncertain demand. A similar SS problem with multiple buyers, which considers uncertainty in currency fluctuations and exchange rates over time, is examined in [40]. Other SS problems have also been studied and addressed using mathematical programming techniques [41–44]; however, none integrate SS with workforce capacity decisions using flexible instruments to mitigate the impact of uncertainty, which is a novel feature of our problem under study.

Considering the discussions on APP and SS problems, it is evident that integrating production planning models with other problems within the supply chain is of great importance. For instance, the integration of an APP problem with a scheduling problem, which they solved using a recursive optimization-simulation approach is proposed in [45]. Similarly, a multi-stage stochastic programming model for the capacitated lot-sizing problem integrated with a task scheduling problem is studied in [11]. The goal is to determine the optimal capacity in the first stage to ensure feasible schedules in the remaining stages.

In [9], the authors report satisfactory results from integrating SCM decisions, such as harvesting, procurement, production, distribution, and sales, compared to addressing these activities separately. In a related study, the integration of workforce training management with production planning is proposed in [46]. This integration resulted in cost reductions of up to 40% and highlighted the benefits of jointly incorporating workforce training and mitigation strategies.

On the other hand, the integration of SS with other activities within SCM is highlighted in [3]. Examples include SS combined with order allocation, inventory management, transportation, production planning, material flows in supply chain network design, and reverse logistics, among others. Typically, the main objective is to determine all SCM decisions jointly, spanning strategic, tactical, and operational levels.

A specific integration of SS with routing decisions is studied in [47]. The overall problem consists of four sub-problems: supplier selection, pick-up, cross-docking, and delivery. A two-stage solution algorithm is employed to solve large-sized instances. Another example of integration is presented in [48], which combines fuzzy logic and mathematical programming for SS and order allocation. This approach effectively generates solutions that approximate aspiration levels and reflect the decision maker's degree of satisfaction. In [49], a heuristic algorithm is employed to integrate SS with inventory management. Additionally, in [50] valid inequalities are proposed for a reduce-and-optimize approach to the integrated SS with a lot-sizing problem.

Another example of integrating SS with SCM activities is presented in [51], where SS is combined with lot-sizing decisions in a serial supply chain. The study highlights that the length of the planning horizon significantly affects supplier selection, lot-sizing allocation, and inventory planning decisions, emphasizing the importance of carefully evaluating the planning horizon. Similarly, [52] considers a novel and realistic quantity discount scheme in which suppliers are selected first, followed by time-period order placement. Finally, as noted in [3], future research directions include further integration of SCM activities, with particular emphasis on tactical production planning and supplier selection. The goal is to improve the alignment of raw material availability and workforce/machinery capacity with customer demand, which is the central focus of our study. Importantly, our work goes beyond prior research by integrating SS with APP while explicitly incorporating uncertainty into the decision-making process, highlighting the novelty and practical relevance of our approach.

Finally, workforce flexibility elements in APP have been considered in [53]. Policies focused on utilizing a seasonal workforce, incorporating part-time employees, and effectively managing seasonal inventories are discussed in [54]. It is evident that the workforce can be regarded as a valuable asset within organizations, as highlighted in [20]. Additionally, various flexibility instruments targeting different production strategies are examined in [1]. In [55], it is acknowledged that incorporating practical flexibility aspects into APP significantly complicates the problem-solving process, but adds a realistic dimension, underscoring the importance and value of such considerations.

3. Problem description and models

We consider the problem faced by a manufacturing company that produces various products using the same raw material, for example furniture [56] or dairy-based products [57]. Each product is manufactured on a dedicated production line, requiring an optimal initial labor capacity (i.e., the number of workers per production line) to meet demand efficiently. The company sources raw materials from multiple suppliers, each with a maximum supply capacity. Selecting a supplier incurs a fixed transaction cost, along with a unit cost that aggregates production and transportation expenses. Therefore, the company aims to determine the optimal supplier selection for each period.

Additionally, over the planning horizon, the company solves an aggregate production planning problem. This involves determining the optimal production batch sizes for each product and the required inventory levels for both raw materials and finished goods. To mitigate the negative impact of demand fluctuations, the company employs labor transfers between production lines as a flexibility instrument, within a certain degree of flexibility, thus creating a network of production lines. The final objective is to minimize the costs associated with the optimal acquisition of initial labor capacity and key time-period decisions, including supplier selection and aggregate production planning activities such as raw material procurement, lot sizing, inventory management, and worker transfers.

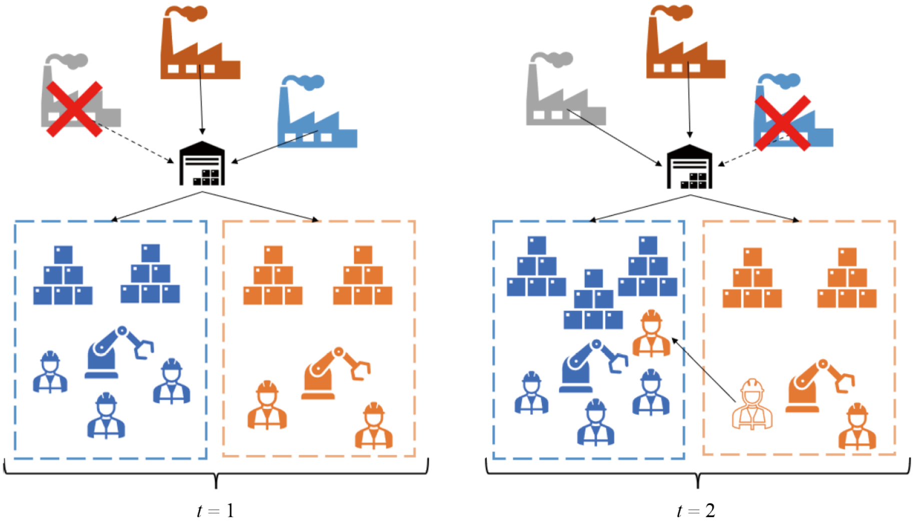

Figure 1. Supplier selection and aggregate production planning problem description

Figure 1 presents the problem under study. Three suppliers (represented by factory icons) provide raw materials to the company. There are two production lines (depicted as blue and orange boxes with dotted lines), each with an initial labor capacity (represented by worker icons). The raw materials can either be utilized immediately for production or stored as inventory. In the first time period, two suppliers are selected, while the third (marked with a red cross) is excluded, and no labor transfer occurs. In the subsequent time period, only two suppliers are selected again. However, to better align capacity and meet customer demand, a worker from the orange production line is transferred to the blue production line.

3.1 *Deterministic mathematical formulation*

First, we consider a deterministic version of the Supplier Selection with Aggregate Production Planning (SSwAPP) problem. The assumptions are as follows:

- Demand is known for all periods within the production planning horizon.
- All suppliers reliably fulfill their orders, though at different fixed costs (which can be interpreted as transaction costs). Additionally, each supplier has a limited capacity.
- Production and inventory costs remain constant for each product across all periods in the production planning horizon.
- Raw material can be used to produce any of the final products.
- The model operates at a tactical level, focusing on determining aggregate labor capacity and supplier selection.

The notation used in the deterministic mathematical formulation for the SSwAPP is presented below.

Sets and parameters:

- T: Set of time periods.
- P: Set of suppliers.
- J: Set of products.
- O_p: Transaction cost of ordering raw material from a supplier $p \in P$.
- K_p: Available capacity for supplier $p \in P$ during the production planning horizon.
- C_j^{LA}: Initial installed labor capacity in production line for product $j \in J$.
- C_{jl}^{TR}: Unitary worker transference cost from the production line for product $j \in J$ to the production line for product $l \in J$, $j \neq l$.
- C_p: Unitary cost for raw material from supplier $p \in P$.
- C_j^z: Unitary production cost in production line for product $j \in J$.
- H': Unitary inventory cost for raw material.
- H_j: Unitary inventory cost for product $j \in J$.
- D_{tj}: Demand for each period $t \in T$ and production line j.
- φ_j: Conversion factor for the quantity of raw material required to produce one unit of product $j \in J$.
- ϕ_j: Production capacity per worker in production line for product $j \in J$.
- α: Percentage of degree of flexibility for transfer workers.

The decision variables are as follows:

- y_{pt}: 1 if supplier $p \in P$ is selected in time period $t \in T$; and 0 otherwise.
- x_{pt}: Quantity of raw material ordered from supplier $p \in P$ in time period $t \in T$.
- z_{tj}: Amount of finished products $j \in J$ manufactured in time period $t \in T$.
- K_j^{LA}: Initial installed capacity of the production line for product $j \in J$.
- TR_{ljt}: Workers transferred from production line for product $j \in J$ to production line for product $l \in J$, $j \neq l$, in time period $t \in T$.

It is worth emphasizing that the decision variables associated with the supplier selection problem are y_{pt} for all $p \in P$ and $t \in T$, while those related to the aggregate production planning problem are x_{pt}, z_{tj}, K_j^{LA}, and TR_{ljt} for all $p \in P, t \in T$, and $j, l \in J$, with $j \neq l$.

The proposed formulation yields a mixed-integer programming model, which is presented next.

$$\min \sum_{p \in P} \sum_{t \in T} O_p y_{pt} + \sum_{j \in J} C_j^{LA} K_j^{LA} + \sum_{p \in P} \sum_{t \in T} C_p x_{pt} + \sum_{j \in J} \sum_{t \in T} C_j^z z_{tj} + \sum_{j \in J} H_j \sum_{t \in T}$$

$$\left(\sum_{k=1}^{t}\left(z_{kj}-D_{kj}\right)\right)+\sum_{t\in T}H'\left(\sum_{p\in P}\sum_{k=1}^{t}x_{pk}-\sum_{j\in J}\sum_{k=1}^{t}\varphi_j z_{kj}\right)+\sum_{j\in J}\sum_{\substack{l\in J:\\ l\neq j}}\sum_{t\in T}C_{jl}^{TR}TR_{ljt} \tag{1}$$

Subject to: $x_{pt}\leq K_p y_{pt}, \qquad \forall p\in P,\ t\in T$ (2)

$$\sum_{k=1}^{t}z_{kj}-\sum_{k=1}^{t}D_{kj}\geq 0, \qquad \forall j\in J,\ t\in T \tag{3}$$

$$\sum_{p\in P}\sum_{k=1}^{t}x_{pk}-\sum_{j\in J}\sum_{k=1}^{t}\varphi_j z_{kj}\geq 0, \qquad \forall t\in T \tag{4}$$

$$z_{tj}\leq \phi_j\left(K_j^{LA}+\sum_{\substack{l\in J:\\ l\neq j}}\left(TR_{ljt}-TR_{jlt}\right)\right), \qquad \forall j\in J,\ t\in T \tag{5}$$

$$\sum_{\substack{l\in J:\\ l\neq j}}TR_{ljt}\leq \alpha K_j^{LA}, \qquad \forall j\in J,\ t\in T \tag{6}$$

$$y_{pt}\in\{0,\,1\}, \qquad \forall p\in P,\ t\in T \tag{7}$$

$$x_{pt}\geq 0, \qquad \forall p\in P,\ t\in T \tag{8}$$

$$z_{tj}\geq 0, \qquad \forall t\in T,\ j\in J \tag{9}$$

$$K_j^{LA}\geq 0, \qquad \forall j\in J \tag{10}$$

$$TR_{ljt}\geq 0, \qquad \forall l,\ j\in J: l\neq j,\ t\in T \tag{11}$$

The objective function (1) minimizes the costs associated with labor capacity installation, supplier selection, and production planning, including raw material procurement, production, inventory, and worker transfers. Constraint (2) ensures that raw material sent does not exceed supplier capacity limitations. Constraint (3) ensure that all demand in production lines is met by finished goods, meanwhile constraint (4) ensure that that sufficient raw material is supplied when needed to produced finished goods. Constraint (5) defines the production capacity of each production line, allowing for worker transfers between production lines. Lastly, constraint (6) restricts the extent of worker transfers between production lines. Constraints (7)-(11) indicate the nature of the decision variables.

3.2 *Two-stage stochastic programming formulation*

Next, we incorporate uncertainty into the SSwAPP, specifically in customer demand. Consequently, some of the previously established assumptions must be revised or updated. The revised assumptions are as follows:

• Demand is uncertain for all periods in the production planning horizon and follows a normal probability distribution function. [58] suggests that family of normals distribution is appropriate for approximating customer demand.

• Supplier compliance is modeled using a Bernoulli distribution, as we assume either full compliance or non-compliance.

• The proposed model is a two-stage stochastic programming model and will be referred to as Two-Stage Supplier Selection with Aggregate Production Planning (TS-SSwAPP). The first-stage decision variables determine the initial labor capacity size and the selected suppliers, while the remaining decision variables serve as recourse variables, representing the optimal course of action for each scenario based on decisions made before the stochastic event occurs [59].

• Since the random variables in the proposed TS-SSwAPP model are continuous and have infinitely many realizations, Monte Carlo procedures are applied to approximate the true optimal value of the stochastic programming model. Thus, we approximate the original stochastic problem with a scenario-based approach problem, where each scenario represents a realization of the random variables obtained through Monte Carlo sampling.

In addition to the previously defined sets and parameters, the following notation is introduced:

• S: Set of scenarios.

• $\mathscr{P}^s$: Probability of each scenario $s \in S$, where $\mathscr{P}^s = 1/|S|$ since we are using a Monte Carlo procedure and the sample average approximation.

• D_{tj}^s: Demand for each period, production line, in scenario $s \in S$.

• K_p^s: Capacity for each supplier $p \in P$ in scenario $s \in S$.

The added decision variables are as follows:

• x_{pts}: Quantity of raw material ordered from supplier $p \in P$ in time period $t \in T$ in scenario $s \in S$.

• z_{tjs}: Amount of finished products $j \in J$ manufactured in time period $t \in T$ in scenario $s \in S$.

• TR_{ljts}: Workers transferred between production lines for products $j \in J$ and $l \in J$, $j \neq l$, in time period $t \in T$ in scenario $s \in S$.

Therefore, the scenario-based approach of the TS-SSwAPP results in the following model:

$$\min \sum_{p\in P}\sum_{t\in T} O_p y_{pt} + \sum_{j\in J} C_j^{LA} K_j^{LA} + \sum_{s\in S} \mathscr{P}^s \sum_{p\in P}\sum_{t\in T} C_p x_{pts} + \sum_{s\in S} \mathscr{P}^s \sum_{j\in J}\sum_{t\in T} \left(C_j^z z_{tjs} + H_j \sum_{k=1}^{t} \left(z_{kjs} - D_{kj}^s \right) \right)$$

$$+ \sum_{s\in S} \mathscr{P}^s \sum_{t\in T} H' \left(\sum_{p\in P}\sum_{k=1}^{t} x_{pjs} - \sum_{j\in J}\sum_{k=1}^{t} \varphi_j z_{kjs} \right) + \sum_{s\in S} \mathscr{P}^s \sum_{j\in J} \sum_{\substack{l\in J:\\ l\neq j}} \sum_{t\in T} C_{jl}^{TR} TR_{ljts} \tag{12}$$

Subject to: $x_{pts} \leq K_p^s y_{pt}, \qquad \forall p \in P,\ t \in T,\ s \in S$ (13)

$$\sum_{k=1}^{t} z_{kjs} - \sum_{k=1}^{t} D_{kj}^s \geq 0, \qquad \forall j \in J,\ t \in T,\ s \in S \tag{14}$$

$$\sum_{p\in P}\sum_{k=1}^{t} x_{pks} - \sum_{j\in J}\sum_{k=1}^{t} \varphi_j z_{kjs} \geq 0, \qquad \forall t \in T,\ s \in S \tag{15}$$

$$z_{tjs} \leq \phi_j \left(K_j^{LA} + \sum_{\substack{l\in J:\\ l\neq j}} \left(TR_{ljts} - TR_{jlts} \right) \right), \qquad \forall j \in J,\ t \in T,\ s \in S \tag{16}$$

$$\sum_{l \in J} TR_{ljts} \leq \alpha K_j^{LA}, \qquad \forall j \in J,\ t \in T,\ s \in S \tag{17}$$

$$y_{pt} \in \{0, 1\}, \qquad \forall p \in P,\ t \in T \tag{18}$$

$$x_{pts} \geq 0, \qquad \forall p \in P,\ t \in T,\ s \in S \tag{19}$$

$$z_{tjs} \geq 0, \qquad \forall t \in T,\ j \in J,\ s \in S \tag{20}$$

$$K_j^{LA} \geq 0, \qquad \forall j \in J \tag{21}$$

$$TR_{ljts} \geq 0, \qquad \forall l,\ j \in J : l \neq j,\ t \in T,\ s \in S \tag{22}$$

The description of formulation (12)-(22) is analogous to the one defined in (1)-(11); that is, the constraints serve the same purpose, but now the consideration of different scenarios is incorporated, this is expressed through the indexation of s in the second-stage decision variables and in some constraints, while y_{pt} and K_j^{LA} serve as the first-stage decision variables.

4. A two-phase matheuristic for the TS-SSwAPP

The TS-SSwAPP is a highly complex computational problem that combines elements of supplier selection and production planning models with worker transfer capabilities, forming a network across time periods and production lines. Due to the nature of the problem and the large size of the scenario-based approach, solving it within a reasonable time frame becomes challenging. To efficiently handle large size instances, we propose a two-phase heuristic for the TS-SSwAPP, resulting in a matheuristic procedure. In recent years, the integration of exact methods with heuristics, metaheuristics, or surrogate models, commonly known as matheuristics, has demonstrated strong performance in solving various complex combinatorial optimization problems [60, 61].

Recall that we are addressing a problem that integrates two subproblems: SS and APP. There is a clear hierarchy between them, as decisions in the SS problem are crucial for solving the APP problem. Therefore, in our two-phase procedure, we first focus on the SS problem, followed by the APP problem. Two-phase strategies are widely studied in the literature for a broad class of hard combinatorial problems [62–64]. However, most of these approaches do not rely on exact methods. [65] noted that, at least for certain production planning models with capacity constraints, recent solution approaches primarily involve solving reduced-size Mixed-Integer Programs (MIPs), while constructive methods are rarely used. Although reduced-size MIPs provide high-quality solutions, they may have faster computational times than construction heuristics.

In the first-phase the proposed procedure begins by solving a surrogate model that focuses solely on SS throughout the planning horizon, ensuring that customer demand is properly met, this problem is a twp-stage stochastic programming model. We introduce an auxiliary variable $i_{ts} \geq 0$, that tracks the overall inventory of raw material. The surrogate model is as follows:

$$\min \sum_{p \in P} \sum_{t \in T} O_p y_{pt} + \sum_{s \in S} \mathscr{P}^s \left[\sum_{p \in P} \sum_{t \in T} C_p x_{pts} + \sum_{t \in T} i_{ts} H' \right] \tag{23}$$

$$\text{s.t. } x_{pts} \leq K_p^s y_{pt}, \qquad \forall p \in P,\ t \in T,\ s \in S \tag{24}$$

$$\sum_{p\in P} x_{pts} - \sum_{j\in J} D_{tj}^s \varphi_j \geq i_{ts}, \qquad \forall t \in T,\ s \in S \tag{25}$$

$$\sum_{t\in T}\sum_{p\in P} K_p^s y_{pt} \geq \sum_{t\in T}\sum_{j\in J} D_{tj}^s \varphi_j, \qquad \forall s \in S \tag{26}$$

$$y_{pt} \in \{0, 1\}, \qquad \forall p \in P,\ t \in T \tag{27}$$

$$x_{pts} \geq 0, \qquad \forall p \in P,\ t \in T,\ s \in S \tag{28}$$

$$i_{ts} \geq 0, \qquad \forall t \in T,\ s \in S \tag{29}$$

Formulation (23)-(29) focuses solely on SS, aiming to satisfy customer demand while accounting for potential supplier disruptions. Solving this surrogate model helps identify the most promising suppliers and optimal ordering periods. This approach resembles a two-stage stochastic programming model, where the first-stage decisions involve selecting suppliers for a given time period, while the second-stage decision variables determine the order quantities from the chosen suppliers. Our formulation is similar to the one proposed by [66] for inventory lot-sizing with SS. The main difference is that, in our approach, we aggregate the demand of production lines, as they all require the same raw material, and, importantly, our model accounts for demand stochasticity.

To strengthen the formulation used in the surrogate model of the first phase, we introduce valid inequalities designed to reduce the computational time of the surrogate model. The added inequalities are:

$$\sum_{p\in P} sy_{1t} \geq 1, \qquad \forall s \in S \tag{30}$$

$$\sum_{p\in P} K_p^s y_{1t} \geq \sum_{j\in J} D_{1j}^s \varphi_j, \qquad \forall s \in S \tag{31}$$

Valid inequalities (30) ensure that, at least in the first time period, a supplier is selected, meanwhile that (31) ensures that the first required customers demand is achieved. The surrogate model (23)-(31) in the first phase is solved using a general-purpose solver. As a result, the most promising suppliers and ordering time periods are identified by the variables y'_{pt} under this approach.

Once the first phase is solved, the second phase addresses a reduced feasible region problem based on the original model (12)-(22), with an additional constraint that incorporates the supplier-related solution obtained in the first phase, as defined in Eq. (32). Constraint (32) enables general-purpose solvers to reduce the model (12)-(22) during the presolve phase. Moreover, instead of using a fix-and-optimize approach with y'_{pt} as the solution for the TS-SSwAPP, constraint (32) allows general-purpose solvers to find a better incumbent solution, if one exists.

$$y_{pt} \leq y'_{pt}, \quad p \in P,\ t \in T \tag{32}$$

Therefore, after solving the problem in the first phase, in the second-phase, some of the decision variables are fixed to zero, specifically, those for which $y'_{pt} = 0$ in the first phase, while others are allowed to vary in the second phase, namely those where $y'_{pt} = 1$. Hence, the problem solved in the second phase is formulated as follows:

$$\min \sum_{p\in P}\sum_{t\in T} O_p y_{pt} + \sum_{s\in S}\mathscr{P}^s \sum_{p\in P}\sum_{t\in T} C_p x_{pts} + \sum_{s\in S}\mathscr{P}^s \sum_{j\in J}\sum_{t\in T}\left(C^z_j z_{tjs} + H_j \sum_{k=1}^{t}\left(z_{kjs} - D^s_{kj}\right)\right)$$

$$+\sum_{s\in S}\mathscr{P}^s \sum_{t\in T} H'\left(\sum_{p\in P}\sum_{k=1}^{t} x_{pjs} - \sum_{j\in J}\sum_{k=1}^{t}\varphi_j z_{kjs}\right) + \sum_{j\in J} C^{LA}_j K^{LA}_j + \sum_{s\in S}\mathscr{P}^s \sum_{j\in J}\sum_{\substack{l\in J:\\ l\neq j}}\sum_{t\in T} C^{TR}_{jl} TR_{ljts} \tag{33}$$

Subject to: (13)-(22)

$$y_{pt} \leq y'_{pt}, \qquad p\in P,\ t\in T \tag{34}$$

In summary, in the first phase, a SS procedure is carried out to determine which suppliers are the most promising and during which periods, with the aim of achieving low transaction costs and a feasible production plan. In the second phase, using those selected suppliers and time periods, the solver reduces the search space by solving a reduced version of the original TS-SSwAPP model.

Although this two-phase heuristic based on exact methods does not guarantee optimality, it produces high-quality solutions within a short computational time. Furthermore, since the problem is at the tactical level, achieving a good trade-off between computational time and solution quality is essential for evaluating the impact of parameters not governed by uncertainty, such as the flexibility of labor transfers between production lines. This, in turn, helps decision-makers negotiate with labor unions on policies regarding the maximum number of workers allowed to transfer between production lines.

5. Computational experimentation

In this section, we present the results obtained using the proposed TS-SSwAPP approach and the two-phase matheuristic algorithm. The computational experiments were conducted on a personal desktop equipped with an Intel® Core™ i7-11370H @ 3.30 GHz processor. All models were implemented in Python 3.10 and solved using the general-purpose solver Gurobi 12.0. Each instance was run with a time limit of 1,800 sec and included 30 scenarios suggested as [25]. For the proposed two-phase matheuristic, the total time limit was set to 1,800 sec, with 60 sec specifically allocated to the first-phase model.

5.1 *Generation of test instances*

Due to the novelty of the problem under study, no benchmark instances exist. Therefore, we generate a set of test instances that aim to capture realistic aspects. For example, we avoid trivial supplier selection solutions to prevent instances from being too easy to solve. In particular, we adapt the procedure from [66] to generate partial instances, as the problem shares similarities with the inventory lot-sizing problem with supplier selection.

Transaction costs O_p and labor capacity costs C^{LA}_j are randomly chosen integers in the range [10,000, 12,000], multiplied by the number of time periods $|T|$. Transfer worker costs C^{TR}_{jl} are integers in [1,000, 2,000], while the raw material unit cost C_p is drawn from [20, 50], and the cost of producing a finished good C^z_j is in [60, 90].

The inventory holding cost for raw materials, H', is taken from [2, 4], while for finished goods, H_j is drawn from [1, 5]. Production capacity per worker in each production line, ϕ_j, is sampled from [50, 55], and the raw material conversion factor, φ, is drawn from [1, 5]. Instead of using a uniform distribution as [66], demand values, D^s_{tj}, follow an independent and identically distributed (i.i.d.) normal distribution with a mean of 100 and a standard deviation of 25. To ensure all demand values are positive, we take the maximum between zero and the sampled value with similar idea as [1].

Supplier capacities, K^s_p, follow a Bernoulli distribution with a θ% probability of failure and are independently and identically distributed (i.i.d.), where θ is random number [0, 0.25], based on the data provided by [67]. For suppliers that are selected (i.e., do not fail), their capacities are randomly set between two bounds: the average total demand across all production lines and time periods, divided by the number of suppliers, and the overall average demand across production lines. With this we avoid having instances that can be solved very easily, but without reaching the point of having infinite capacity. The parameter α was set to 0.35. The set of test instances used in this study is available upon reasonable request from the authors. Dimensions of the problem are reported in the Appendix A.

5.2 *Summary of results from test instances*

To evaluate the performance of the proposed method, we consider six subsets of instances, each varying in size. Five instances were generated for each subset, resulting in a total of 30 instances. The results are presented in Table 1, where a problem size of $|T|$, $|J|$, $|P|$ represents the number of time periods ($|T|$), production lines ($|J|$), and suppliers ($|P|$), respectively. Table 1 reports the average values for the Expected Recourse Problem (ERP) solution, computational time in sec (CPU time), and MIP gap (in percentage). As expected, as the problem size increases, it becomes more challenging to solve.

Table 1. Results of the proposed TS-SSwAPP scenario-based model using a general-purpose solver

Instance	ERP	CPU time (s)	Gap (%)
6-5-20	1,221,655.60	4.65	0.00
12-5-20	1,633,267.67	1,552.32	0.32
6-10-50	2,175,652.85	53.35	0.00
12-10-50	2,990,075.81	1,800.00	2.82
6-20-500	4,115,051.74	1,800.00	1.46
12-20-500	5,770,815.41	1,800.00	4.33

The results in Table 1 highlight the limitations of using a direct formulation with a general-purpose solver. In particular, medium- and large-sized instances fail to yield optimal solutions. Although the proposed TS-SSwAPP model operates at the tactical level, decision-makers often run it multiple times to explore various scenarios through what-if analyses. Nonetheless, we emphasize that solution quality remains essential.

Table 2 presents the results obtained by the proposed two-phase matheuristic. The first column reports the instance label, while the second column shows the average values of the ERP solution. The third column indicates the computational time spent on the surrogate model (CPU time 1), and the fourth column presents the computational time for the reduced-size MIP (CPU time 2). Additionally, the fifth column includes the percentage deviation of the Objective Function value (Δ OF) and computational time (Δ time) compared to the TS-SSwAPP scenario-based model, as well as the percentage reduction in the number of binary variables in the second-phase model (% MIPred). The latter is calculated as the difference between the original number of binary variables in the TS-SSwAPP model and the number of remaining binary variables in the second-phase model, divided by the original number of binary variables in the TS-SSwAPP model.

Table 2. Results of the proposed TS-SSwAPP using the proposed two-phase matheuristic

Instance	ERP	CPU time 1 (s)	CPU time 2 (s)	Δ OF	Δ time	% MIPred
6-5-20	1,221,655.60	0.02	0.65	1.47	-516.71	71.00
12-5-20	1,633,267.67	0.03	74.70	0.48	-1,975.90	63.25
6-10-50	2,175,652.85	2.97	1.95	0.41	-782.99	91.20
12-10-50	2,990,075.81	58.91	1,188.79	0.10	-44.14	89.00
6-20-500	4,115,051.74	60.01	18.32	-0.05	-2,198.26	99.31
12-20-500	5,733,304.57	60.00	1,740.00	-0.65	0.00	99.37

The results shown in Table 2 clearly demonstrate a significant reduction in the computational effort required to solve the TS-SSwAPP. Furthermore, for the largest instances, the two-phase matheuristic performs notably better, yielding lower average objective function values. This improvement is primarily attributed to the reduction in the number of first-stage binary variables. In fact, for large instances, the reduction reached approximately 99% compared to the original number of binary variables.

We observe that the required computational time for the first phase in the large instance 12-20-500 is approximately 60 sec, making it the only case where the matheuristic does not finish within the desired time limit. Nevertheless, the solutions obtained result in lower costs compared to directly solving the TS-SSwAPP model, demonstrating the advantage of using this approach. Given that this model operates at the strategic-tactical level, computational speed is a key factor, allowing decision-makers to explore numerous scenarios and perform what-if analyses by adjusting uncontrollable parameters. However, as mentioned earlier, a direct formulation using general-purpose solvers does not always guarantee high-quality results.

It can be concluded that our proposal performs better as the number of suppliers and time periods increases. In the case of a tactical decision problem, the advantage of our proposal persists due to its ability to explore various business scenarios more efficiently. This is crucial for analyzing different situations, such as demand or capacity disruptions, varying costs, and different production rate levels. The efficiency of this data-driven optimization tool enables quicker exploration of business scenarios, helping practitioners make informed decisions and effectively compare diverse situations.

5.3 *Analyzing the importance of incorporating uncertainty into the model*

To evaluate the impact of uncertainty, the Expected Value of Perfect Information (EVPI) is calculated through the Wait-and-See (WS) solution, while the Value of the Stochastic Solution (VSS) is not calculated. This is because the Expected Value (EV) solution and the Expected result of using the EV solution (EEV) are required to calculate the VSS. It is important to note that, in some cases, evaluating the EEV is not possible because the EV solution may lead to an infeasible EEV problem. As a result, the VSS cannot be evaluated.

Table 3. Results of the WS and EVPI for the TS-SSwAPP

Instance	ERP	WS	EVPI	% EVPI
6-5-20	1,221,655.60	1,019,545.77	220,291.55	17.77
12-5-5	1,633,267.67	1,431,171.72	210,042.69	12.80
6-10-50	2,175,652.85	1,943,043.15	241,609.49	11.06
12-10-50	2,990,075.81	2,733,977.28	259,216.12	8.66
6-20-500	4,115,051.74	3,774,834.52	338,026.51	8.22
12-20-500	5,733,304.57	5,278,098.36	455,206.21	7.94

Table 3 presents the results of the WS solution (a model that omits the non-anticipativity constraints) in the third column. The fourth column shows the EVPI (i.e., the difference between the ERP and WS solutions), while the final column (% EVPI) indicates the EVPI as a percentage of the ERP value. As expected, the WS solution results in lower costs, as the model can now respond better to each individual scenario. The EVPI metric always has positive values, indicating that decision-makers should focus on better acquisition of data to improve the probability distribution parameters. Finally, the % EVPI is higher in smaller instances, suggesting that having more available suppliers helps mitigate uncertainty related to compliance. The findings imply that decision-makers should consider increasing their supplier base. Although not all suppliers may be used in the optimal solution, a broader selection enhances resilience in the face of uncertainty.

5.4 *Impact of the degree of flexibility in worker transfers*

In this section, we analyze the impact of the degree of flexibility (α) in transferring workers between production lines. We solve the instance group 6-20-500, starting with $\alpha = 0.1$ (i.e., 10% of workers are allowed to transfer) and increasing by increments of 0.1 up to 1.0, where all workers can shift between lines, for each α value we ran 5 times the model. Figure 2 shows a decrease in the average values of the ERP solution as α increases. In particular, values above 0.4 lead to a significant reduction in the average ERP. However, the marginal difference between α values of 0.5 and above is relatively small. From a managerial perspective, negotiating agreements with labor unions to allow greater worker mobility is crucial for further cost reductions. Nevertheless, in practice, achieving high levels of labor transfer flexibility may be challenging due to operational or contractual constraints.

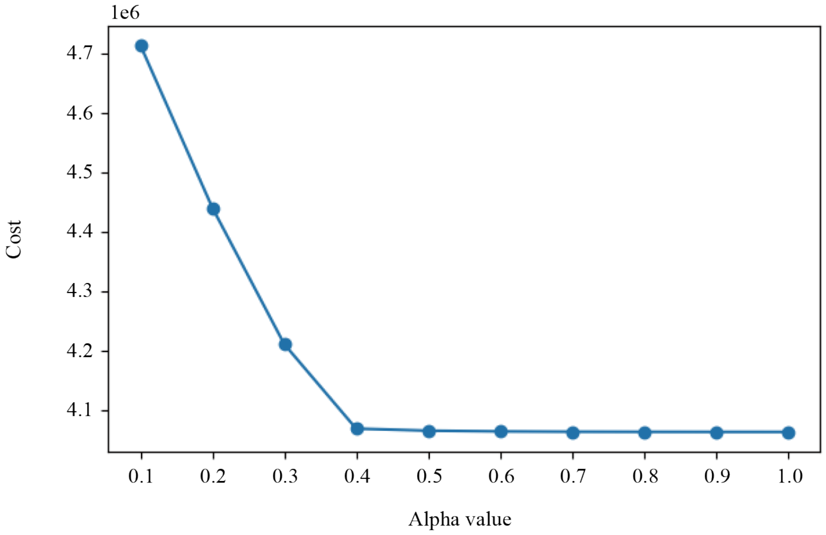

Figure 2. Impact of the degree of flexibility regarding workers transfers

Figure 3 illustrates the impact of flexibility on the optimal acquisition strategy and procurement costs, considering both supplier transaction costs and the expected cost of batch ordering raw materials. At lower levels of flexibility, the model recommends investing less in supplier transactions, leading to higher initial installed labor capacity and greater inventory accumulation over time. Conversely, values greater than 0.3 of α reduce overall costs, allowing the firm to allocate more resources toward supplier selection. For values of α above 0.5, the procurement cost values tend to decrease, indicating that high levels of labor transfers can mitigate the procurement costs.

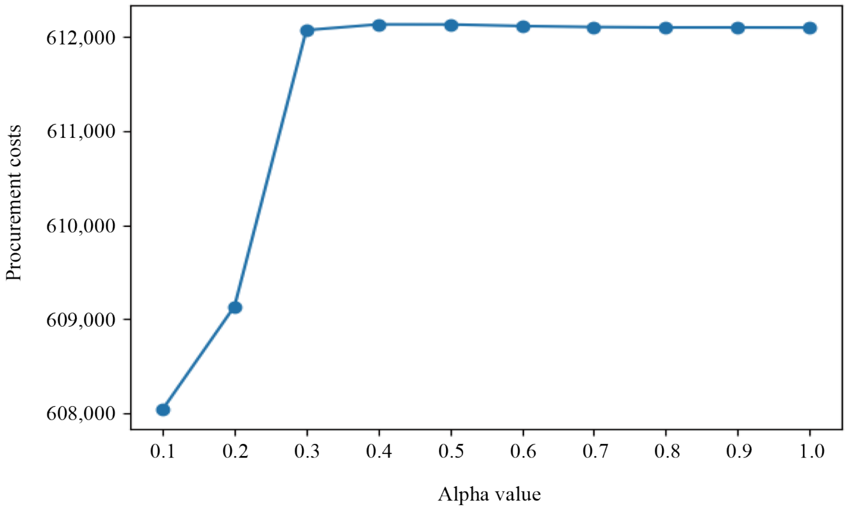

Figure 3. Impact of the degree of flexibility regarding procurement costs

5.5 *Analysis of cost impacts and demand variation*

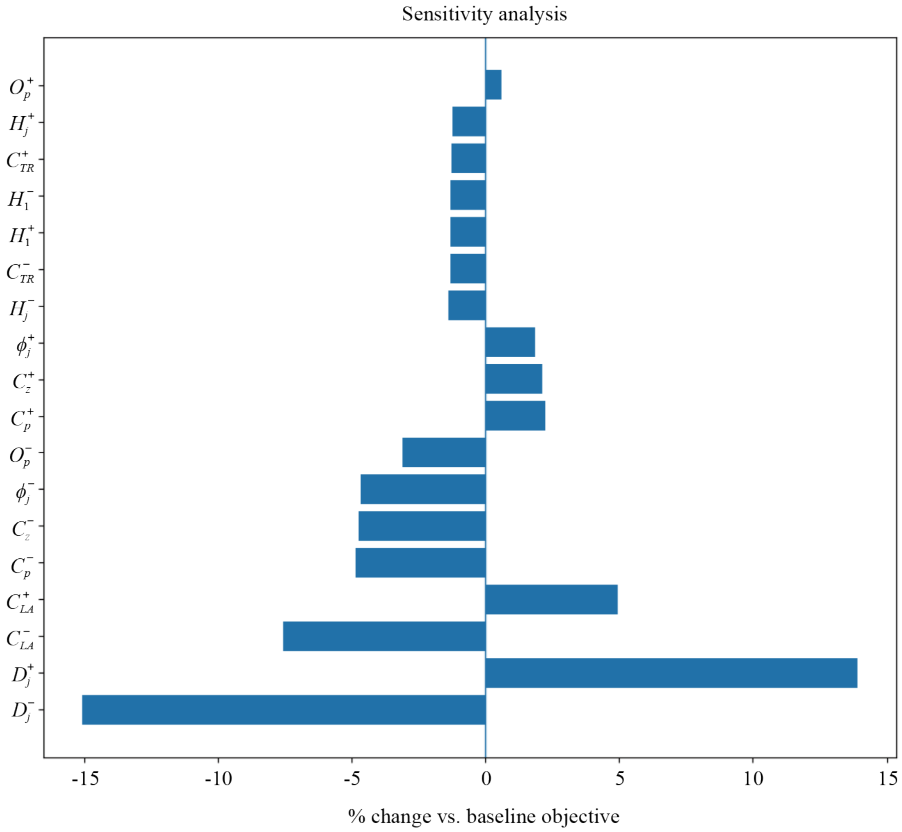

Figure 4. Sensitivity analysis

We evaluate the relevance of other parameters in the proposed model by conducting a sensitivity analysis. Specifically, each parameter is perturbed upward and downward by 15% from its baseline value. This range was selected to reflect plausible deviations in practical settings, such as fluctuations in costs, demand levels, or supplier capacities, while maintaining computational tractability. By exploring both positive and negative shifts, we assess the stability of the solution and the robustness of the proposed framework. We utilized instance 6-20-500, and for each parameter analyzed we ran the model five times. The results are summarized and presented in Figure 4.

As noted, demand has the highest impact, followed by labor-installed capacity costs. These costs have a greater impact than supplier procurement costs. Due to the nature of the stochastic model, reducing labor costs allows for an increase in installed labor capacity, thereby enhancing the flexibility between production lines. Production costs also play a significant role, as do the inventory costs of finished goods. Finally, it is worth noting that the quantity of raw materials is an important factor, as reducing the amount required to produce a single unit of finished product can substantially lower overall costs.

5.6 *Key findings and managerial insights*

In this section, we present some managerial insights derived from our research. One of our aims is to help managers identify the necessary labor capacity and selected suppliers across time periods. As discussed earlier in this paper (in Sections 1 and 2), integrating both supplier selection and production planning at the tactical level is crucial. However, there is limited research on this topic. Therefore, further research on integrating supplier selection with tactical strategies is both necessary and valuable. The main findings are:

- Integrating SS with other SCM activities is highly desirable. In this study, we examine the importance of integrating SS activities and highlight the benefits of promoting synergy to enhance decision-making at both tactical and operational levels. Our findings demonstrate that the SS problem and APP can be effectively integrated. Furthermore, when solution time is a limiting factor, we propose an approach that addresses the problem efficiently. Within the same framework, this integration enables improved tactical decision-making by considering transportation and allocation costs, as well as workforce estimation processes.
- Demand was modeled with a normal distribution and supplier availability with a Bernoulli distribution. While these are common and computationally convenient assumptions, alternative distributions (e.g., Poisson or uniform for demand, beta-binomial for suppliers) may be more appropriate in other contexts. But the methodology is flexible enough to accommodate richer stochastic representations if required, due to the fact of using Monte Carlo methods approaches.
- Labor transfers help reduce costs while protecting workers. Flexibility mechanisms allow companies to safeguard jobs during disruptions and serve as an effective means of mitigating the negative effects of uncertainty. Our results clearly demonstrate the positive impact of these mechanisms.
- Considering stochasticity is crucial. Employing a stochastic programming approach yields robust solutions in situations where supplier availability for raw materials is uncertain. In contrast, relying solely on the expected values of random variables may result in infeasible plans when supplier compliance is uncertain.
- The combination of exact methods with heuristic approaches appears to be a convenient strategy. However, we demonstrate that using properly formulated, reduced-size MIPs provides high-quality solutions. In this case, the reduced feasible region can be solved efficiently using general-purpose solvers.

6. Conclusions and further research directions

In this paper, we presented an integrated model addressing the supplier selection problem and aggregate production planning under uncertainty, aimed at properly selecting suppliers and determining the installed labor capacity. This problem is referred to as the Supplier Selection with Aggregate Production Planning. To the best of the authors' knowledge, this problem has not been previously studied in the literature, representing a novel contribution of our study. A two-stage stochastic programming model is employed to account for uncertainties in demand and supplier compliance. As the number of production lines, scenarios, customers, or suppliers increases, the complexity of the problem grows due to the scenario-based formulation.

To address the problem under study, we propose a two-phase solution approach that enhances both computational efficiency and solution quality. In the first phase, a surrogate model is solved to identify the most promising raw material acquisitions from suppliers. In the second phase, a reduced feasible region problem is solved. We evaluate and compare the solutions using a set of adapted instances from the hard optimization problem of inventory lot-sizing with supplier selection. For small instances, using general-purpose solvers is a good alternative; however, as the instance size increases, our approach demonstrates superior performance, enabling decision-makers to conduct more effective what-if analyses.

To mitigate the impact of uncertainty, we propose a flexibility mechanism that allows workers to shift between production lines over time. This approach is commonly observed in countries with strict employment regulations and in industries such as semiconductors and automotive manufacturing [1], with potential applications in other manufacturing and service sectors [68]. Our analysis indicates that higher worker mobility is crucial for achieving significant cost reductions. At the same time, labor union negotiations must be managed carefully, as frequent worker transfers may face resistance. These findings provide practical guidance for decision-makers, supporting effective negotiation with labor unions and enabling the implementation of workforce flexibility strategies to enhance operational efficiency.

Future research could extend the proposed formulation to consider multiple raw material types and incorporate technological or machinery constraints. Another promising direction is to explore alternative flexibility mechanisms, such as temporary workers, and assess the impact of relaxing dedicated product policies on production lines.

Data availability statement

The data and code supporting this study's findings are available from the first author upon reasonable request.

Conflict of interest

The authors declare no conflict of interest.

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Appendix A

Table 4 in this appendix provides a summary of the instances dimensions, detailing the number of constraints, the number of variables per stage, and their respective types.

Table 4. Dimensions of the instances considered in the computational experimentation

Instance	Variables	Binary variables	Constraints
6-5-20	9,125	120	6,480
12-5-20	18,245	240	12,960
6-10-50	29,110	300	14,580
12-10-50	58,210	600	29,160
6-20-500	168,620	3,000	100,980
12-20-500	337,220	6,000	201,960