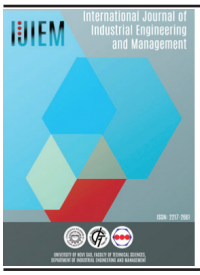
ISSN 2683-345X



journal homepage: http://ijiemjournal.uns.ac.rs/

International Journal of Industrial Engineering and Management

Volume 17 / No 4 / December 2026 / 411 - 428

Original research article

A Scheduling Framework for Green Supplier Selection and Dynamic Order Allocation: A Case Study in the Textile Industry

R. G. Silva[a] 0000-0002-7929-0367, A. C. Ferreira[a,b,*] 0000-0002-4775-5713,

B. Ramos[a,c] 0000-0002-5203-5964, A. Araújo[a] 0000-0002-2879-1225

[a] *COMEGI, Centro de Investigação em Organizações Mercados e Gestão Industrial, Universidade Lusíada, Vila Nova de Famalicão, 4760-108, Portugal;*

[b] *MEtRICs Research Centre, University of Minho, Guimarães, 4804 - 533, Portugal;*

[c] *ALGORITMI, University of Minho, Guimarães, 4804 - 533, Portugal*

ABSTRACT

This study introduces an innovative framework for order allocation and scheduling in the textile industry, addressing the complex challenges of multi-objective production planning across diverse processes, multiple outsourcing entities, and interconnected production departments. The proposed approach uses advanced genetic algorithms to deliver efficient and sustainable scheduling solutions, integrating a state-of-the-art production process simulator. A core innovation of this research is a novel chromosome representation, complemented by refined genetic operators and a heuristic pruning and selection mechanism. Green supplier criteria are integrated through a lexicographic scoring mechanism that governs allocation tie-breaking, ensuring that sustainability preferences are structurally embedded in the decision process without displacing primary economic objectives. The production process simulator is designed to replicate real-world industrial dynamics, significantly boosting the model's accuracy and practical applicability. The study pioneers advanced methodologies, including a gendered genetic algorithm and a hybrid genetic algorithm, specifically developed to optimize scheduling in multi-supply chain and open shop environments. These techniques improve computational efficiency and promote sustainable practices by optimizing resources, reducing waste and minimizing production costs. Validation using real industrial data underscores the model's capability to outperform conventional practices, demonstrating higher performance relative to the company's prior manual scheduling practice, mostly in terms of operational efficiency, cost-effectiveness and sustainability. The framework offers substantial potential for practical implementation, providing robust tools to enhance market competitiveness and support greener and resilient production strategies within the textile industry and beyond.

ARTICLE INFO

Article history:

Received September 16, 2025
Revised May 7, 2026
Accepted June 4, 2026
Published online October 5, 2026

Keywords:
Scheduling;
Supplier Selection;
Order Allocation;
Genetic Algorithms

*Corresponding author:
Ana Cristina Ferreira
d1325@fam.ulusiada.pt

1. Introduction

Supply chains are complex, integrated and synchronised processes that address the acquisition, transformation and distribution of materials, often including concurrent processes and/or subcontracting. One of the most impacting aspects on a Supply Chain (SC) pertains to supplier selection and order allocation since it involves a wide range of variables with a multitude of combinations that must be optimized to attain competitive advantages over competitors [1].

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.
This is an open access article distributed under the CC BY 4.0 terms and conditions.
https://doi.org/10.24867/IJIEM-426

Further, increased access to global markets widens the choice of suppliers and drives constantly changing costs that impact on a company's performance. In a more recent global trend [2] Supply Chain Management (SCM) has matured from an operational and economic perspective alone to integrate broader environmental and social issues, both known green SCM [3]. Hiring subcontractors is nowadays a common practice in the global market to take advantage of specialized firms, lower labour costs and innovative services, being increasingly important to dynamically select suppliers and order allocation scheduling [4], [5].

Implementing customized and optimized logistics has become the *modus operandi* of companies to overcome global competitiveness and achieve an effective means to enhance performance. Textile industries in particular are nowadays operating mostly through subcontracting since most brands do not even possess their own manufacturing facilities [6]. The textile SCM is currently long and complex depending heavily on subcontracting that often ranges from local to global specialized manufacturing companies [7].

Choosing the right service that enhances performance, or competitiveness is a difficult and increasingly more complex task, thus requiring flexible and dynamic approaches to handle specificity pertaining to ever more mass customization production.

This paper presents a framework for SCM optimization applied to a textile large industry manufacturer under a significant number of constraints including green supplier selection and order allocation, performing dynamic adaptive multi-objective optimization. The paper is organized in the following way: first, order allocation and supplier selection are addressed setting the background on global operating dynamics and trends; a short review is then given on the different approaches and considerations pertaining to the optimization of SCMs; the second part of this paper sets the scenario of a SCM concerning a large textile company, presents a framework for the operation and optimization of the SC and results of the implementation. The paper ends with a conclusion on the use of such framework as well as some general guidelines towards the application of the framework.

2. Literature Review

Today's competitive environment has led industry to diversify their sources of material and services while pursuing low cost, high quality, flexibility and specialized manufacturers in a global and increasingly competitive market [8]. Outsourcing has become the modus operandi for many manufacturing companies, from textile to automotive industry, since it provides flexibility, improved overheads, cost reduction and access to highly specialized services and technologies.

2.1 Supplier Selection and Order Allocation

The selection of suppliers is a complex decision-making process that involves qualitative and quantitative criteria in a broad multi-criteria scenario [9]. Traditionally supplier selection evolved from traditional criteria e.g., cost, quality, lead time, response rate, to cumulative green criteria e.g., eco transportation, packing, management, environment and social impact [10], [11]. Among all criteria cost, quality and delivery time are the most prevalent [5], [11], [12] and there is registered patterns pertaining to the increased use of multi-criteria approaches [13]-[16]. All these criteria are often underpinned as being the most important factors but there are other aspects that may interfere and sometimes condition the overall choice of suppliers, such as supplier availability or response capacity. The latest aspects may interfere in scheduling, handling or inventory costs, leading to changes in suppliers' selection to comply with delivery times.

Supplier selection is considered a crucial factor in purchasing or subcontracting of services since it might contribute to the reduction in operational costs and improve thus total SC performance [11], [17]. An acceptable cost or quality are no longer enough to determine appropriate suppliers [11], other factors such as lead time, responsiveness, warranties, capacity, among others, have to be taken into account [18]. Further, diversification as well as specialization of suppliers demands that an increased number of small batches have to be allocated to different suppliers, hence increasing the complexity of the SC [19]. Since outsourcing has become widely adopted, governance mechanisms must be improved as well as the selection of suppliers and the prioritization in allocations, hence requiring improved frameworks to support such intertwined and time-consuming job. Some research from the literature, shows different frameworks integrating supplier choices and ordering decisions under uncertainty. The study in [20] provide a broad review of order allocation models and solutions to improve SC processes. Models were systematically classified by decision criteria (e.g. cost, quality), supplier characteristics and SC structure, highlighting the gaps and research opportunities.

The study discloses key insights about the need to align allocation criteria with item/product characteristics, and to integrate emerging SC trends (e.g. Industry 4.0 technologies) into ordering decisions. It clarifies how different modelling approaches and solution methods have been applied to order allocation. Authors in [21] report an approach for order allocation in the manufacturing context, where cross-supplier order and logistics scheduling (ICSOLS) are addressed. The study concerns a non-deterministic polynomial-time problem (NP-hard) to model the assignment of orders across multiple suppliers and to schedule third-party logistics. With the model application, it was possible to verify the efficiency of the approach, since it reduces the production and transport costs while satisfying all orders. Thus, the study illustrates an optimization-based integration of ordering and logistical scheduling focused on real manufacturing demand, highlighting how algorithmic models can allocate orders across suppliers to optimize overall SC performance.

2.2 Scheduling and Optimization Approaches

SC optimization can be categorized according to nine main categories: SC network, facility location, supply planning, production planning, distribution planning, inventory planning, capacity planning, lot sizing and supplier selection [3]. Some of these topics are studied on an isolated way like: capacity planning [22], SC network [23], [24], and the facility location [25]. However, the trend and the majority of the studies are focused on integrated approaches such as: the integration of production, distribution and inventory planning [26], the integration of lot sizing and supplier selection and the integration of supply and distribution planning [27]. Almost every decision made in SCM is affected by supplier evaluation and selection [28]-[30]. Besides the supplier selection, the lot sizing problem [31], which deals with sourcing decisions, is also among the most important challenges that organizations are facing, and actually, some researchers tried to combine the supplier selection and order allocation problems to align and analyse the available strategies [32]-[35].

A common optimization problem is finding the optimal selling price and lot-size of multiple products in multiple periods while selecting the best suppliers. This problem faces several constraints, namely, the budget limitation, storage and supplier capacity [36], [37].

The problem with scheduling, rescheduling and supplier selection is thus a multi-objective problem that should be handled in a dynamic way, considering that the realistic SCs are not immune to disruption. There are few combined research addressing simultaneously outsourcing and disruption and indeed this is quite common in industrial operations where a large number of suppliers are involved giving place to long and complex SCs [38]-[40]. Most studies address machine rescheduling or otherwise outsourcing selection ignoring most often that these two problems gain complexity when dealt in conjunction [38]. Recent work has further reinforced this challenge: integrated formulations combining sustainable supplier selection, order allocation, and production scheduling under supply disruption have been shown to significantly outperform isolated approaches [41], while rescheduling frameworks capable of accommodating new order arrivals in real time – whether through bounded-disruption algorithms [42] or digital twin-enhanced Genetic Algorithms (GA) [43] – represent the current frontier of dynamic scheduling research. Further, green supplier selections add a significant number of constraints that dynamically affect SCs and thus limit the use of traditional optimization approaches.

Optimization techniques have been used to operate SC processes effectively handling complexity while integrating procurement, production, distribution and demand planning [3]. There are many optimization techniques used in SC processes such as Linear Programming [24], [44]-[46], Multi-Objective Programming [23], [47], Stochastic Programming [48] and Heuristics [25]-[27], [49]. Each category has techniques associated with it, and some of the most common [18], [19] are: the Analytic Hierarchy Process [11], [50]-[52], Technique for Order Preference by Similarity to Ideal Solution [11], [15], [53]-[55], Decision-Making Trial and Evaluation Laboratory [16], [18], [27].

Further, new research reinforces the use of search techniques, such as the use of quantum annealing, for larger problems compared to classical metaheuristics, since parameter selection complexities urge further exploration [56], [57]. These approaches have proved useful in a wide variety of problems, although their applicability is often hindered by the non-deterministic nature. The majority of the decisions in SCM belong to the class of non-deterministic problems [58], and thus heuristic methods have been applied to improve decisions. These methods define a completely new approach on optimization and are characterized by their search algorithm for potential solutions while searching for the overall optimal one, testing and evaluating solutions along the way,

further supporting the appropriateness of simulation-coupled metaheuristics when exact optimization becomes intractable and decisions must be updated online [59].

In dynamic market conditions and manufacturing contexts, customer requirements, operational resources, and supply channels are prone to swift alterations, thereby requiring the implementation of agile and adaptive methodologies. Proficient SCM serves a crucial function in mitigating these variances, empowering organizations to react expeditiously to changing consumer preferences and market dynamics [60]-[62].

A realistic SCM is normally a multi-objective problem and as such, it points to a Pareto optimal solution set being hardly attainable the entire Pareto set except for the simplest cases. The use of GA is in these cases extremely useful since it can be easily adapted to find optimum multi-objective solutions [63], [64] and, thus produce multiple Pareto optimum solutions. GA can simultaneously search solutions in different parts of the solution space and hence handle different objectives in a single run and explore the Pareto frontiers without requiring limiting or scaling objectives. GA have been used in a multitude of optimization problems [65]-[68] and results demonstrate their ability and flexibility in handling complex problems without the numerous limitations of traditional techniques [69].

Authors in [70] propose an optimization model that considers supplier selection, inventory decisions and inbound logistics under stochastic demand. GA are used to select suppliers, whereas, analytic formulas are described for base-stock inventory levels, with discrete-event simulation updating lead times under supply disruption. The case-based simulations have shown that selection criteria weights should depend on item characteristics and that mitigation strategies' effectiveness varies with disruption patterns.

Further, dynamic scheduling is fundamental since it can manage uncertainties by making real-time decisions, adapting to variable conditions, enhancing the ability to both optimize economic and environmental outcomes, while contributing to a more sustainable environment [71]-[73]. [74] presented a two-stage Distributionally Robust Optimization (DRO) model for supplier selection and order allocation under disruption risks. The model includes both mean and Conditional Value-at-Risk (CVaR) in the objective (a Mean–CVaR approach) to reflect a risk-averse decision-maker. Therefore, this robust-optimization framework allows for ambiguous probability distributions of supplier disruptions, linking supplier selection with order quantities, giving managers a way to deal with supply disruptions.

Authors in [75] develop a robust SC design mixed integer linear programming (MILP) model that introduce new integrator "risk measures" and apply robust optimization to account for uncertainty. Tested on randomly generated data and a real European aerospace case, the model helps quantify the trade-off between integrator benefits and their potential failure costs.

This study's key methodological contribution is embedding integrators as decision variables in supplier selection, with a robust formulation to guide original equipment manufacturers' tier decisions under uncertainty.

In a different scientific approach, authors in [76] apply graph neural networks (GNN) to recommend alternative suppliers in large SCs. A GNN of a major automotive supply network and train was defined to capture relationships (buyer–supplier links, disruptions, and other variables). The model suggests substituting suppliers when disruptions occur. This study contributes to a data-driven, AI-based framework for dynamic supplier selection under disruption, demonstrating the value of machine learning in SC decision support.

In [77], authors take a game-theoretic approach to sourcing decisions under risk. In their research, the model was applied considering two competing companies, choosing between a risky (cheaper) and a responsible (costlier) supplier, under different consumer segments and product-line strategies. Results have shown that factors like cost differences, product-line expansion and dual-sourcing options affect whether companies source from the "responsible" supplier. The model highlights how demand segmentation (e.g. green consumers) can induce sustainable supplier choices. Yet, the methodological contribution is analytical, i.e., a strategic framework linking product design and sourcing diversification to supplier selection in competitive markets.

A fuzzy multiple criteria decision making (MCDM) framework for circular economy-oriented supplier selection demonstrated how it can quantify "circularity" in supplier management. This work contributes to a novel set of circularity metrics and an advanced fuzzy decision process, emphasizing environmental and resource reuse criteria in supplier selection [78]. Sustainable supplier selection to multi-tier supply chains through an hybrid model combining fuzzy sets, stepwise weight assessment ratio analysis (SWARA) and Bayesian networks also being studied [79]. The study highlights how sustainable SC strat-

egies should be adapted to different networks, providing a multi-method decision method, able to both capture subjective weights and probabilistic relationships among criteria.

Different methods have been employed to improve and optimize supplier selection and order allocation – optimization algorithms, metaheuristics, fuzzy-logic, game theory, and AI – addressing uncertainty, sustainability and technological complexity, as summarized by Table 1.

In summary, to address the complexity involved in the optimization of large SCs, to enable dynamic scheduling and rescheduling, and further, to address multi-objective complex decision support systems, it is presented a framework based on natural selection that incorporates heuristic methods that deal with tangible and intangible aspects pertaining to supplier selection. This framework was built to support operations at a large textile organization that has both local production as well as subcontracted services.

3. Materials and Methods

A description of the problem to be handled is described in this section in detail to set the scenario for the development of the optimization framework. The problem concerns the outsourcing of jobs to a multitude of small companies that must be managed by a manufacturer and hence fulfil its needs while optimizing costs and delivery time subject to several constraints, e.g. outsourcing capacity, production capacity, supplier selection criteria, piecewise cost, quality, to name a few. The main manufacturer is a big corporation that outsources frequently some of the orders they get both to suppress shortage in available resources and when specialized jobs are required. The main manufacturer must handle several hundred orders per month and hence is urged to provide an optimum response since disruption or badly planned outsourcing may threaten the company's sustainability and thus leverage its competitive advantage.

3.1 Problem and Optimization Model

In today's competitive and quality-driven textile manufacturing environment, companies increasingly rely on hybrid production models where internal capabilities are supplemented through outsourcing. This strategy is driven by economic efficiency, responsiveness, and product diversity. However, outsourcing introduces complexities in supplier selection, capacity management, quality assurance, and scheduling under uncertainty. The problem addressed in this work revolves around the allocation and scheduling of manufacturing orders, each composed of multiple items, to a portfolio of third-party suppliers. The key operational challenge lies in selecting feasible,

Table 1. Different methods applied to improve and optimize supplier selection and order management

Authors	Methodology	Context	Key Contributions
[20]	Systematic literature review	General supply chains	Comprehensive classification of order allocation models/criteria; research gaps identified
[70]	Simulation–optimisation (GA + sim)	Global SC (case)	Hybrid model for joint supplier selection and inventory under stochastic demand/disruptions
[21]	Mixed-integer model + heuristic	Cloud manufacturing platform	Formulated cross-supplier order allocation with 3PL scheduling; heuristic solution
[78]	Fuzzy MCDM (BWM, regret, DHFS)	General (sustainable supply chains)	Defined circularity metrics and introduced a new fuzzy MCDM model for supplier selection
[74]	Two-stage DRO (Mean–CVaR)	Electronics	DRO model incorporating disruption risk with Mean–CVaR; validated on Huawei case
[79]	Fuzzy SWARA and Bayesian network	Multi-tier supply chains	Multi-tier sustainable supplier model using fuzzy logic and Bayesian networks
[75]	MILP with robust optimization	Aerospace (integrator focus)	MILP model for choosing integrators versus part suppliers under uncertainty
[77]	Game-theoretic modelling	Consumer products	Strategic sourcing model with consumer-driven preference for responsible suppliers
[76]	Graph Neural Network (GNN)	Automotive SC	GNN-based dynamic supplier recommendation using knowledge graph

cost-effective, and timely outsourcing options while considering varying supplier capabilities, processing times, prices, and performance metrics.

Moreover, orders arrive dynamically and must be evaluated within tight lead times. The manufacturer has on average, a 4-day decision window to assess new order profitability and feasibility. In the interest of reproducibility, and due to the industrial partner's confidentiality constraints, the key distributional characteristics of the dataset are as follows: orders follow an approximately uniform distribution across item types, with quantities ranging from 10 to 109 units per item; supplier processing times per item vary by a factor of up to 3× across the supplier pool; and monthly capacity limits range from approximately 200 to 800 time units per supplier. Researchers wishing to replicate experiments at comparable scale may use these distributions to generate synthetic instances. A formal anonymized instance generator is identified as a future dissemination objective.

Once commissioned, suppliers must initiate production within one week, reflecting contractual obligations. These temporal constraints, coupled with operational volatility, necessitate dynamic rescheduling capabilities and robust optimization methods that can quickly adapt to changes. We formalize the outsourcing problem using a multi-objective mixed-integer model, incorporating both economic and scheduling objectives. Indices and Parameters:

- S: Set of available suppliers, indexed by s
- O: Set of production orders, indexed by o
- I_o: Set of items in order o, indexed by $i \in I_o$
- $C_{i,s}$: Unit cost of outsourcing item I to supplier s
- $Q_{i,o}$: Quantity of item I in order o
- $P_{i,s}$: Unit processing time of item I by supplier s
- T_s: Monthly processing capacity (in time units) of supplier s
- LED_o: Latest execution date (deadline) for order o
- R_i: Required capabilities for item i
- V_s: Capabilities offered by supplier s
- $\alpha_s \in [1, 5]$: supplier performance index

Decision variables:

- $\delta o,s \in \{0,1\}$: Binary decision variable indicating whether order o is assigned to supplier s

Objective functions:

- Cost minimization - Minimize total outsourcing cost across all assigned orders (equation (1)):

$$\min Cost = \sum_{o \in O} \sum_{s \in S} \delta_{o,s} \sum_{i \in I_o} C_{i,s} Q_{i,o} \quad (1)$$

- Makespan Minimization - Minimize the maximum workload assigned to any supplier, defined as the time horizon (equation (2)):

$$\min Makespan = \max_{s \in S} \left(\sum_{o \in O} \delta_{o,s} \sum_{i \in I_o} P_{i,s} Q_{i,o} \right) \quad (2)$$

Constraints

- Order exclusivity: $\sum_{s \in S} \delta_{o,s} = 1, \forall o \in O$
- Supplier capability: $R_i \subseteq V_s, \forall i \in I_o$ *such that* $\delta_s = 1$
- Supplier capacity: $\sum_{o \in O} \delta_{o,s} \sum_{i \in I_o} P_{i,s} Q_{i,o} \leq T_s, \forall s \in S$
- Deadline constraint: $PED_o = LED_o, \forall o \in O$
- Supplier ranking (optional tiebreaker): $\max \sum_{o \in O} \sum_{s \in S} \delta_{o,s} \alpha_s$

The primary goal of the company is to optimize outsourcing decisions by minimizing overall costs and reducing the makespan or time horizon required to complete all orders, while ensuring that deliveries are made within their respective deadlines and that each order is allocated to a supplier with the necessary capabilities. However, the complexity of the problem extends well beyond these core objectives. Disruptions, changing supplier availability, and the arrival of new orders occur unpredictably, requiring continuous monitoring and dynamic rescheduling.

Order commissioning must typically be executed with a one-week lead time, as stipulated in supplier agreements to allow for production preparation. Moreover, upon receiving an order request, the manufacturer has on average a four-day window to assess its feasibility and profitability before acceptance, though this may vary by contract. In certain instances, orders are declined either due to insufficient production capacity or the anticipation of more advantageous future opportunities, particularly when current suppliers are near capacity.

A centralized database underpins the decision-making process by maintaining up-to-date information on each supplier's capabilities, monthly production availability, and their historical performance. It also tracks the production status of all orders, including commissioning dates, itemized job details, estimated processing times, forecasted execution dates, and current status (e.g., commissioned, in production, completed). Supplier selection, conducted at the point of commissioning, incorporates both economic and risk-based considerations such as price, quality consistency, and on-time delivery performance. In practice, the composite score αs is computed periodically by the purchasing department based on verifiable records:

economic criteria are assessed through invoice and delivery history, social criteria through occupational health compliance reports and audit records, and environmental criteria through suppliers declared environmental management practices and, where available, certified standards (e.g., ISO 14001). While the current implementation uses an unweighted ordinal index – reflecting the pragmatic data constraints of the industrial partner – the scoring model is designed to be extensible to weighted or certified criteria as data availability improves. To support this, suppliers are evaluated and ranked on a normalized scale from 1 to 5, based on cumulative conformity to a set of economic (e.g., cost efficiency or lead time adherence), social (e.g., occupational health and safety standards), and environmental (e.g., sustainability practices) criteria. This ranking is not weighted but serves as a tiebreaker when multiple allocation solutions are feasible, effectively embedding green supplier preference as a constraint-satisfying selection layer. While the primary objectives remain cost and makespan minimization – reflecting contractual and operational priorities – the environmental and social scoring ensures that, among equally feasible allocations, greener suppliers are systematically preferred. This constitutes a lexicographic approach to multi-objective optimization: economic objectives are optimized first, and sustainability criteria govern tie-breaking. Further developments may elevate this component to a full third objective within a Pareto framework, particularly as richer ESG audit data become available.

3.2 Scheduling Strategy and Search Algorithm

Due to the real-time and high-dimensional nature of the problem (with multiple items per job, variable lead times, and heterogeneous suppliers), traditional exact methods are computationally infeasible. Therefore, we implement a GA tailored to the structural characteristics of the problem. Each chromosome encodes a complete allocation of orders to suppliers (equation (3)):

$$X = \{(o, s) | \delta_{o,s} = 1\} \tag{3}$$

The proposed representation is designed to accommodate the complexity and variability of real-world manufacturing scheduling. It supports: (i) variable numbers of items per order; (ii) heterogeneous suppliers with distinct capabilities and processing times; and (iii) context-specific constraints such as feasibility based on supplier capabilities Vs, delivery deadlines, and available capacity. To address these challenges, the GA integrates domain-specific operators that closely mimic real-world rescheduling actions. The crossover operator swaps supplier allocations for subsets of orders between two parent solutions, but only when such swaps respect all feasibility conditions, including supplier capability, available time, and deadlines.

The mutation operator reassigns an individual order from one supplier to another, selected at random, and similarly only applies the change if all constraints are satisfied. These operators differ from generic encodings by being semantically meaningful, enabling more realistic and interpretable evolutionary steps such as job reallocation or re-commissioning due to disruptions.

Fitness evaluation relies on a weighted aggregation multi-objective function that combines total outsourcing cost, makespan, and — optionally — the supplier ranking index into a scalar fitness value. This approach was chosen for its computational simplicity and suitability for real-time rescheduling environments, where a single ranked solution set must be produced rapidly. Formally, the fitness of individual X is defined as:

$$F(X) = w_1 . Cost_{norm}(X) + \\ + w_2 . Makespan_{norm}(X) - w_3 . \propto_{norm} (X) \tag{4}$$

where $w_1, w_2, w_3 \in [0,1]$ are user-defined weights with $w_1+w_2+w_3=1$, and each term is the min-max normalized counterpart of the objectives defined in equations (1) and (2), and of the supplier ranking index α_s defined in Section 3.1, respectively, all normalized to [0,1] across the current population. Minimizing $F(X)$ thus simultaneously drives solutions toward lower outsourcing cost, shorter makespan, and higher ranked (greener) suppliers. Selection pressure is applied through tournament selection, a standard selection mechanism in GA implementations that balances exploration and exploitation without requiring explicit fitness scaling. While this does not yield a full Pareto front, it produces a ranked pool of near-optimal solutions that decision-makers can navigate. Future extensions may incorporate nondominated sorting (e.g., NSGA-II) to expose the full cost–makespan trade-off surface. This ranking incorporates economic, social, and environmental criteria and guides selection toward both cost-efficiency and supplier reliability.

Crucially, the algorithm is designed for dynamic environments. It supports real-time rescheduling

and is re-executed upon the arrival of new orders. Each time a job is commissioned, the corresponding supplier's available monthly capacity is updated. This continuous adaptation ensures robustness by maintaining a pool of near-optimal solutions. These alternatives can be rapidly deployed if the preferred schedule becomes infeasible due to unexpected disruptions or evolving supplier conditions. Complementing the problem formulation and supplier monitoring framework outlined previously, this scheduling strategy leverages the flexibility and efficiency of a GA tailored for dynamic order allocation. The goal is twofold: to minimize outsourcing costs and shorten the production makespan. Given the inherent variability and interdependence of scheduling variables, even small deviations in delivery times can cause cascading failures and financial penalties. As such, the proposed approach emphasizes responsive, adaptive decision-making capable of continually integrating new information as operational conditions evolve.

The proposed GA follows the fundamental principles of natural selection, beginning with the generation of an initial population and iteratively evolving this population through selection, crossover, and mutation operations. The evolutionary process converges toward a near-optimal solution by favouring the survival and reproduction of fitter individuals. Unlike conventional encodings, typically fixed sequences of tuples that define operations, machines, jobs, or cells [80], often inflexible and poorly suited to real-world scenarios involving variable substructures, the model presented here adopts a context-sensitive and structurally mutable representation. Specifically, each chromosome is a variable-length nested structure: at the top level, genes correspond to suppliers; within each supplier gene, a variable-length list of assigned orders is maintained; and within each order, the item set and quantities are carried as metadata. This three-level hierarchy – supplier, order, item – is structurally distinct from flat assignment vectors (e.g., a fixed array where position i encodes the supplier for job i), because it naturally accommodates variable numbers of orders per supplier and variable numbers of items per order without requiring padding or length normalization. As a direct consequence, crossover and mutation operate at the semantically meaningful supplier-assignment level rather than at arbitrary positional offsets, substantially reducing the rate of infeasible offspring compared to generic encodings applied to equivalent problem instances.

Individuals are structured according to supplier-job allocations, where each supplier may be assigned a variable number of jobs, and each job may contain a different number of items, reflecting realistic industrial settings. This flexible design enables meaningful implementation of crossover and mutation operations that directly mirror physical scheduling actions. Crossover involves the exchange of supplier-job allocations between compatible individuals, while mutation consists of relocating a job from one supplier to another within the same individual, provided the recipient supplier has the required capabilities. This approach not only increases the feasibility of generated individuals but also avoids the limitations associated with traditional crossover operators, which often produce a high proportion of unfit solutions when applied to complex representations [81]. The entire scheduling framework is implemented in Julia, a high-performance programming language developed at MIT, specifically chosen for its numerical efficiency and flexibility [82]. This implementation avoids the limitations imposed by commercial simulation platforms, which often rely on rigid, predefined structures that restrict problem-specific adaptations. Notably, some prior works claim to introduce novel GA-based approaches, but they depend heavily on generic solvers like LINGO [83], which are inadequate for modelling the kind of dynamic, constraint-intensive environment addressed here.

The heuristic pruning mechanism operates as a feasibility filter applied after crossover and mutation. Specifically, any offspring individual is evaluated against three hard constraints before entering the population: (i) each order must be assigned to exactly one supplier possessing the required capabilities ($Ri \subseteq Vs$); (ii) the total assigned processing time must not exceed the supplier's monthly capacity Ts; and (iii) the projected execution date must not exceed the order deadline LEDo. Individuals violating any of these conditions are discarded rather than penalized, ensuring the population remains entirely feasible throughout evolution. This pruning incurs $O(|O|\cdot|I|)$ per individual per generation, which is negligible relative to fitness evaluation. Importantly, pruning does not systematically disadvantage greener suppliers: infeasibility is determined solely by capability, capacity, and deadline constraints, which are independent of the αs score.

To ensure responsiveness, the algorithm reruns the scheduling procedure whenever a new order is received, adjusting supplier availability in real-time. Job commissioning – currently performed manually – is already embedded into the workflow and can be automated in future versions. Each commissioning event updates the monthly availability of the selected supplier by deducting the duration required for the

assigned job. Furthermore, the GA does not yield a single deterministic solution but a ranked set of near-optimal candidates, allowing decision-makers to choose alternatives if disruptions affect the preferred schedule. By closely aligning the representation and evolutionary operations with real industrial processes, the proposed framework ensures adaptability, robustness, and relevance, making it suitable for highly variable manufacturing environments where scheduling precision and flexibility are critical. Figure 1 provides a representation of orders/jobs disposition per individual and GA operators.

Overall, the proposed framework offers a practical and scalable solution to the complex and dynamic challenge of order allocation and scheduling in distributed manufacturing environments. By re-running the scheduling algorithm upon the arrival of new orders, it ensures timely job commissioning and real-time updates to supplier availability. Although currently managed manually, job commissioning is seamlessly integrated into the algorithmic workflow and is designed for future automation. Each commissioned job dynamically reduces the supplier's available capacity, ensuring accurate planning across monthly production windows. Importantly, the use of GA yields not just a single solution but a diverse set of ranked near-optimal alternatives. This enables decision-makers to pivot effectively when facing disruptions, supplier overloads, or last-minute changes, thereby enhancing the system's resilience and operational flexibility. The ability to adapt continuously, combined with the tailored encoding and evolutionary logic, makes this framework a robust foundation for intelligent, cost-efficient, and sustainable production scheduling.

4. Results

The following test results were obtained with the information contained in three main tables within an SQL database: “Orders”, “Suppliers” and “Supplier Capacity”. The table “Orders” contains all the information pertaining to each order to be scheduled, including items and requested number, order status and due date. Table “Suppliers” contains the information pertaining to each of the available suppliers, including monthly production time availability and scoring indexes related to economic, social and environmental criteria. In table “Supplier Capacity” is registered the capacity of suppliers to manufacture certain items and their corresponding practiced prices and required manufacturing time. All information is maintained and updated regularly by the purchasing department upon the completion of each job. At the time of this simulation there were 21 suppliers in the database and 119 jobs/orders to be scheduled. Each job contained an average of 4 items with varying number of ordered items, ranging from 10 to 109. There were 20 different registered items in the supplier, and, on average, each supplier was able to manufacture 6 of these items, mainly household, e.g., bedding, tablecloths and towels.

Figure 2 and Figure 3 show the evolution of the heuristic search from a randomly created population trough 1500 iterations optimization. There are three indicators on performance shown that represent overall efficiency, e.g. combined efficiencies, as well as optimized measured cost and optimized execution time (makespan) pertaining to all jobs ready to be dispatched. Efficiency measures are all normalized to provide comparable results.

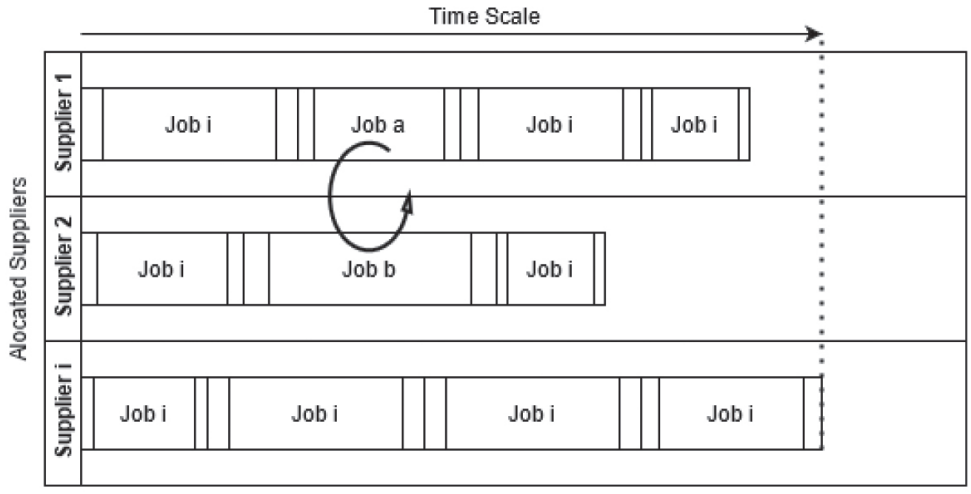


Figure 1. Visualization of Orders/Jobs disposition per individual and GA operators (Mutation).

While in Figure 2 it is shown the evolution of the population with a 10% mutation probability, in Figure 3, with the same population size, it can be seen evolution with a mutation probability of 30%. It can be clearly seen that with a higher mutation probability convergence takes place faster and thus with a mutation probability of 30% population stabilizes after 1000 iterations, while with 10% mutation probability the population is still evolving with 1500 iterations. A further increase in the mutation probability does not produce better results. As expected, efficiency associated to overall cost for the optimum schedule does not change much since practiced prices among suppliers do not change considerably.

Figure 4 plots population evolution for different mutation probabilities. With lower mutation probabilities the population tends to evolve slowly and fail to attain an optimum scheduling option.

Figure 5 depicts the evolution of a smaller population, when compared to the one in Figure 2, and clearly shows slower conversion rates.

Figure 6 and Figure 7 show the effect of population size on convergence rates for two mutation probabilities. Once again higher population sizes tend to

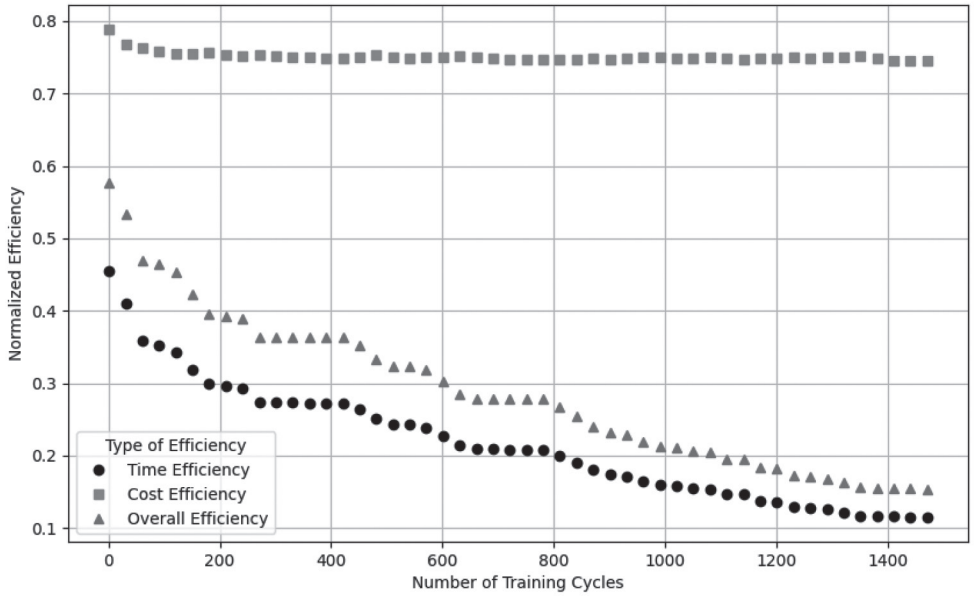


Figure 2. Efficiency indicators versus training cycles for a population of 190 individuals and mutation probability of 10%.

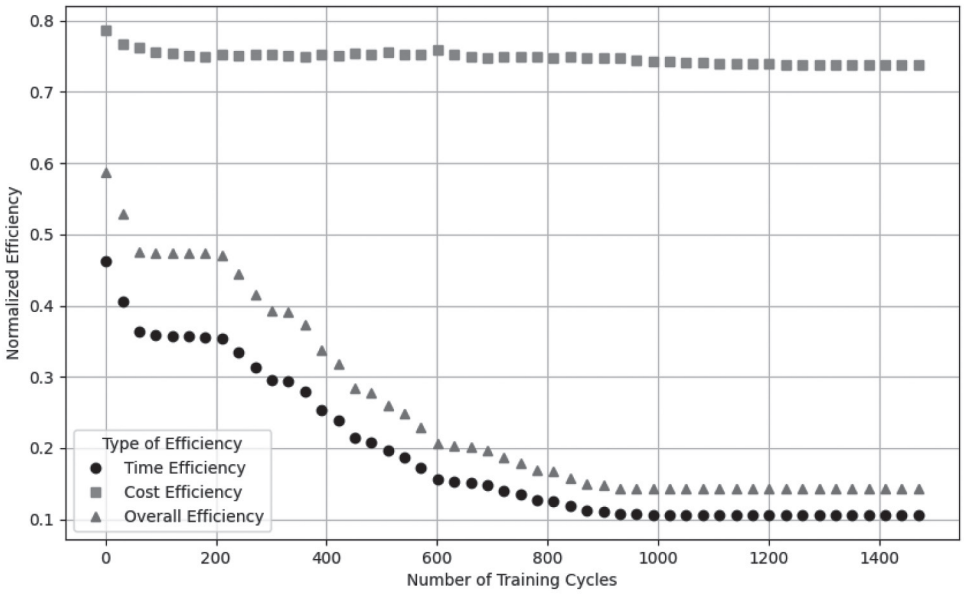


Figure 3. Efficiency indicators versus training cycles for a population of 190 individuals and mutation probability of 30%.

converge faster and hence produce an optimized solution in fewer iterations. Lower mutation probabilities also produce slower convergence.

Figure 8 show the overall influence of mutation probability and population size on overall efficiency. Both parameters have an influence on convergency rates, but mutation probability shows a higher impact, and below a mutation probability of 10% converge may even not take place.

It is noted that the comparisons presented in this work are against the company's prior manual scheduling practice, which serves as the operational baseline. Formal benchmarking against algorithmic comparators such as MILP, NSGA-II, or priority-rule heuristics (e.g., earliest due date) was not conducted in this study and represents a clear avenue for future work. Nevertheless, the magnitude of improvement over operational practice, particularly the 45% makespan reduction, demonstrates the framework's value in an industrial deployment context. Optimum scheduling solutions are obtained for a population with 180 individuals or more with a mutation probability of about 30%. The normalized efficiency aids on understanding the extent of gained performance individually or

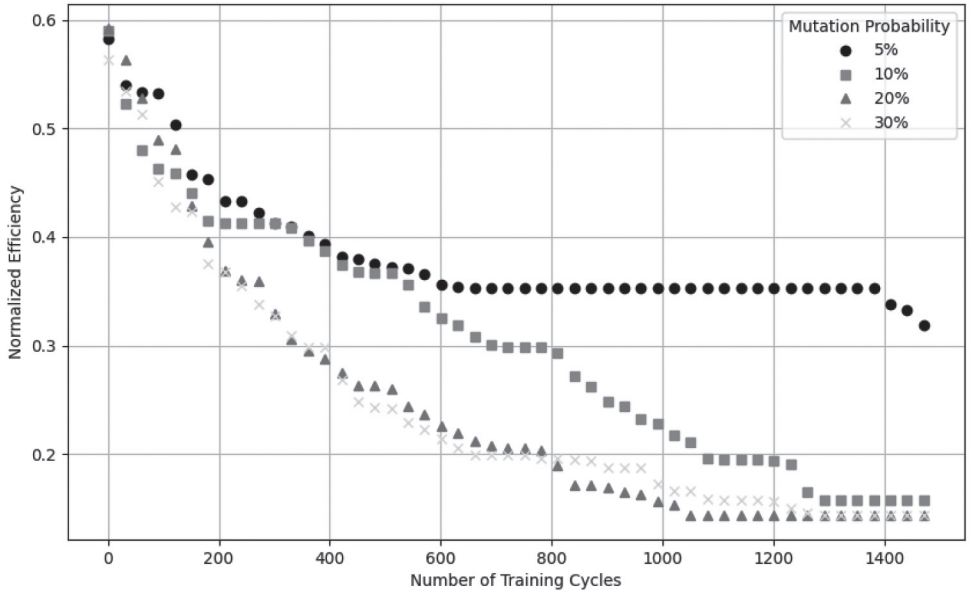


Figure 4. Best scheduling option upon training for different mutation probabilities with a population of 200 individuals.

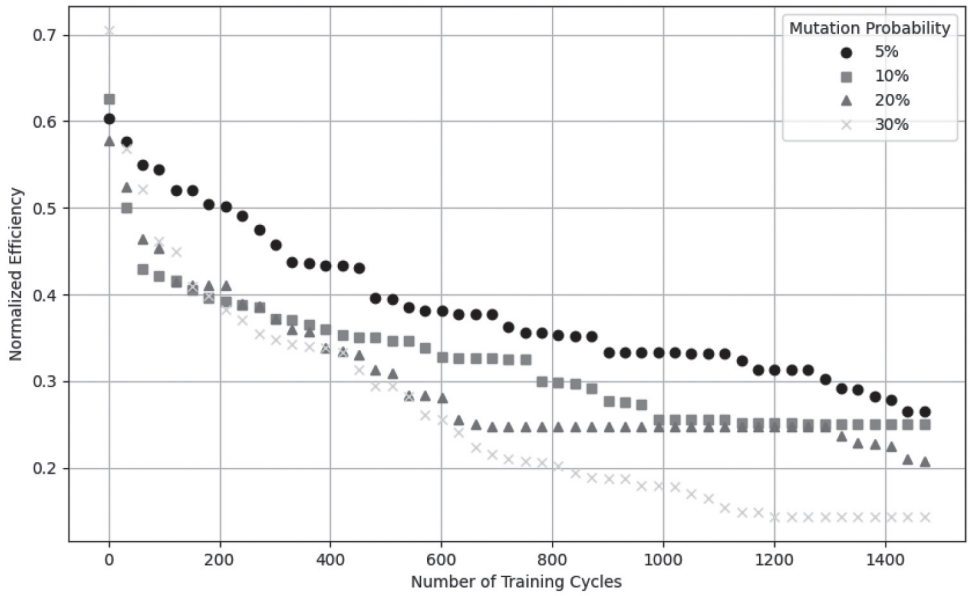


Figure 5. Best scheduling option upon training for different mutation probabilities with a population of 50 individuals.

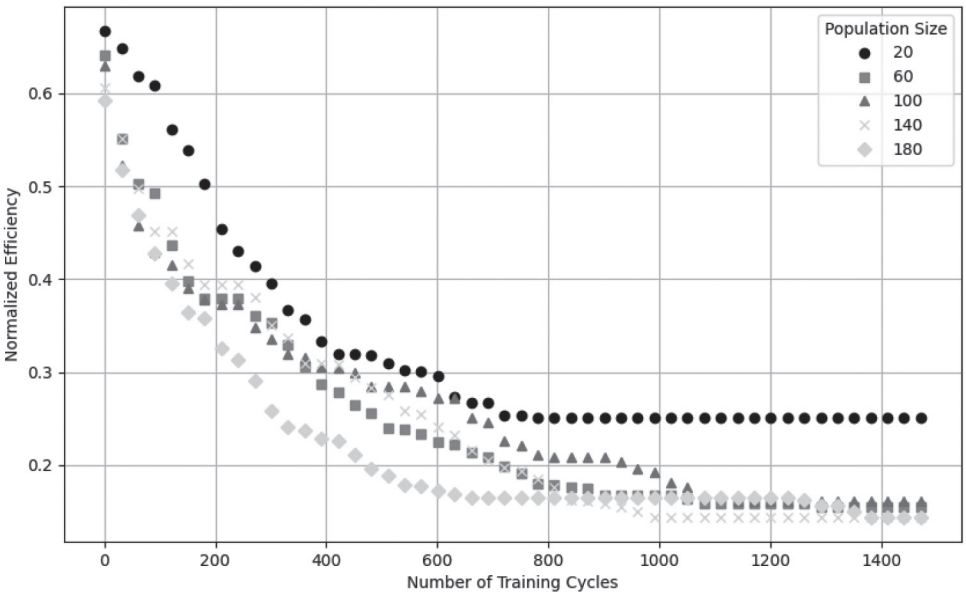


Figure 6. Best scheduling option upon training for different population sizes with a mutation probability of 30%.

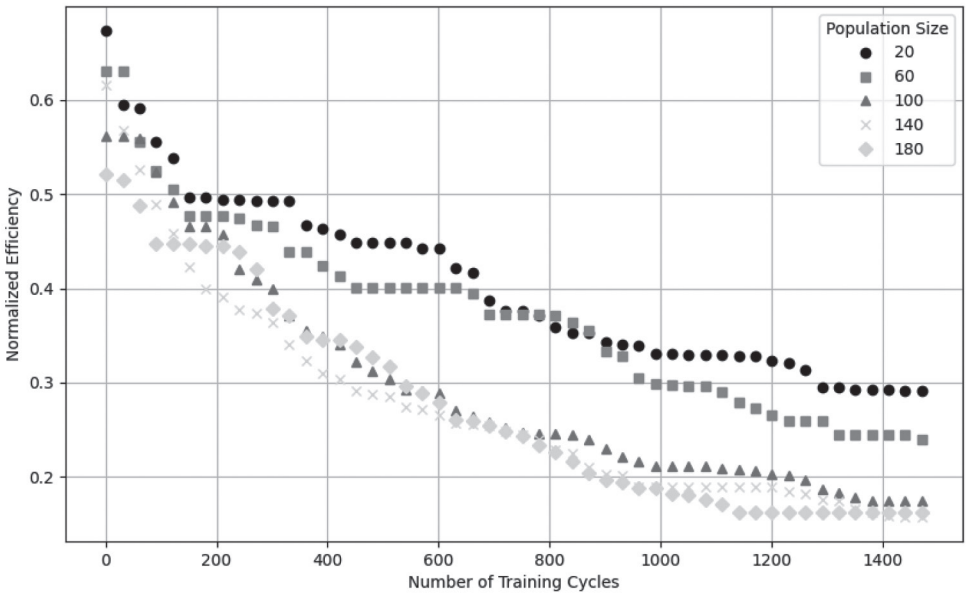


Figure 7. Best scheduling option upon training for different population sizes with a mutation probability of 10%.

combined. Figure 3 presents the best set of results for a population size of 190 individuals and a mutation probability of 30%. The overall efficiency gain evolves from a value of 0.46 to a value of 0.10, a total gain of 0.36 – this combined indicator integrates both cost and makespan normalized efficiency.

To get a grasp on the real impact of the results both indicators must be analysed separately, hence, the cost efficiency has a gain of 0.04, from 0.78 to 0.74, which represents a reduction in costs by 4%. The makespan efficiency has a gain of 0.45, from 0.59 to 0.14, which represents a reduction in makespan by 45%.

To contextualize these results in managerial terms: the 4% cost reduction, while modest in relative terms, corresponds to meaningful absolute savings given the volume of orders processed monthly by the manufacturer. More significantly, the 45% reduction in makespan translates directly into earlier order completion, reduced exposure to contractual late-delivery penalties, and improved capacity to accept new orders within the same planning window, directly impacting service level and revenue potential. The marginal cost improvement is consistent with the industrial context, where supplier prices are subject to negotiated contracts with limited short-term vari-

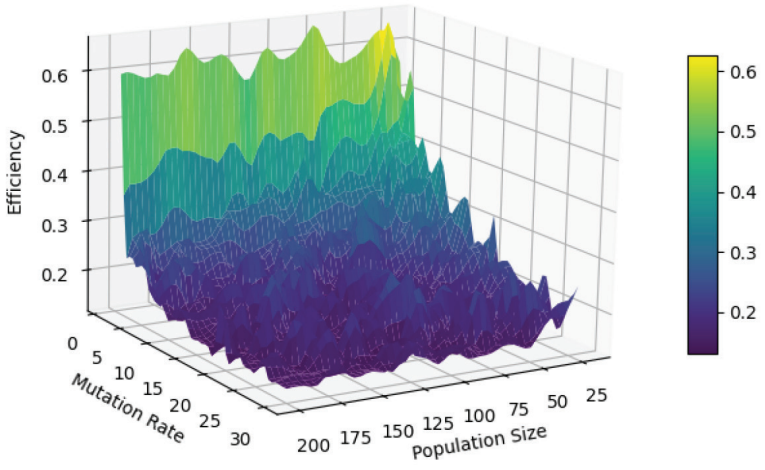


Figure 8. Performance versus mutation probability and population size.

ability; the principal lever for competitive advantage is therefore scheduling efficiency rather than price arbitrage. The small reduction in costs comes has no surprise since the variability in prices among suppliers is small. Major gains are attained by the reduction in the makespan as one would expect since jobs are initially allocated randomly to suppliers within each individual. Each of the scenarios had an execution time below 10 seconds, a time perfectly sound for making technical decisions in practice.

5. Discussion

5.1 Framework contributions to SC optimization

The experimentation's results offer valuable insights into the efficiency and effectiveness of the proposed approach to order allocation and scheduling within the textile industry. Drawing upon data from three primary tables within an SQL database – "Orders", "Suppliers" and "Supplier Capacity" – the study conducts comprehensive analyses, providing a robust foundation for its findings. By tracking the evolution of the heuristic search through 1500 iterations of optimization, utilizing a population-based approach with varying mutation probabilities, the study illustrates the impact of mutation probability on convergence rates. Figures 2 and 3 showcase this evolution, highlighting that higher mutation probabilities lead to faster convergence, as evidenced by Figure 3's progression compared to Figure 2.

Similarly, Figure 4 underscores how lower mutation probabilities result in slower convergence rates. Moreover, the investigation delves into the effect of population size on convergence rates, as depicted in Figures 5, 6, and 7. Here, larger population sizes demonstrate faster convergence, yielding optimized solutions in fewer iterations. However, lower mutation probabilities contribute to slower convergence, as evidenced in Figure 7. Figure 8 offers an overview of the overall influence of mutation probability and population size on efficiency. Notably, both parameters significantly impact convergence rates, with mutation probability exhibiting a higher impact.

Optimal scheduling solutions are attained with a population size of 180 individuals or more and a mutation probability of approximately 30%. Normalized efficiency metrics further enhance the understanding of the performance gains achieved through optimization. For example, Figure 3 showcases a substantial improvement in overall efficiency, with a total gain of 0.36 in the combined indicator integrating both cost and makespan efficiency. The reduction in makespan efficiency by 45% indicates a significant enhancement in scheduling effectiveness, while the marginal reduction in costs reflects the minimal variability in prices among suppliers. Importantly, all scenarios exhibit execution times below 10 seconds, indicating the practical viability of the proposed approach for making technical decisions in real-world settings.

The alignment between the experimentation's findings and the broader trends and challenges outlined in the review of SCM dynamics is striking. The review underscores the increasing complexity of supply chains driven by globalization, outsourcing practices, and the emergence of Green Supply Chain Management (GSCM). This complexity underscores the need for dynamic and flexible approaches to supplier selection and order allocation, precisely what the proposed optimization framework aims to achieve.

The study's exploration of heuristic search algorithms and their application to SCM optimization resonates with the review's discussion on the integration of advanced optimization techniques in SCM processes. By leveraging a population-based approach with varying mutation probabilities, the study sheds light on the impact of these parameters on convergence rates and overall efficiency, aligning with the review's emphasis on dynamic decision-making in SCM. Furthermore, the study's findings regarding the influence of population size and mutation probability on convergence rates reinforce the review's discussion on the challenges posed by outsourcing practices and the need for efficient decision schemes.

The emphasis on larger population sizes and higher mutation probabilities for faster convergence echoes the review's insights into achieving optimal solutions in complex SCM environments. Also, the discussion on normalized efficiency metrics in the study's findings resonates with the review's exploration of performance evaluation criteria in SCM, particularly in the context of GSCM. The significant improvements in scheduling effectiveness, coupled with marginal reductions in costs, reflect the broader trend towards prioritizing sustainability and efficiency in SCM operations, as discussed in the review.

Regarding the contribution of the research from a methodological point-of-view. the algorithm was designed for real-time optimization. Whenever a new order arrives, the GA is iteratively to update the supplier's remaining capacity. Instead of a single solution, the GA produces a ranked set of near-optimal schedules, allowing the decision makers to switch between supply alternatives in case of disruptions, greatly enhancing the adaptability of the proposed method when compared to one-step SC scheduling approaches. It should be acknowledged that the presented experimental results reflect a static scenario of 119 orders and 21 suppliers, as available at the time of evaluation. Disruption scenarios – such as supplier capacity loss or late delivery cascades – are supported by the algorithmic design (re-triggering the GA upon any state change) but were not formally simulated in the current experiments due to the industrial partner's data constraints. This represents a limitation of the present validation, and structured disruption simulation is identified as a priority for future work, including controlled capacity-reduction and delivery-delay injection experiments.

Another important aspect of the presented study is the fact that the framework was fully implemented in Julia, allowing to integrate a detailed production-process simulator that replicates real industrial dynamics. Thus, since it is not a commercial tool, the code can handle the dynamic constraints of the textile case with flexibility within reduced computational time.

Overall, unlike MILP-based models from literature, this approach continuously adapts to new data and information, allowing to integrate green supplier selection with optimization scheduling, whereas many other studies treat these aspects separately [20], [75]. The use of multi-objective GA with rich problem encoding represents a clear advance in computational realism and flexibility compared to traditional supply-chain optimization models.

5.2 Framework contributions for decision makers in industry

The model was tailored to a real textile manufacturer, considering multiple production capacities, several suppliers handling small-batch orders and close-fitting delivery deadlines. By modelling constraints like supplier availability, the framework allows to coordinate several concurrent outsourcing relationships. This delivers more flexibility to scheduling than conventional methods [68], [84]. The case study explicitly applies to green supplier selection and provides a structured basis for modelling institutional policy levers – such as green procurement thresholds and non-compliance penalties – as parameters that shift stable allocation patterns under disruption [85]. This is a pathway consistent with recent work demonstrating how behavioural heterogeneity, audit probabilities, and incentive-compatible contracts can be incorporated into adaptive supplier selection models [86]. Each supplier is scored, and the GA can prioritize greener options. By optimizing resource use (shortening makespan and reducing delays), the framework promotes waste reduction and more sustainable operations. This aligns with industry trends toward greener, circular supply chains and provides a practical tool for implementing such policies [78].

From a wider perspective, the framework proved capable of handling dynamic order inflows and multi-objective decisions within low run-times. Its built-in order-update nature suggest that the framework could be integrated into different production planning systems, offering a scalable solution that makes SC scheduling more efficient and competitive while supporting greener production strategies.

6. Conclusions

In conclusion, this research paper introduces a framework model tailored for green supplier selection and order allocation within the dynamic textile market. The framework adeptly incorporates various constraints related to supplier selection, emphasizing sustainability criteria. By leveraging the flexibility and performance advantages of GA, the approach offers diverse action scenarios to optimize scheduling for order allocation and supplier selection while adhering to contractor deadlines. The multi-objective nature of the framework allows for the fine-tuning of parametric settings to prioritize either higher revenues or shorter makespan.

Testing the framework with real data from a prominent textile company validates its efficiency and capability to manage continuous order updates and rescheduling tasks, generating various optimization scenarios based on multi-objective settings. Notably, time emerges as the variable with the most significant impact on optimization, likely influenced by contractor availability, while cost variations among contractors remain minimal. The key factors contributing to enhanced performance of the genetic algorithm are population size and mutation probability, with a mutation probability exceeding 25% yielding superior results. Moreover, increasing the population size from 60-80 individuals enhances performance, with mutation probability exerting a more substantial influence.

However, the study acknowledges several limitations stemming from the use of real data, necessitating further research endeavours. Additionally, the recommended GA parameters – mutation probability of approximately 30% and population size of 180 or more – were identified through sensitivity analysis on the same industrial dataset used for evaluation. This introduces a risk of instance-specific overfitting, and cross-instance or out-of-sample validation on synthetic instances of comparable scale is recommended to confirm the generalizability of these parameter recommendations. The constrained number of orders, suppliers, and selection criteria within the existing dataset may not fully challenge the robustness of the framework under more demanding circumstances. Additionally, conducting sensitivity analyses of the multi-objective optimization function in an automated environment, employing weighted criteria, can elucidate the impact of competing interests. Furthermore, exploring different dimensions or gene stacks within the framework across various industry sectors can provide insights into their suitability, performance, and the benefits they introduce. Furthermore, the sensitivity analysis focused on algorithmic parameters (mutation probability and population size) without exploring the space of objective weights w_1 and w_2 governing the cost–makespan trade-off. Systematic weight-space exploration – for instance, through a grid search over the simplex $w_1 + w_2 = 1$ – would enable decision-makers to explicitly navigate the efficiency frontier and understand the conditions under which cost minimization should be prioritized over makespan reduction, or vice versa. This is identified as a near-term extension of the present work.

In summary, while this study demonstrates promising results and insights into green supplier selection and order allocation in the textile industry, further research is warranted to address the identified limitations and expand the applicability and robustness of the framework across diverse operational contexts. In conclusion, the study's results provide practical insights that complement the theoretical discussions presented in the review. By addressing key challenges and leveraging advanced optimization techniques, the proposed approach offers a promising solution to enhance order allocation and scheduling efficiency within the textile industry, aligning with broader trends and challenges in SCM.

Funding

This work was supported by Fundação para a Ciência e Tecnologia (FCT), I.P., under project "Centro de Investigação em Organizações, Mercados e Gestão Industrial" [project reference UIDB/04005/2020], DOI: 10.54499/UIDB/04005/2020.

References

[1] F. Goodarzi, V. Abdollahzadeh, and M. Zeinalnezhad, "An integrated multi-criteria decision-making and multi-objective optimization framework for green supplier evaluation and optimal order allocation under uncertainty," Decis. Anal. J., vol. 4, Art. no. 100087, 2022, doi: 10.1016/j.dajour.2022.100087.

[2] United Nations Development Programme, "Background of the Sustainable Development Goals," United Nations Development Programme.

[3] Y. Kocaoğlu, A. Taşkın Gümüş, and B. Kocaoğlu, "Supply chain optimization studies: A literature review and classification," Doğuş Univ. Derg., vol. 19, no. 1, pp. 79–98, 2018, doi: 10.31671/dogus.2018.16.

[4] D. Gligor, "Birds of a feather: The impact of race on the supplier selection and evaluation process," Int. J. Prod. Econ., Art. no. 107802, 2020, doi: 10.1016/j.ijpe.2020.107802.

[5] R. Jia, Y. Liu, and X. Bai, "Sustainable supplier selection and order allocation: Distributionally robust goal programming

model and tractable approximation," Comput. Ind. Eng., vol. 140, Art. no. 106267, 2020, doi: 10.1016/j.cie.2020.106267.

[6] P. Guarnieri and F. Trojan, "Decision making on supplier selection based on social, ethical, and environmental criteria: A study in the textile industry," Resour. Conserv. Recycl., vol. 141, pp. 347–361, 2019, doi: 10.1016/j.resconrec.2018.10.023.

[7] Fashion Revolution, Fashion Transparency Index: 2019 Edition, 2019.

[8] P. Ghadimi, F. Ghassemi Toosi, and C. Heavey, "A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain," Eur. J. Oper. Res., vol. 269, no. 1, pp. 286-301, 2018, doi: 10.1016/j.ejor.2017.07.014.

[9] J. Scott, W. Ho, P. K. Dey, and S. Talluri, "A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments," Int. J. Prod. Econ., vol. 166, pp. 226–237, 2015, doi: 10.1016/j.ijpe.2014.11.008.

[10] X. Hu, G. Wang, X. Li, Y. Zhang, S. Feng, and A. Yang, "Joint decision model of supplier selection and order allocation for the mass customization of logistics services," Transp. Res. Part E Logist. Transp. Rev., vol. 120, pp. 76–95, 2018, doi: 10.1016/j.tre.2018.10.011.

[11] S. Hamdan and A. Cheaitou, "Supplier selection and order allocation with green criteria: An MCDM and multi-objective optimization approach," Comput. Oper. Res., 2017, doi: 10.1016/j.cor.2016.11.005.

[12] K. Rashidi, A. Noorizadeh, D. Kannan, and K. Cullinane, "Applying the triple bottom line in sustainable supplier selection: A meta-review of the state-of-the-art," J. Clean. Prod., vol. 269, Art. no. 122001, 2020, doi: 10.1016/j.jclepro.2020.122001.

[13] G. K. Kumar, M. S. Rao, and V. V. S. K. Rao, "Supplier selection and order allocation in supply chain," Mater. Today Proc., vol. 5, no. 5, pp. 12161–12173, 2018, doi: 10.1016/j.matpr.2018.02.194.

[14] H. Moheb-Alizadeh and R. Handfield, "Sustainable supplier selection and order allocation: A novel multi-objective programming model with a hybrid solution approach," Comput. Ind. Eng., vol. 129, pp. 192–209, 2019, doi: 10.1016/j.cie.2019.01.011.

[15] H. W. Lo, J. J. H. Liou, H. S. Wang, and Y. S. Tsai, "An integrated model for solving problems in green supplier selection and order allocation," J. Clean. Prod., vol. 190, pp. 339-352, 2018, doi: 10.1016/j.jclepro.2018.04.105.

[16] S. Sarkar, V. Lakha, I. Ansari, and J. Maiti, "Supplier selection in uncertain environment: A fuzzy MCDM approach," Adv. Intell. Syst. Comput., vol. 458, 2017, doi: 10.1007/978-981-10-2035-3.

[17] J. L. Zhang and M. Y. Zhang, "Supplier selection and purchase problem with fixed cost and constrained order quantities under stochastic demand," Int. J. Prod. Econ., vol. 129, no. 1, pp. 1-7, 2011, doi: 10.1016/j.ijpe.2010.08.003.

[18] H. G. Gören, "A decision framework for sustainable supplier selection and order allocation with lost sales," J. Clean. Prod., vol. 183, pp. 1156-1169, 2018, doi: 10.1016/j.jclepro.2018.02.211.

[19] M. Setak, S. Sharifi, and A. Alimohammadian, "Supplier selection and order allocation models in supply chain management: A review," World Appl. Sci. J., vol. 18, pp. 55-72, 2012, doi: 10.5829/idosi.wasj.2012.18.01.3258.

[20] V. Di Pasquale, M. E. Nenni, and S. Riemma, "Order allocation in purchasing management: A review of state-of-the-art studies from a supply chain perspective," Int. J. Prod. Res., vol. 58, no. 15, pp. 4741–4766, 2020, doi: 10.1080/00207543.2020.1751338.

[21] Q. Wu, N. Xie, and S. Zheng, "Integrated cross-supplier order and logistic scheduling in cloud manufacturing," Int. J. Prod. Res., vol. 60, no. 5, pp. 1633–1649, 2022, doi: 10.1080/00207543.2020.1867921.

[22] C. Lucas, S. A. Mirhassani, G. Mitra, and C. A. Poojari, "An application of Lagrangian relaxation to a capacity planning problem under uncertainty," J. Oper. Res. Soc., vol. 52, pp. 1256–1266, 2001, doi: 10.1057/palgrave.jors.2601221.

[23] M. Varsei and S. Polyakovskiy, "Sustainable supply chain network design: A case of the wine industry in Australia," Omega, vol. 66, pp. 236–247, 2015, doi: 10.1016/j.omega.2015.11.009.

[24] T. Paksoy and C. T. Chang, "Revised multi-choice goal programming for multi-period, multi-stage inventory controlled supply chain model with popup stores in Guerrilla marketing," Appl. Math. Model., vol. 34, no. 11, pp. 3586-3598, 2010, doi: 10.1016/j.apm.2010.03.008.

[25] A. A. Kanani Nezhad, E. Roghanian, and Z. Azadi, "A fuzzy goal programming approach to solve multi-objective supply chain network design problems," Int. J. Ind. Eng. Comput., vol. 4, no. 3, pp. 315-324, 2013, doi: 10.5267/j.ijiec.2013.04.004.

[26] B. Fahimnia, J. Sarkis, and H. Davarzani, "Green supply chain management: A review and bibliometric analysis," Int. J. Prod. Econ., vol. 162, pp. 101–114, 2015, doi: 10.1016/j.ijpe.2015.01.003.

[27] G. A. Keskin, "Using integrated fuzzy DEMATEL and fuzzy C-means algorithm for supplier evaluation and selection," Int. J. Prod. Res., 2015, doi: 10.1080/00207543.2014.980461.

[28] M. Brandenburg, K. Govindan, J. Sarkis, and S. Seuring, "Quantitative models for sustainable supply chain management: Developments and directions," Eur. J. Oper. Res., vol. 233, no. 2, pp. 299-312, 2014, doi: 10.1016/j.ejor.2013.09.032.

[29] H. Fazlollahtabar, "Integration between fuzzy PROMETHEE and fuzzy linear program for supplier selection problem: Case study," J. Appl. Math. Model. Comput., vol. 1, no. 1, p. 8, 2016, doi: 10.20936/JAMMC/160101.

[30] P. Ghadimi and C. Heavey, "Sustainable supplier selection in medical device industry: Toward sustainable manufacturing," Procedia CIRP, 2014, doi: 10.1016/j.procir.2014.06.096.

[31] H. M. Wagner and T. M. Whitin, "Dynamic version of the economic lot size model," Manag. Sci., vol. 50, no. 12, pp. 1770–1774, 2004.

[32] A. H. Azadnia, M. Z. M. Saman, and K. Y. Wong, "Sustainable supplier selection and order lot-sizing: An integrated multi-objective decision-making process," Int. J. Prod. Res., vol. 53, no. 2, pp. 383–408, 2015, doi: 10.1080/00207543.2014.935827.

[33] P. Ghadimi, A. Dargi, and C. Heavey, "Making sustainable sourcing decisions: Practical evidence from the automotive industry," Int. J. Logist. Res. Appl., vol. 20, no. 4, pp. 297–321, 2017, doi: 10.1080/13675567.2016.1227310.

[34] M. A. Sodenkamp, M. Tavana, and D. Di Caprio, "Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading," Eur. J. Oper. Res., vol. 254, no. 3, pp. 859-874, 2016, doi: 10.1016/j.ejor.2016.04.015.

[35] M. S. H. Bhuiyan, I. A. Choudhury, and M. Dahari, "Monitoring the tool wear, surface roughness and chip formation occurrences using multiple sensors in turning," J. Manuf. Syst., vol. 33, no. 4, pp. 476–487, 2014, doi: 10.1016/j.jmsy.2014.04.005.

[36] A. Kr. Purohit, D. Choudhary, and R. Shankar, "Inventory lot-sizing with supplier selection under non-stationary stochastic demand," Int. J. Prod. Res., vol. 54, no. 8, pp. 2459–2469, 2016, doi: 10.1080/00207543.2015.1102354.

[37] J. Rezaei and M. Davoodi, "A joint pricing, lot-sizing, and supplier selection model," Int. J. Prod. Res., vol. 50, no. 16, pp. 4524–4542, 2012, doi: 10.1080/00207543.2011.613866.

[38] L. Liu, "Outsourcing and rescheduling for a two-machine flow shop with the disruption of new arriving jobs: A hybrid variable neighborhood search algorithm," Comput. Ind. Eng., vol. 130, pp. 198–221, 2019, doi: 10.1016/j.cie.2019.02.015.

[39] Z. Zakaria and S. Petrovic, "Genetic algorithms for match-up rescheduling of the flexible manufacturing systems," Comput. Ind. Eng., vol. 62, no. 2, pp. 670–686, 2012, doi: 10.1016/j.cie.2011.12.001.

[40] R. Zhao, Y. Liu, N. Zhang, and T. Huang, "An optimization model for green supply chain management by using a big data analytic approach," J. Clean. Prod., vol. 142, pp. 1085–1097, 2017, doi: 10.1016/j.jclepro.2016.03.006.

[41] S. M. Taghavi, V. Ghezavati, H. Mohammadi Bidhandi, and S. M. J. Mirzapour Al-e-Hashem, "Sustainable and resilient supplier selection, order allocation, and production scheduling problem under disruption utilizing conditional value at risk," J. Model. Manag., vol. 19, no. 2, pp. 658–692, 2024, doi: 10.1108/JM2-10-2022-0250.

[42] S. Lendl, U. Pferschy, and E. Rener, "Rescheduling with new orders under bounded disruption," INFORMS J. Comput., vol. 36, no. 6, pp. 1654–1675, 2024, doi: 10.1287/ijoc.2023.0038.

[43] X. Zhu, B. Liao, Y. Shen, and M. Kong, "Towards Industry 5.0: Digital twin-enhanced approach for dynamic supply chain rescheduling with real-time order arrival and acceptance," Int. J. Prod. Res., vol. 64, no. 13, pp. 5588–5610, 2026, doi: 10.1080/00207543.2025.2481184.

[44] H. Jung, F. F. Chen, and B. Jeong, "Decentralized supply chain planning framework for third party logistics partnership," Comput. Ind. Eng., vol. 55, no. 2, pp. 348–364, 2008, doi: 10.1016/j.cie.2007.12.017.

[45] M. Mirmozaffari, S. M. Hejazi, N. Karamizadeh, and A. Montazeri, "A mixed-integer non-linear no-wait open-shop scheduling model for minimizing makespan and total tardiness in manufacturing," Decis. Anal. J., vol. 10, Art. no. 100403, 2024, doi: 10.1016/j.dajour.2024.100403.

[46] H. Selim, C. Araz, and I. Ozkarahan, "Collaborative production–distribution planning in supply chain: A fuzzy goal programming approach," Transp. Res. Part E Logist. Transp. Rev., vol. 44, no. 3, pp. 396–419, 2008, doi: 10.1016/j.tre.2006.11.001.

[47] D. Choudhary and R. Shankar, "Joint decision of procurement lot-size, supplier selection, and carrier selection," J. Purch. Supply Manag., vol. 19, no. 1, pp. 16–26, 2013, doi: 10.1016/j.pursup.2012.08.002.

[48] A. Gupta and C. D. Maranas, "Managing demand uncertainty in supply chain planning," Comput. Chem. Eng., vol. 27, nos. 8–9, pp. 1219–1227, 2003, doi: 10.1016/S0098-1354(03)00048-6.

[49] A. L. Shiguemoto and V. A. Armentano, "A tabu search procedure for coordinating production, inventory and distribution routing problems," Int. Trans. Oper. Res., vol. 17, no. 2, pp. 179 - 195, 2010, doi: 10.1111/j.1475-3995.2009.00741.x.

[50] X. Deng, Y. Hu, Y. Deng, and S. Mahadevan, "Supplier selection using AHP methodology extended by D numbers," Expert Syst. Appl., vol. 41, no. 1, pp. 156–167, 2014, doi: 10.1016/j.eswa.2013.07.018.

[51] Z. Li, W. K. Wong, and C. K. Kwong, "An integrated model of material supplier selection and order allocation using fuzzy extended AHP and multiobjective programming," Math. Probl. Eng., vol. 2013, pp. 1–14, 2013, doi: 10.1155/2013/363718.

[52] F. Mafakheri, M. Breton, and A. Ghoniem, "Supplier selection-order allocation: A two-stage multiple criteria dynamic programming approach," Int. J. Prod. Econ., vol. 132, no. 1, pp. 52–57, 2011, doi: 10.1016/j.ijpe.2011.03.005.

[53] H. S. Kilic, "An integrated approach for supplier selection in multi-item/multi-supplier environment," Appl. Math. Model., vol. 37, nos. 14–15, pp. 7752–7763, 2013, doi: 10.1016/j.apm.2013.03.010.

[54] B. D. Rouyendegh and T. E. Saputro, "Supplier selection using integrated fuzzy TOPSIS and MCGP: A case study," Procedia Soc. Behav. Sci., vol. 116, pp. 3957–3970, 2014, doi: 10.1016/j.sbspro.2014.01.874.

[55] C.-N. Liao and H.-P. Kao, "An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management," Expert Syst. Appl., vol. 38, no. 9, pp. 10803–10811, 2011, doi: 10.1016/j.eswa.2011.02.031.

[56] P. Schworm, X. Wu, M. Klar, M. Glatt, and J. C. Aurich, "Multi-objective quantum annealing approach for solving flexible job shop scheduling in manufacturing," J. Manuf. Syst., vol. 72, pp. 142–153, 2024, doi: 10.1016/j.jmsy.2023.11.015.

[57] P. Schworm, X. Wu, M. Klar, and J. C. Aurich, "Multi-objective rescheduling of job shop scheduling problems in manufacturing using quantum annealing," Manuf. Lett., vol. 42, pp. 5–10, 2024, doi: 10.1016/j.mfglet.2024.09.066.

[58] C. K. H. Lee, "A review of applications of genetic algorithms in operations management," Eng. Appl. Artif. Intell., vol. 76, pp. 1–12, 2018, doi: 10.1016/j.engappai.2018.08.011.

[59] L. Cheng, M. Li, C. Tan, P. Huang, M. Zhang, and R. Sun, "Computational game-theoretic models for adaptive urban energy systems: A comprehensive review of algorithms, strategies, and engineering applications," Arch. Comput. Methods Eng., vol. 33, no. 2, pp. 2037–2114, 2026, doi: 10.1007/s11831-025-10364-y.

[60] C.-W. Wu, M.-Y. Liao, and T.-T. Yang, "Efficient methods for comparing two process yields—Strategies on supplier selection," Int. J. Prod. Res., vol. 51, no. 5, pp. 1587–1602, 2013, doi: 10.1080/00207543.2012.718450.

[61] C. Yu, T. N. Wong, and Z. Li, "A hybrid multi-agent negotiation protocol supporting supplier selection for multiple products with synergy effect," Int. J. Prod. Res., vol. 55, no. 1, pp. 18–37, 2017, doi: 10.1080/00207543.2016.1189105.

[62] C. Yu and T. N. Wong, "A multi-agent architecture for multi-product supplier selection in consideration of the synergy between products," Int. J. Prod. Res., vol. 53, no. 20, pp. 6059–6082, 2015, doi: 10.1080/00207543.2015.1010745.

[63] B. Du, S. Guo, X. Huang, Y. Li, and J. Guo, "A Pareto supplier selection algorithm for minimum the life cycle cost of complex product system," Expert Syst. Appl., vol. 42, no. 9, pp. 4253–4264, 2015, doi: 10.1016/j.eswa.2015.01.056.

[64] Y. Golizadeh Akhlaghi et al., "A constraint multi-objective evolutionary optimization of a state-of-the-art dew point cooler using digital twins," Energy Convers. Manag., vol. 211, Art. no. 112772, 2020, doi: 10.1016/j.enconman.2020.112772.

[65] H. Damgacioglu, E. Celik, and N. Celik, "Estimating gene expression from high-dimensional DNA methylation levels in cancer data: A bimodal unsupervised dimension reduction algorithm," Comput. Ind. Eng., vol. 130, pp. 348–357, 2019, doi: 10.1016/j.cie.2019.02.038.

[66] V. Martínez-Martínez, F. J. Gomez-Gil, J. Gomez-Gil, and R. Ruiz-Gonzalez, "An artificial neural network based expert system fitted with genetic algorithms for detecting the status of several rotary components in agro-industrial machines using a single vibration signal," Expert Syst. Appl., vol. 42, no. 17–18, pp. 6433–6441, 2015, doi: 10.1016/j.eswa.2015.04.018.

[67] A. Mellit and S. A. Kalogirou, "MPPT-based artificial intelligence techniques for photovoltaic systems and its implementation into field programmable gate array chips: Review of current status and future perspectives," Energy, vol. 70, pp. 1–21, 2014, doi: 10.1016/j.energy.2014.03.102.

[68] A. Bleiweis and T. Travnikar, "Maize vulnerability and implications for short food supply chains in Slovenia," Int. J. Emerg. Trends Manag., vol. 2, no. 2, pp. 90–95, 2026, doi: 10.65984/ETM2.2.4.

[69] Q. Long, "A constraint handling technique for constrained multi-objective genetic algorithm," Swarm Evol. Comput., vol. 15, pp. 66–79, 2014, doi: 10.1016/j.swevo.2013.12.002.

[70] T. E. Saputro, G. Figueira, and B. Almada-Lobo, "Integrating supplier selection with inventory management under supply disruptions," Int. J. Prod. Res., vol. 59, no. 11, pp. 3304–3322, 2021, doi: 10.1080/00207543.2020.1866223.

[71] H.-W. Lo, C.-J. Pai, and M. Deveci, "A multi-objective model for integrated supplier order allocation and supply chain network transportation planning decision-making," Inf. Sci., vol. 689, Art. no. 121487, 2025, doi: 10.1016/j.ins.2024.121487.

[72] J. C. Serrano-Ruiz, J. Mula, and R. Poler, "Job shop smart manufacturing scheduling by deep reinforcement learning," J. Ind. Inf. Integr., vol. 38, Art. no. 100582, 2024, doi: 10.1016/j.jii.2024.100582.

[73] C. Zhang, M. Juraschek, and C. Herrmann, "Deep reinforcement learning-based dynamic scheduling for resilient and sustainable manufacturing: A systematic review," J. Manuf. Syst., vol. 77, pp. 962–989, 2024, doi: 10.1016/j.jmsy.2024.10.026.

[74] Y. Feng, Y. Chen, and Y. Liu, "Optimising two-stage robust supplier selection and order allocation problem under risk-averse criterion," Int. J. Prod. Res., vol. 61, no. 19, pp. 6356–6380, 2023, doi: 10.1080/00207543.2022.2127963.

[75] N. Falcão E Cunha, T.-S. Gan, E. Curcio, P. Amorim, B. Almada-Lobo, and M. Grunow, "Robust supply chain design with suppliers as system integrators: An aerospace case study," Int. J. Prod. Res., vol. 61, no. 15, pp. 5244–5265, 2023, doi: 10.1080/00207543.2022.2099769.

[76] Y. Tu et al., "Using graph neural network to conduct supplier recommendation based on large-scale supply chain," Int. J. Prod. Res., vol. 62, no. 24, pp. 8595–8608, 2024, doi: 10.1080/00207543.2024.2344661.

[77] F. Lv and Z. Yin, "Mitigating risky sourcing with a responsible supplier in a competitive environment: The implication of product line design and sourcing diversification," Int. J. Prod. Res., vol. 62, no. 17, pp. 6146–6166, 2024, doi: 10.1080/00207543.2024.2309311.

[78] C. Bai, Q. Zhu, and J. Sarkis, "Circular economy and circularity supplier selection: A fuzzy group decision approach," Int. J. Prod. Res., vol. 62, no. 7, pp. 2307–2330, 2024, doi: 10.1080/00207543.2022.2037779.

[79] L. Cui, H. Wu, and J. Dai, "Modelling flexible decisions about sustainable supplier selection in multitier sustainable supply chain management," Int. J. Prod. Res., vol. 61, no. 14, pp. 4603–4624, 2023, doi: 10.1080/00207543.2021.1924412.

[80] K. Castillo-Villar, "Metaheuristic algorithms applied to bioenergy supply chain problems: Theory, review, challenges, and future," Energies, vol. 7, no. 11, pp. 7640–7672, 2014, doi: 10.3390/en7117640.

[81] M. A. Abido and A. Elazouni, "Improved crossover and mutation operators for genetic-algorithm project scheduling," in Proc. IEEE Congr. Evol. Comput. (CEC), Trondheim, Norway, 2009, pp. 1865–1872, doi: 10.1109/CEC.2009.4983168.

[82] J. Bezanson, A. Edelman, S. Karpinski, and V. B. Shah, "Julia: A fresh approach to numerical computing," SIAM Rev., vol. 59, no. 1, pp. 65–98, 2017, doi: 10.1137/141000671.

[83] S. H. Zegordi, I. N. K. Abadi, and M. A. B. Nia, "A novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain," Comput. Ind. Eng., vol. 58, no. 3, pp. 373–381, 2010, doi: 10.1016/j.cie.2009.06.012.

[84] W. Chen, L. Lei, Z. Wang, M. Teng, and J. Liu, "Coordinating supplier selection and project scheduling in resource-constrained construction supply chains," Int. J. Prod. Res., vol. 56, no. 19, pp. 6512–6526, 2018, doi: 10.1080/00207543.2018.1436782.

[85] L. Cheng, P. Huang, M. Zhang, R. Yang, and Y. Wang, "Optimizing electricity markets through game-theoretical methods: Strategic and policy implications for power purchasing and generation enterprises," Mathematics, vol. 13, no. 3, Art. no. 373, 2025, doi: 10.3390/math13030373.

[86] L. Cheng et al., "Evolutionary smart contracts for virtual power plant trading: Integrating prospect theory and multi-stage negotiation in cross-regional energy markets," Int. J. Electr. Power Energy Syst., vol. 173, Art. no. 111453, 2025, doi: 10.1016/j.ijepes.2025.111453.