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Dynamic small-series fashion order allocation and supplier selection: a ga-topsis-based model

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ABSTRACT

The fashion industry is currently confronted with significant economic and environmental challenges, necessitating the exploration of novel business models. Among the promising approaches is small series production on demand, though this poses considerable complexities in the highly competitive sector. Traditional supplier selection and production planning processes, known for their lengthy and intricate nature, must be replaced with more dynamic and effective decision-making procedures. To tackle this problem, GA-TOPSIS hybrid model is proposed as the methodology. The model integrates Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) evaluation into the fitness function of Genetic Algorithm (GA) to comprehensively consider both qualitative and quantitative criteria for supplier selection. Simultaneously, GA efficiently optimizes the order sequence for production planning. The model's efficacy is demonstrated through implementation on real orders, showcasing its ability to handle diverse evaluation criteria and support supplier selection in different scenarios. Moreover, the proposed model is employed to compute the Pareto front, which provides optimal sets of solutions for the given objective criteria. This allows for an effective demand-driven strategy, particularly relevant for fashion retailers to select supplier and order planning optimization decisions in dynamic and multi-criteria context. Overall, GA-TOPSIS hybrid model offers an innovative and efficient decision support system for fashion retailers to adapt to changing demands and achieve effective supplier selection and production planning optimization. The model's incorporation of both qualitative and quantitative criteria in a dynamic environment contributes to its originality and potential for addressing the complexities of the fashion industry's supply chain challenges.

INTRODUCTION

In the last decade, "fast fashion" has become the major model in the fashion industry but has also been increasingly criticized for its environmental and social impact. Consequently, many efforts have been made in the fashion industry to switch to more sustainable business models. In a fast-fashion strategy, the retailers' orders to their suppliers are composed of a high quantity of standard products with a low degree of customization. The supply chain is based on the "Push System" from the sales forecasts and marketing plan established from the customers' historical purchases [1]. In the last decade, faced with different ecological, health, or geopolitical crises, on-demand production of small series emerges as a new trend for the fashion sector. This strategy enables the customers to rapidly adapt designs and product styles to the market. On-demand production of small series is also an opportunity for the fashion market to address the current hot issues and trends in terms of (1) relocation of production and supply chain to decrease the risks with the off-shore supply chain in the context of the pandemic, geopolitics issues, (2) sustainability with waste and unsold reduction, less consumption but better quality and longer lifetime products, (3) personalization of products in a high-speed society powered by individualism, digitalization, e-commerce, mobile technology, and (4) collaborative technologies such as cloud for real-time sharing data.

In recent times, e-commerce retail platforms have significantly redesigned fashion. The emergence of fashion e-commerce platforms is an enabler of a small series of on-demand production. Customers can dynamically generate orders for a high variety of products. These orders should be processed in real-time to reduce the delivery time. Consequently, the growing of customer orders has generated a huge amount of data on e-shopping platforms. The processing of these data in real-time, and more particularly the allocation to suitable suppliers, is a challenging and complex decision problem [2].

In this context, a small-series fashion supply chain can be considered as a "Pull System", where the real-time customer orders on the e-platform drive the key supply chain decisions such as supplier selection, order management, production planning, and distribution. In a such supply chain, the data flows are initiated by real-time customers' purchases and generate dynamic management of raw materials and accessories through the supplier network to fulfill the order as required. The most challenging issue in this system is to dynamically meet the customers' orders and the retailer's objectives considering the supplier capacities and capabilities. This requires the development of a dynamic multi-criteria decision model based on operational parameters such as lead time, return rates, lot sizes, and customer satisfaction.

In the literature, order planning problems are widely addressed with optimization-based decision methods. For instance, an optimization-based mathematical model is developed by Ait-Alla et al. [3] for production planning and scheduling problems in the fashion industry with different production costs and delivery time. Some studies [4]-[6] propose multi-objective optimization methods integrating production costs and delivery time. More recently, other factors, and more especially sustainable factors, are considered in the optimization process [7]-[9]. An approach is presented in Guo et al. [10] where the multi-objectives optimization is addressed by using a weighted-sum method and goal programming. The data collected with RFID techniques enable a more responsive decision. Supplier selection and order allocation can be also combined with a demand forecasting system to enhance the responsiveness of the decision process, as illustrated in Islam et al. [11] and Islam et al. [12]. However, these studies mainly rely on a 2 step-process where supplier selection is performed before and separately from the order allocation and are more suitable for traditional push systems based on demand forecast. In terms of techniques, genetic algorithms, knowledge-based models, fuzzy logic models, and expert systems are the most used in the literature for production planning problems.

1. Problem Statement and Research Objectives

In supply chain management of small-series production of fashion products, the decision process is based on the customer demand-pull, and consequently, requires efficient techniques for supplier allocation and production planning in real-time. The selection of suitable garment suppliers for real-time customers' orders is a complex issue, especially when the objectives are multifactorial including both business and operational parameters. In an e-commerce environment, the fulfillment of the objectives for the order allocation to the best supplier should rely on an automated and responsive decision process. Thus, the allocation of

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customers' orders to the most suitable suppliers is a real-time and multi-criteria decision-making and optimization problem.

To the best of the authors' knowledge, existing studies in the literature did not fully address the problem of decision-making for both order processing and supplier selection from real-time customers' orders in the context of small-series on-demand production, and more specifically in the fashion environment. Building on this gap, this paper aims to propose a methodology for small-series fashion production based on real-time order assignment of product batches. In this paper, a multi-criteria decision model is proposed, combining both Genetic Algorithm (GA) optimization and the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) method for solving dynamic order allocation decision problems. From data related to product orders and suppliers, a simulation based on GA and TOPSIS techniques assigns customers' orders to the most suitable suppliers. GA is selected for its popularity and efficiency in solving multi-objective optimization problems [13]-[16] in a wide range of applications and, more particularly in our context, its capability for addressing the dynamic order assignment problem. More specifically, the main contributions of the proposed model are the multiple objectives optimization of (1) both supplier selection and order planning, (2) by utilizing customer's orders and supplier's attributes in real-time and (3) considering quantitative and qualitative data.

The organization of the rest of the paper is structured as follows. Section 2 presents a brief literature review on order allocation and supplier selection approaches and supplier selection criteria is provided. In section 3, the general principle of the methodology based on GA and TOPSIS methods for order allocation to the best suppliers is described. An experimental work integrating the proposed approach is elaborated and the results and significance of the proposed framework are discussed in Section 4. Finally, concluding remarks, limitations, and future works are presented in Section 5.

2. State of the art and Research Contribution

In the small-series make-to-order production of fashion products, where e-commerce has been predominately adopted as a digital platform for sales, the generation of customer orders and order processing that entail order ranking and allocation to the best suppliers constitute a dynamic decision problem. Besides, customers' diverse and rapidly varying product choices give rise to uncertain and conflicting criteria based on which suppliers are evaluated and the decision to allocate the customer orders to the best suppliers is made [17]. Owing to many diverse criteria, including both qualitative and quantitative criteria, that are considered for supplier evaluation, supplier selection becomes a multi-criteria dynamic decision problem [18], [19].

A wide number of studies in the literature deal with the decision problems related to supplier selection and order allocation. These approaches mostly fall into two broad method categories: MCDM (multi-criteria decision methods) and combinatorial optimization methods. Moreover, there are several studies in which both of these methods have been combined to construct hybrid models.

Broadly, MCDM methods are considered to be appropriate when many criteria are used for the evaluation process of multiple alternatives [20]. One of the first steps in the supplier evaluation process, besides the identification of the relevant criteria, is the computation of weights for each specific criterion that signify the degree of importance of the criteria. For calculating accurate criteria weights as part of supplier selection decisions, Hamdan and Cheaitou [21] proposes the TOPSIS method integrated with a hierarchical fuzzy method. Computed criteria weights provide an importance ranking that allows decision-makers to evaluate the performance of the considered suppliers. Several extensions of the fuzzy method have been used for the evaluation of alternatives for suppliers. For example, Chou and Chang [22] proposes a simple multi-attribute rating technique (SMART) based on a strategy-aligned fuzzy method to perform vendor selection. Several criteria from a social perspective are considered by Bai et al. [23] to develop a decision framework to select potential suppliers. MCDM method-based group decision-making framework is proposed by Harale et al. [24] to select the best suppliers in the small-series fashion industry. A de-centralized multi-level model based on a fuzzy-logic approach is proposed by Adhami et al. [25] to find a compromise solution in terms of the best-competing suppliers with conflicting levels of competencies. In another interesting study, Kwong et al. [26] integrates SMART and fuzzy set theory to develop a two-stage model for evaluating the supplier's performance. Shemshadi et al. [27] uses the VIKOR method, which is one of the widely used MCDM methods, and integrates it with a fuzzy set theory based on entropy measure to compute objective weightage of the criteria in the supplier selection process. Many hybrid models have been previously proposed for supplier selection decision-making, e.g. integrated model based on grey system theory and uncertainty theory in Memon et al. [28]; fuzzy-AHP (Analytic Hierarchy Process) model in Bruno et al. [29]; fuzzy-TOPSIS in Kannan et al. [30]; and ANN (Artificial Neural Network) in Tavana et al. [31]. To explore the interdependencies among the criteria, measure their strength, and select the best suppliers based on the relationship between the criteria, Büyüközkan and Ifi [32] develops a hybrid model based on fuzzy-DEMATEL (Decision-Making Trial and Evaluation Laboratory), fuzzy-TOPSIS and fuzzy-ANP (Analytical Network Programming) as in Galankashi et al. [33]. Using fuzzy logic and fuzzy inference system, Amindoust et al. [34] proposes criteria and supplier ranking model. From a sustainability perspective, Kannan et al. [35] extracts and identifies several crucial criteria based on fuzzy axiomatic design, while in Santos et al. [36] AHP, TOPSIS, and entropy methods are combined to evaluate supplier ranking based on sustainability performances. The data envelopment analysis (DEA) method is implemented in Dobos and Vörösmarty [37] to categorize composite criteria factors based on a common weight analysis. For facilitating multi-criteria group decision-making regarding supplier selection, the study by Ghorabaee et al. [38] uses interval type-two fuzzy sets to propose a ranking method to perform a complex proportional assessment (COPRAS). In Islam et al. [11] and Islam et al. [12], a fuzzy evaluation of suppliers combined with a demand forecasting system is proposed to enhance the synchronization of order allocations.

It is noteworthy to mention that suppliers compete with each other for order fulfillment, and operate in the market under various constraints while considering clear business and operational objectives. Optimization methods have been considered to be effective in solving supplier evaluation problems given their multiple objectives. Various optimization models are developed, transformed, and applied as hybrid models following the specific contexts including production planning logistics and supply chain management. In Che [39], the MMPSO (the metric multi-objective particle swarm optimization) hybrid algorithm is proposed to address the supplier selection decision problem by considering assembly line balancing and assembly sequence planning as part of production planning aspects. Given the rise of environmental regulatory compliance pressure, companies are operating under new forms of constraint that include carbon footprints, waste, and energy consumption. To manage supplier selection under such constraints, Hashmi et al. [40] combines goal programming and fuzzy concepts to construct a multi-objective supplier selection optimization problem in an uncertain environment. This approach is found to have effectively dealt with the human subjectivity problem by adopting a linguistic preference-based scale and studying the impact of supplier selection results on the environmental efficiency of the company. To handle the decision makers' vague judgments, Faez et al. [41] proposes an approach based on a fuzzy set theory-based model in which the linear membership function is utilized for mapping the linguistic judgment values.

As mentioned earlier, hybrid models combining MCDM and optimization methods have also been proposed to build a supplier evaluation framework. The study by Fallahpour et al. [42] presents one such model that combines DEA and GA (Genetic Programming) methods to solve robust nonlinear programming problems in the form of a supplier selection decision. From the perspective of data-driven supplier selection, Faez et al. [43] relies on historical data to combine MIP (Mixed-integer Programming) and integrated case-based reasoning to allocate orders to the best suppliers and automate the selection of quantities to order. In Xia and Wu [44], the AHP model is improved by integrating rough set theory and multi-objectives MILP (mixed-integer linear programming) to evaluate suppliers based on discounts they offered on the total quantities of multiple products. In another interesting study by Demirtas and Üstün

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[45], a two-stage order allocation and supplier selection model are developed using ANP and the MOMIP (multi-objective mixed-integer programming) to optimize product return, purchase quantity, and operating and production cost. From the strategic perspective, Haeri and Rezaei [46] combines the fuzzy-LP (fuzzy linear programming) method and two-stage integrated quantified SWOT analysis to solve the order allocation problem. As an extension of the SWOT technique for order allocation and supplier selection, Ghorbani et al. [47] and Feng and Gong [9] adopt the entropy method for supplier evaluation and ILP (integer linear programming) to compute the optimal order quantities. A novel combination of fuzzy multiple-goal programming and fuzzy AHP is developed by Lee et al. [48] to solve supplier selection. For solving the multi-supplier selection problem for a multi-product order allocation, Killic [17] constructed a hybrid model using fuzzy-TOPSIS and MILP. Other commonly used hybrid models such as AHP–GP in Perçin [49]; a two-stage order allocation hybrid model based on fuzzy-TOPSIS and multi-choice GP in Rouyendegh and Saputro [50]; an integrated model based on group decision-making in Sodenkamp et al. [51]; and a hybrid model for criteria ranking, supplier selection and order processing based on Delphi method, ANP and MOMIP in Wu et al. [52] are hybrid models that combined MCDM and optimization methods for supplier selection decision making.

From the literature, it is important to highlight that most of the models developed to solve order allocation and supplier selection problems are based on the MCDM and optimization methods. However, the data utilized for such models are mostly of static type (time-independent) and suitable for traditional push-flow supply chains. To the best of our knowledge, the dynamic allocation of customer orders to the most suitable suppliers based on retailers' objectives from real-time data in the context of production on-demand of fashion products has not been addressed in the existing literature. Therefore, we propose a novel approach based on GA and TOPSIS methods to address the relevant decision problem of order allocation and supplier selection for small-series production on demand of fashion products.

The main contributions of the proposed hybrid model can be summarized as follows: (1) a multi-objective optimization model for order allocation and supplier selection is constructed in a novel way by considering dynamically generating customer order data and supplier data retailers' objectives, (2) developing the group decision-making model for order allocation and supplier selection by utilizing customer order and supplier data of dynamic nature, and (3) considering the objectives of the fashion retailers and both the static and dynamic criteria that entail qualitative and quantitative data, the order allocation and supplier selection problem is solved using a hybrid model based on GA and TOPSIS methods.

METHOD

After identifying the gaps between the considered problem and existing studies in the literature, we develop a method that integrates both supplier selection and order allocation, quantitative and qualitative evaluation, and static and dynamic parameters. The model proposed is then tested on real data and compared with the well-known Weighted Sum method. The research method is illustrated in the flowchart given in Figure 1.

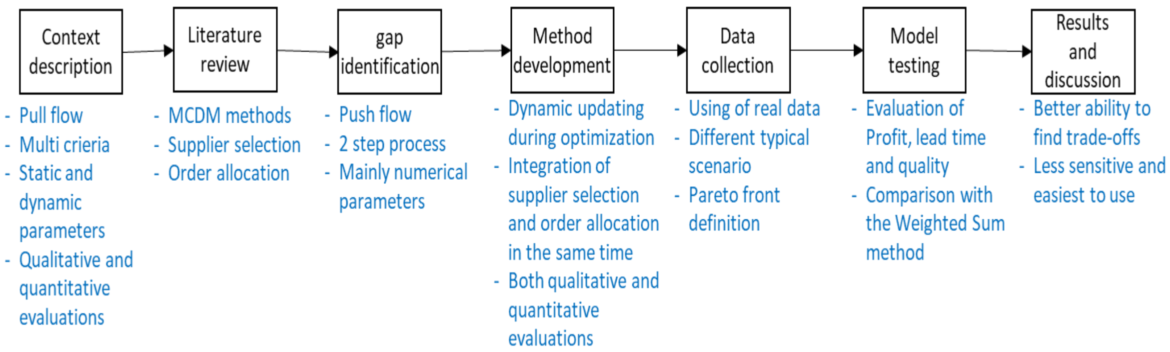

Figure 1. Research flowchart

1. General principle

Figure 2 illustrates the general framework of the GA-TOPSIS-based method for order allocation and supplier selection. Firstly, the customer order data are obtained from the fashion retailer's e-platform database. Depending upon the retailers' activities and needs, batches of orders are formed from received order during a specific time window. Secondly, the supplier data provide the supplier's capability and capacity-related attributes. Then, the proposed dynamic order allocation model selects the best suppliers and order sequences to manufacture the required products.

The fashion retailer’s objectives are crucial for the order allocation to the supplier. These objectives may be both quantitative and qualitative. Quantitative criteria such as profit or customers' expected shipment time can be easily integrated into an objective function and used as the fitness function of the GA. The qualitative criteria are based on the retailer's judgment on different parameters related, for instance, to the overall quality of products, shipment reliability, and social assessment of a supplier. To incorporate these qualitative criteria into the order allocation process, a TOPSIS model is implemented in the fitness function of the GA to weigh the different criteria according to the retailer's objectives. The GA model output provides the optimal order allocations to the most suitable suppliers that have obtained the highest score of the fitness function.

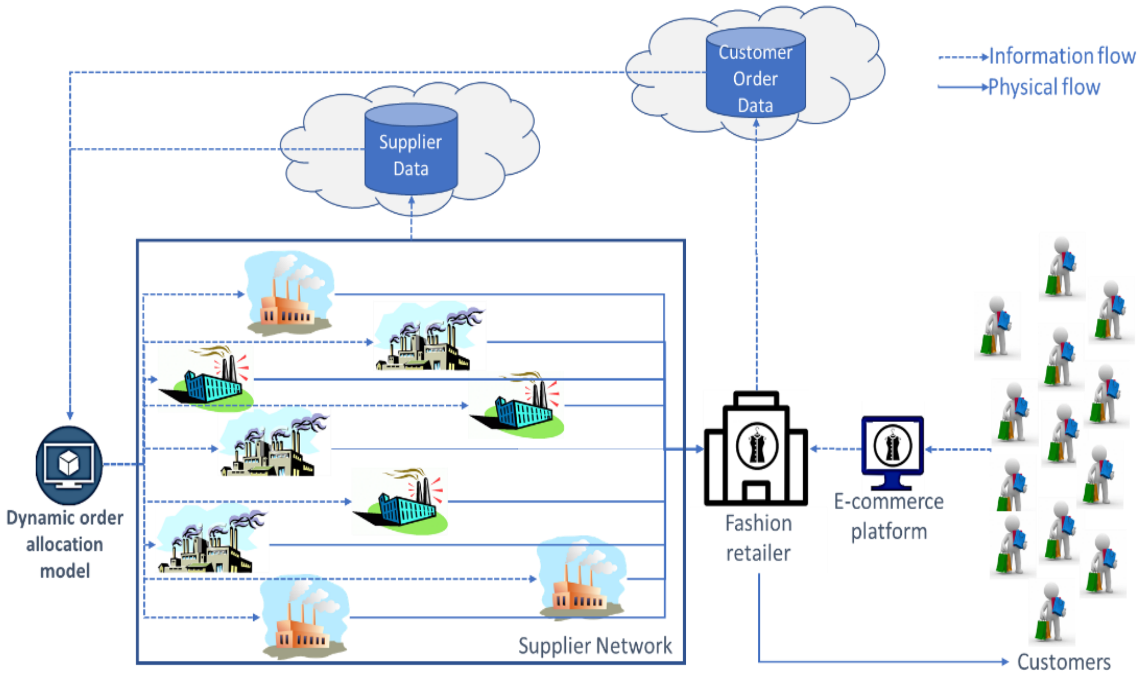

Figure 2. The general framework of the GA-TOPSIS method for order allocation and supplier selection

2. GA-TOPSIS model for dynamic order allocation

As explained previously, the fitness functions of the GA are based on the fashion retailers’ objectives for the selection of suppliers and the order sequence. The TOPSIS model is applied in the fitness function to quantify the evaluation criteria, both static and dynamic, quantitative and qualitative, in the supplier selection decision-making. The TOPSIS evaluation scale allows fashion retailers an easy integration of the subjective evaluation of their suppliers. The proposed GA-TOPSIS hybrid model provides original and effective decision-making based on qualitative and quantitative retailers' judgments of their suppliers' historical performances, and not only based on quantitative supplier and customer operational data such as the time and cost decision variables. Figure 3 provides an overview of the proposed algorithm and the different steps are presented in Algorithm 1.

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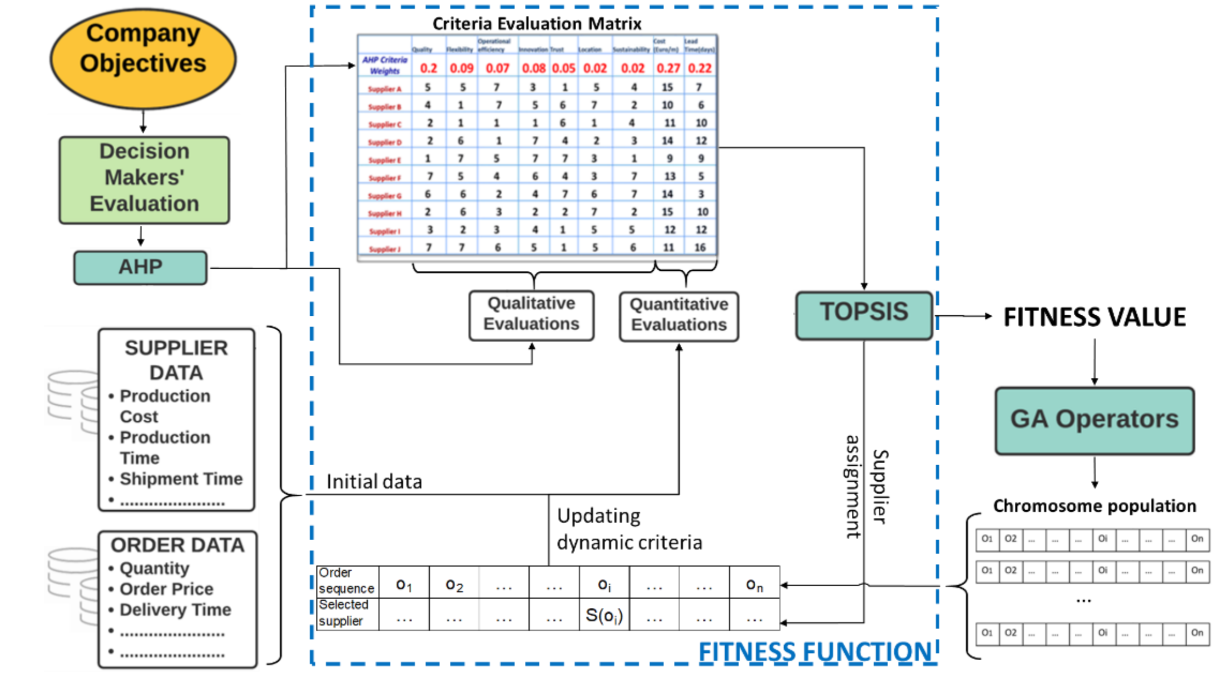

Figure 3. Overview of the GA-TOPSIS algorithm.

Algorithm 1. GA-TOPSIS algorithm

Inputs:
Order data
Supplier data
N = size of batch of orders
S = number of suppliers
DEO = Delay to produce ordered products due to Existing Orders in the queue

Initialization:
Generate a population of *M* chromosomes of size *N*

Processing:
Until the end criterion is not reached
For each chromosomes *{1,…,M}*
I For each gene *n = {1,…,N}*
I I For each supplier *s = {1,…,S}*
I I I Evaluate the TOPSIS score of the supplier *s* when producing the order *n*
I I end
I I Allocate the order *n* to the supplier with the best TOPSIS score
I I Update the *DEO* of the selected supplier
I End
End
Fitness of each chromosomes = sum of the *N* TOPSIS scores of suppliers allocated to the *N* orders
Apply GA operators and generate a new population from the fitness of the *M* chromosomes

Outputs:
The optimal solution is the chromosome with the best fitness
Compute profit, lead time, and quality for the batch of order of this solution.

3. Decision and evaluation matrices

The supplier's objectives are determined through the evaluation of the importance of the different criteria considered in the decision-making. Based on an AHP methodology, a decision maker evaluates the importance of each criterion by a pairwise comparison. The weights of each criterion considered for supplier selection can be represented in a decision matrix as shown in Figure 4, where X, Y, and Z are values obtained by Saaty's comparison scale (Table 1).

	Criteria 1	Criteria 2	Criteria 3
Criteria 1	1	X	Y
Criteria 2	1/X	1	Z
Criteria 3	1/Y	1/Z	1

X - Comparison between Criteria 1 and Criteria 2

Y- Comparison between Criteria 1 and Criteria 3

Z - Comparison between Criteria 2 and Criteria 3

Figure 4. Decision matrix representing the weights of supplier selection criteria

Table 1. Saaty's pairwise comparison scale

Linguistic definition	Saaty's scale value
Equally important	1
Slightly more important	3
Much more important	5
Very much more important	7
Extremely more important	9
Intermediate values	2, 4, 6, 8

From this decision matrix, translating the retailer's preferences or objectives, the weights of each criterion are computed with a standard AHP process. The criteria evaluation matrix is obtained from the supplier evaluation from the static and qualitative criteria and quantitative and dynamic criteria. The static qualitative criteria are given by the retailer from a subjective comparison of the suppliers using a Likert scale (Table 2). The quantitative dynamic criteria are obtained from the supplier data and then updated during the optimization process from order and supplier data.

Table 2. Likert scale for supplier evaluation with qualitative criteria

Linguistic description	Likert's scale value
Worst	1
Good	3
Better	5
Best	7
Intermediate values	2, 4, 6

4. Problem encoding and fitness evaluation

As stated in Section 2, order allocation and supplier selection are multi-criteria dynamic optimization problems. Given a network of J suppliers and a batch of I orders with their related attributes, the optimum solution consists in defining both what is the sequence of orders and what are the suppliers for each order which optimize the objective function. In the implementation of GA, each solution is converted into a chromosome which represents a sequence of order allocation as illustrated in Figure 5. During the fitness evaluation of a chromosome, the orders are allocated to the best supplier one at a time and follow the sequence given by their gene number (from 1 to I). The best supplier is determined from the TOPSIS evaluation considering the attributes of all suppliers at a given time. After each supplier allocation to an order, the dynamic attributes of the supplier, such as the production lead time considering the existing orders in the queue, are updated. Thus, it is important to note that a chromosome provides a unique solution (order sequence with supplier allocation) at a given time but will lead to another solution at a different time considering the past order allocations.

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Gene number	g_1	g_2	…	g_{I-1}	g_I
Order ID	…	…	o_i	…	…
Selected supplier	…	…	$S(o_i)$	…	…
$S(o_i)$ = best supplier for O_i according to TOPSIS score and order allocations performed in genes g_1 to g_{i-1} $i \in [1,I]$					

Figure 5. Chromosome structure

5. Optimization process

The chromosome selection is based on a probability related to the fitness value formulated for each chromosome based on the Roulette wheel method. Individuals represented by each chromosome are selected for the next generation according to their fitness score. Thus, chromosomes with the highest fitness score are more likely to be selected and to pass over their genetic material.

Crossover and mutation are then applied on individuals selected for the next generation to produce a new population of solutions. This process is iterated until the termination criterion is reached. Finally, the chromosome with the best fitness score produced during the generations is considered the optimal solution for the considered problem. The termination criterion used in this work is a maximum number of iterations. It is important to control the processing time of the GA to deal with successive batches of orders.

6. Data description

Order data

In order to test and validate the proposed model, an implementation on historical transactional data of a ready to wear retailer is performed. Batches of orders are formed from the orders received every day. The time or size of batches can be modified according to the case study requirements. However, in a make-to-order production of small series, the frequency between two batches should not be too long to keep the process reactive. On the data used in this study, a size batch is composed of 30 orders on average.

The attributes of the customer's orders considered are the following:

- Order ID – ID assigned to the customer order
- Quantity – Quantity of the product items ordered by the customer
- Order Price - Total price of the order placed by the customer
- Expected Del_Time – Customer's expected delivery time for the product order

Supplier data

The number of considered suppliers is dependent on the supply chain and partnership of the retailer. In this study, considering that small series production of fashion products is more suitable with local supply chain, a supplier network of five competing suppliers is considered for the implementation of our model.

The supplier data considered for the order assignment are the following:

- Supplier ID – ID assigned to each candidate Supplier
  - Prod_Cost – Cost to the supplier to produce a unit quantity of the ordered product
  - Shipment_Cost - Cost to the supplier to deliver the order to the customer
  - DEO - Delay to produce ordered product due to Existing Orders in the queue
  - Prod_Time – Time required by the supplier to produce a unit quantity of the ordered product
  - Shipment_Time - Time required by the supplier to deliver the ordered products to the customer

The supplier attributes used at time t0 as an initial value for the order allocation and sequence optimization is shown in Figure 6. We assume that there is no existing order in the queue at t0 (DEO = 0).

Supplier_ID	Product_Cost	Shipment_Cost	DEO	Production_Time	Shipment_Time
11	25	10	0	2	4
12	28	8	0	3	5
13	20	20	0	3	9
14	30	5	0	2	2
15	29	5	0	1	3

Figure 6. Supplier datasheet at time t0

The supplier performances are evaluated from three criteria, namely profit, lead time (production and shipment), and quality of products. The profit and lead time are dynamic criteria since they continuously change according to the orders and the production load of the supplier. The quality of products is a qualitative criterion evaluated by the retailer with the Likert scale (Table 2) from a subjective assessment of historical transactions.

7. Scenarios developed

In the optimization process of the proposed model, it is useful to remind that the fitness score of a solution is related to the TOPSIS evaluation of the suppliers when they produce the considered sequence of orders. The TOPSIS evaluation includes subjective judgements (or objectives) of the retailers obtained by pairwise comparison of supplier selection criteria (both static and dynamic) using Saaty's scale (Figure 4) into the dynamic order assignment problem solving. In order to understand and quantify how the subjectivity of the evaluation of these selection criteria can impact the final optimization, the four following scenarios are designed for generating different and typical configurations of supplier selection criteria evaluation decision matrix: (10 profit-oriented scenario, (2) delay-oriented scenario, (3) quality-oriented scenario, and (4) cost and delay-oriented scenario

For each scenario, the performance evaluation (Profit, Cost, Quality) is based on the same customer's order and supplier data. These different configurations can also be used by decision-makers as a baseline according to their business objectives. The variables, X, Y, and Z, of the decision matrix illustrated in Figure 4 are then three parameters used to simulate the different scenarios. In the following, the notation used to define the different configurations of the GA-TOPSIS models obtained from X, Y, and Z variables is GA_TOPSISXYZ.

Profit-oriented scenario

The Profit oriented scenario emphasizes Cost at the expense of the other two criteria, which are delay and quality. Therefore, the decision matrix is obtained with X = w, Y=w, and Z=1, where w = {1, 2, 3, 5, 7, 9} represents the weight of the Cost compared to the two other criteria (Figure 7). The GA-TOPSIS models related to this scenario are defined as GA_TOPSISww1.

	Cost	*Delay*	*Quality*
Cost	1	w	w
Delay	1/w	1	1
Quality	1/w	1	1

Figure 7. Decision matrix for the profit-oriented scenario

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Delay-oriented scenario

Similarly, when Delay is more important the other two criteria, i.e. Cost and Quality, the parameters of decision matrix become X = 1/w, Y=1 and Z=w (see Figure 8). The GA-TOPSIS models of this scenario are called GA_TOPSIS1/w- 1-w.

	Cost	*Delay*	*Quality*
Cost	1	1/w	1
Delay	w	1	w
Quality	1	1/w	1

Figure 8. Decision matrix for the delay-oriented scenario

Quality-oriented scenario

For the Quality-oriented scenario, the decision matrix is composed of X = 1, Y=1/w and Z=1/w (see Figure 9), and the related GA-TOPSIS models are defined as GA_TOPSIS1-1/w-1/w.

	Cost	*Delay*	*Quality*
Cost	1	1	1/w
Delay	1	1	1/w
Quality	w	w	1

Figure 9. Decision matrix for the quality-oriented scenario

Cost and delay-oriented scenario

In the Cost & Delay oriented scenario, Cost and Delay have the same importance, higher than Quality. In the decision matrix, X = 1, Y=w and Z=w (refer to Figure 10). The GA-TOPSIS models are indicated as GA_TOPSIS1ww.

	Cost	*Delay*	*Quality*
Cost	1	1	w
Delay	1	1	w
Quality	1/w	1/w	1

Figure 10. Decision matrix for the cost & delay-oriented scenario

8. Simulation and performance evaluation

Mathematical simulations are generated with w = {1,…, 9} for each of the four scenarios. The results in terms of Profit; Delay; and Quality obtained for the best fitness score are considered as the performance indicators for each simulation. The Cost and Lead time of a batch of orders Oi (iϵ[1,..,I]) are computed as follow:

$$Cost_I = \frac{1}{I}\sum_{i=1}^{I} Quantity(O_i).Prod\_Cost\big(S(O_i)\big) + Shipment\_Cost\big(S(O_i)\big) \quad (1)$$

$$Lead\_time_I = \frac{1}{I}\sum_{i=1}^{I} DEO\big(S(O_i)\big) + Quantity(O_i).Prod_{time(S(O_i))} + Shipment\_time(S(O_i)) \quad (2)$$

$$Quality_I = \frac{1}{I}\sum_{i=1}^{I} Q(S(O_i)) \quad (3)$$

With: *Q(S(Oi))* the quality of the supplier *S(Oi)* evaluated by the retailer from the likert scale (see Table 2), *S(Oi)* the supplier selected to produce the order *Oi*. In other words, supplier *S(Oi)* obtained the highest TOPSIS score for the production of the order *Oi* during the evaluation process of the order sequence. Table 3 indicates the GA parameters implemented for the simulations.

Table 3. GA parameters

Parameter	Amount
Population size	100
Crossover rate	0.8
Mutation rate	0.2
Number of generations	200

9. Comparison with benchmark method

In order to evaluate the performances of our methods in comparison with a benchmark method, we implement the same scenarios with the well-known weighted sum methods. This method is widely applied in multi-criteria decision-making problems, and more especially in supplier selection problem such as in [11] and [12]. The supplier selection and order allocation are determined from a Score obtained as follow:

$$Score = \alpha * Profit_{Norm} + \beta * LeadTime_{Norm} + \gamma * Quality_{Norm} \quad (4)$$

where $Profit_{Norm}$, $LeadTime_{Norm}$ and $Quality_{Norm}$ are the Min-Max normalized values.

The different Profit-, Delay- and Quality-oriented scenarios are simulated with different coefficients α, β, γ generating different Weighted Sum models called WS$\alpha\beta\gamma$:

- Weighted Sum model for Profit-oriented scenario: WS*w-1/w-1/w*
- Weighted Sum model for Delay-oriented scenario: WS*1/w-w-1/w*
- Weighted Sum model for Quality-oriented scenario: WS*1/w-1/w-w*

With *w = {1,…,9}*

RESULTS AND DISCUSSION

1. Results

For every simulation, the three performance indicators are presented for each scenario separately and then compared as a whole to highlight the Pareto optimal solution.

Profit-oriented scenario

The GA_TOPSISww1 and WS*w-1/w-1/w* models are executed for w= {1,…,9}. Figure 11 presents the Profit, Lead Time and Quality obtained with the best fitness scores related to the different values of w. For reasons of clarity, the values of Quality criterion have been indexed on 1000 (highest possible quality score = 1000).

From the Figure 11, it can be observed consistent results of the GA_TOPSIS models for the three performance indicators with the increase of the importance of the profit criteria. As expected for the profit-oriented scenario, the GA_TOPSISww1 models provide solutions with higher profit when the value of w increases, at the expense of the other criteria. These consistent results demonstrate the ability of the proposed models to take into account the retailer's objectives or preferences. These simulations can also be a valuable decision support to optimize the profit while by preserving an efficient trade-off for the lead time and quality. To be more specific, it obviously appears that the GA_TOPSIS991 enables the maximum profit but with a significant decline of the lead time and quality. The solution proposed by the

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GA_TOPSIS551 model could emerge as an optimum pragmatic solution to deal with the considered orders.

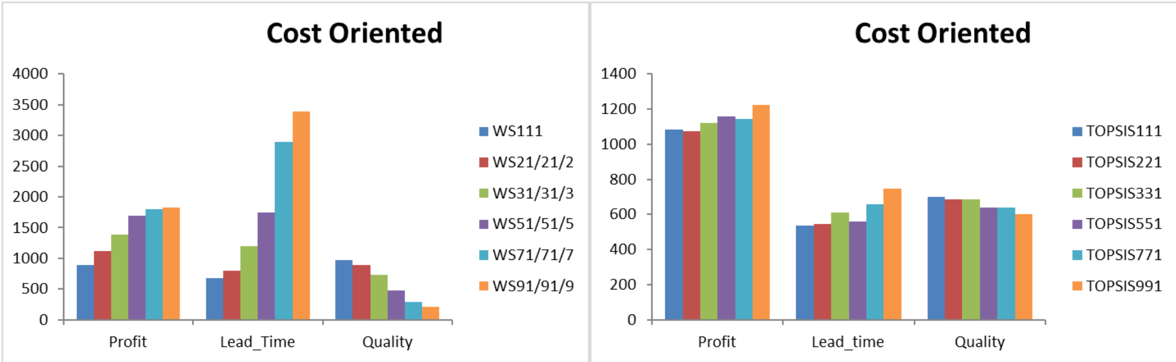

Figure 11. Comparison of the WS and the GA_TOPSIS methods for the Profit-oriented scenario

In comparison with the WS*w-1/w-1/w* models, it obviously appears that the proposed solution enables a better trade-off between the three performance indicators. For extreme values of *w*, the WS*w-1/w-1/w* models become a mono-objective optimization model. it can reach higher profits but at the expense of significant decline of the lead time and quality.

Delay-oriented scenario

Delay oriented configurations are evaluated based on the same principle. Figure 12 presents the comparison of the three criteria obtained from the GA-TOPSIS1/w-1-w.

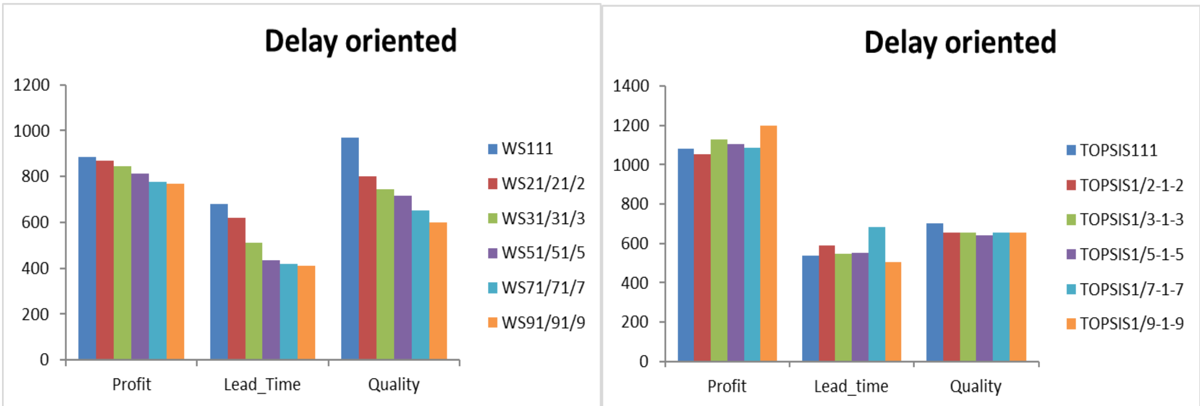

Figure 12. Comparison of the WS and the GA_TOPSIS methods for the delay-oriented scenario

For these configurations, the optimization of the most important criteria, the lead time, seems more complicated. The proposed optimization is only able to provide a slight reduction of the lead time for the highest values of w (5, 7, and 9). The comparison with WS*w-1/w-1/w* models also demonstrates that the proposed models have a better ability to find optimum trade-off.

Quality-oriented scenario

The Quality-oriented configurations simulated on the considered order and supplier datasets, presented in Figure 13, offer distinctive results: the GA-TOPSIS1-1/w-1/w models generate a significant gap when *w* is equal or higher than 3. From this tipping point, the Quality criterion reaches its maximum value, and the Profit and Lead time criteria are strongly degraded. The simulation demonstrates that the GA-TOPSIS1-1/5-1/5 model proposes the best solution in terms of Quality and trade-off between Profit and Lead time for managers who want to obtain the maximum quality score. The WS*w-1/w-1/w* models quickly converge towards the maximum quality and fail to explore possible trade-offs.

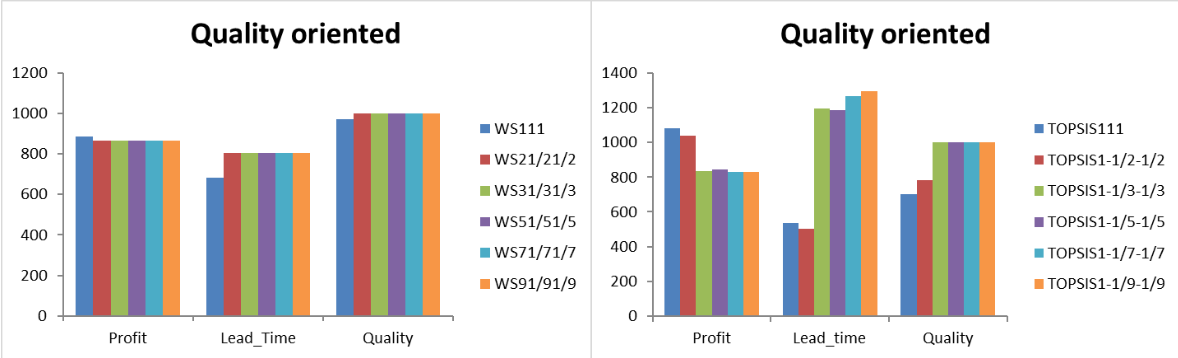

Figure 13. Comparison of the WS and the GA_TOPSIS methods for the quality-oriented scenario

Cost and delay-oriented scenario

Cost and delay are traditionally considered to be negatively correlated in production planning and supplier selection. The Cost & Delay oriented scenario is very challenging since Profit and lead time have the same importance in the performance evaluation. The GA-TOPSIS1ww models try to find the best balance between the two most important criteria and it becomes difficult to detect a clear trend when *w* is increasing (refer to Figure 14).

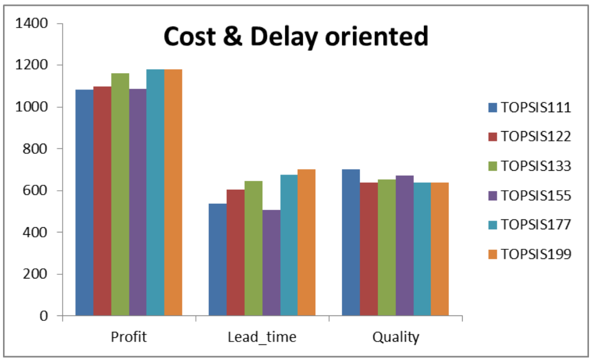

Figure 14. Best solutions for each configuration of for cost and delay-oriented scenario

Overall, through these results it is possible the identify the impact of the weights of the supplier selection criteria evaluations for each of the proposed scenario. This analysis also highlights the importance of the trade-off between supplier selection criteria for the decision making. The proposed GA-TOPSIS model can also be used as a simulation tool for small-series fashion retailers to obtain a more comprehensive view of the solutions and performances for the processing of their customer orders.

Pareto optimal solutions

Considering the three criteria such as Profit, Lead time, and Quality as the objectives of a small-series fashion retailer company, we develop a heuristic to explore the solution domain provided by the proposed GA-TOPSISXYZ model on the experimental data. A simulation is composed of all the combinations of {X,Y,Z} with the value of the Saaty's scale {1/9, 1/7, 1/5, 1/3, 1, 3, 5, 7, 9}. The solutions obtained from the 9x9x9 = 729 combinations are then represented in 2D plot of each pair of criteria to highlight the Pareto optimal front. A Pareto front enables the definition of non-dominated solutions and can be used as an efficient decision support tool for multi-criteria problems.

In the Figures 15, Figure 16, and Figure 17 representing the Pareto fronts, the values of each criterion are normalized with a min-max method and the optimal solution is obtained for the value 1. The Pareto optimal solutions for the two criteria Profit and Lead time are shown in Figure 15. The Pareto front in this configuration includes the solutions obtained in the Cost and Delay oriented scenario analyzed in section 4.4.4). The convex shape of the front indicates that an interesting trade-off can be envisaged with normalized between 0.8 and 0.9 for the two

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criteria, representing a cumulative profit between 1150 and 1200 and a cumulative lead time between 400 and 500 on the considered data. However, it also clearly appears that the values of the Quality criteria, represented in legend, of the Pareto optimal solutions for the Profit and Lead time are very low.

Figure 16 shows the Pareto optimal solutions for the criteria Profit and Quality. The straight shape makes the decision process complicated since a rise of Profit generates a quality loss of the same order. In a such situation, the decision maker should rely upon his own judgment based on the objective and policy of the company.

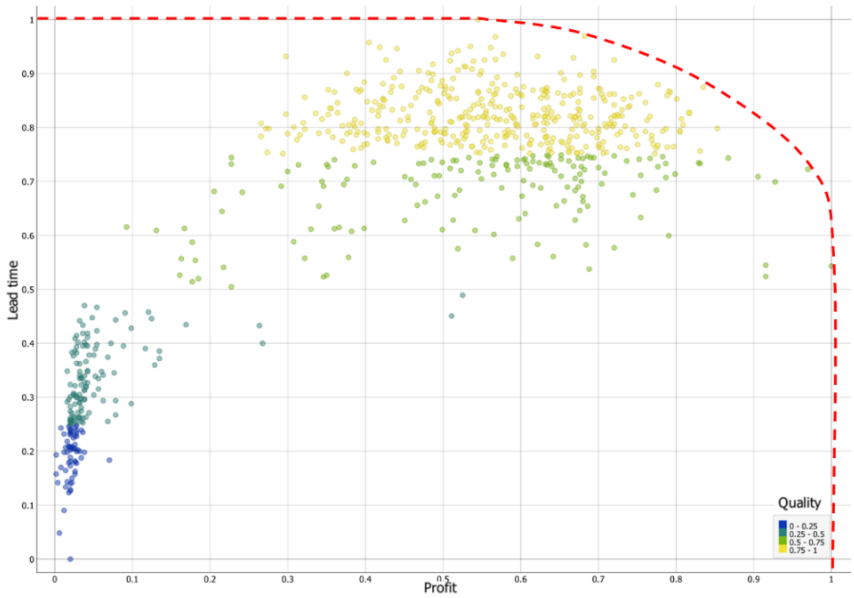

Figure 15. Pareto front for profit and lead time with quality in legend (normalized values)

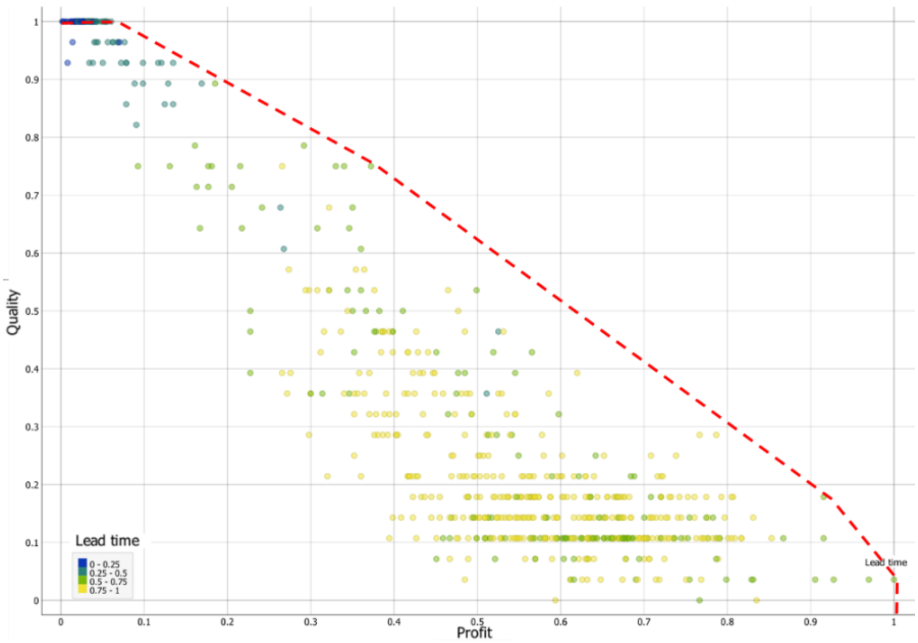

Figure 16. Pareto front for profit and quality with lead time in legend (normalized values)

Figure 17 illustrates the Pareto optimal solutions for two objective criteria Lead time and Quality. The front also presents a convex shape but less pronounced than Figure 15. An optimal trade-off between lead time and quality should be around the normalized values 0.7 and 0.8.

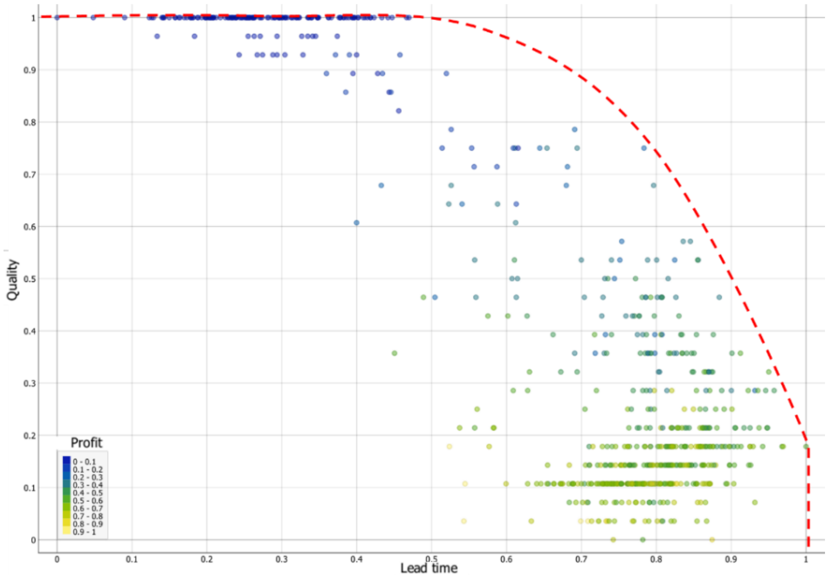

Figure 17: Pareto front for lead time and quality with profit in legend (normalized values)

2. Discussion

The proposed GA-TOPSIS model enables a quantitative optimization of a multi-criteria problem from a subjective evaluation of the importance of the criteria. This model can be used to find the best sequence and allocation of orders to suppliers considering a focused strategy on one criterion. The first finding highlighted by the simulations of different scenarios implemented on real orders demonstrates the ability of the proposed model to optimize the target criterion while maintaining the best possible performances on other criteria. The criterion-oriented scenario enables the selection of the best weights (importance) for the criteria that it should be used for the considered sets of data, orders, and suppliers. In comparison with the well-known Weighted Sum method, our model demonstrates a better ability to find optimum trade-offs between the three considered performance indicators. From a practical point of view, the proposed GA-TOPSIS have less sensibility, and thus, it can be easier for decision-makers to select the suitable parameters (e.g. weight of importance of each criterion) to find solutions which reach their objective criterion without giving up the others criteria.

When the user has no clear strategy or would like to explore all the possibilities, the proposed GA-TOPSIS model can also be implemented as a decision support system to find the best trade-off [13-16]. The weight of each criterion becomes then a parameter for the optimization problem. In this situation, the analysis of the Pareto fronts obtained from the solutions simulated with the GA-TOPSIS model provides a valuable support for decision makers. For instance, the results in this experimental study show that interesting trade-offs can be expected between the profit and the lead time, and to a lesser degree, between Lead time and quality. Above all, the three generated Pareto front indicate that it is not possible to reach the optimum ranges for the three criteria, especially because of the antagonism between the profit and the quality. This analysis is limited to the considered data, and the proposed heuristic based on GA-TOPSIS model should be executed for each new sets of data. When executing the proposed model on a wide range of parameter values, the second findings of this study is the ability of the proposed model to identify a Pareto front specifically for a set of suppliers and orders, and thus, enables a deeper analysis and more accurate decision making in a dynamic environment. The combination of supplier selection and order allocation and planning into the same optimization process is the key factor to reach this performance.

CONCLUSION

This paper developed a framework based on GA-TOPSIS method to address the problem of order allocation and supplier selection for small series production on demand of

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fashion products. The proposed approach aims at prioritizing several decision factors according to the objectives of retailer with the integration of both qualitative and quantitative, and static and dynamic, criteria. The proposed GA-TOPSIS model, composed of a TOPSIS method for multiple-criteria evaluation and a GA optimization, dynamically deals with batches of orders from order and supplier datasets. From criteria wise scenarios, an implementation on real orders demonstrates the usability of GA-TOPSIS model to make the supplier selection as per the specific dominant criteria. In comparison with the well-known Weighted Sum method, the proposed model demonstrates a better ability to find the trade-offs between the considered criteria and also less sensitivity when tuning the parameters. The proposed model is also used to compute the Pareto front for obtaining the optimal sets of solutions, or non-dominated solutions, for the given objective criteria and considered data. The ability of the model to find trade-offs and the integration of both supplier and order data into the optimization process make this Pareto front particularly interesting for accurate decision making in the dynamic environment of a demand driven production. From the point of view of practical validation of the proposed model, the study has a few limitations. The validation of the proposed approach relies on limited number of suppliers and criteria. This choice is justified to make the understanding of model and analysis of the results easier. The number of considered suppliers directly impacts the computational time. When the number of criteria involved in the decision process increase, a comprehensive analysis of the results, and more especially of the Pareto front, becomes more complex. These issues make the definition of the Pareto front with a heuristic approach as implemented in this study not possible. The future works should focus on the development of a Pareto Front Estimation model. Finally, there is also a future scope for testing the adaptability of the proposed approach beyond the fashion industry and scaling it up to the other industries where dynamic order allocation is a challenging and evolving decision problem.

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