A MULTI-OBJECTIVE DECISION-MAKING MODEL FOR SUPPLIER SELECTION CONSIDERING TRANSPORT DISCOUNTS AND SUPPLIER CAPACITY CONSTRAINTS

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Abstract. The present study considers the transport discounts and capacity constraints for the suppliers and manufacturers simultaneously to provide a multi-objective decision-making model for supplier selection on a three-level supply chain. For this purpose, it begins with presenting a nonlinear mixed-integer model of the problem, where the objectives include the minimization of the logistics costs and lead time. Subsequently, the NSGA-II algorithm is developed to solve the large-scale model of the problem and simultaneously optimize the two objectives to achieve Pareto-optimal solutions. To test the efficiency of the proposed algorithm, several synthetic examples of various sizes are then generated and solved. Finally, the paper compares the performance of the proposed metaheuristic algorithm with the augmented epsilon-constraint method. In summary, the findings of this study provided researchers and industries to easily access to a cohesive model of supplier selection considering transportation that are essential to the solution of many real-world challenging logistics issues.

1. Introduction. The constant pressure toward globalization and the vital role of the competitive advantages have forced companies toward seeking effective strategies for selecting their supplier(s) [1, 8, 10]. The goal of supplier selection is to identify the optimal supplier(s) who can provide the client with the best products or services, contributing to the supply chain of the organization [14, 16]. As a part of the supply chain, the supplier(s) imposes a long-lasting effect on the efficiency and effectiveness of the entire supply chain. Accordingly, effective supplier assessment and selection strategies can directly affect the supply chain performance and, in turn, the productivity and profitability of the entire organization. Various researchers have argued that, as far as customer evaluation and selection are concerned, the multi-criteria decision-making methods provide better results than the traditional cost-based decision-making methods. To select the best supplier(s),

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it is necessary to establish a compromise among different tangible and intangible criteria [16].

The main piece of information that must be considered when supplier selection is concerned is that which product or service is provided by which supplier and when? The choice of the right supplier reduces the cost of purchasing the materials dramatically and directly improves the competitiveness of the company. That is why experts in this field have referred to the supplier selection as the most important activity undertaken by a buyer organization [5]. Many factors affect the overall performance of a supplier, but the fact that each supplier has different performance characteristics and functionalities for different metrics makes the problem extremely complicated. For example, a provider that supplies a particular item at the lowest single unit may not necessarily have the best quality performance or service among competing suppliers. The supplier selection is a multi-purpose decision that seeks to minimize the cost while maximizing the quality and functionality of the services simultaneously. Oftentimes, what makes the supplier selection even more problematic for the buyer is the price discounts offered by different suppliers, which, many times, are dependent on the monetary value of the purchase rather than the volume or type of the purchased goods in a given period [36].

In most order-based production systems, the manufacturer must be flexible enough to adapt itself to the changing demands across different markets and deliver the products to the customers at the desired level of quality on time. Accordingly, many manufacturers face the challenge of limiting their production capacities and prioritizing the responses to market demand. So far, in most production scheduling models, the demands for products in different time intervals have already been set and introduced into the model as an uncontrollable factor beyond the manufacturing system. Due to the competitive nature of the market, the relatively constant growth of demand, and the limited production capacities, there are cases where the manufacturer cannot meet all demands [10]. Other limitations that keep the manufacturer from meeting the existing demand in full include the delivery time constraints, limitations on the number of suppliers selected to supply an item, the supplier capacity limitations, transportation limitation, and the limitations imposed by the customer satisfaction [13].

In traditional quantitative discount pricing, the discounted price is seen as a function of the monetary value of the order and applied to any product regardless of the total volume of purchases in a given period. Adopting the just-in-time (JIT) strategy to this traditional approach, the purchasers figured out that a smaller lot size was more feasible and rational. Therefore, the suppliers found that, for certain buyers, it makes more sense to apply discounts based on the total value of the multi-product orders (i.e. total volume of trade) [36]. The present work explores the supplier selection problem based on multiple criteria considering possible transport discounts and limited supplier capacity.

The choice of supplier is important in different sectors. For example, a factory that supplies its raw material from external workshops and factories is always looking for the best possible inputs. The suppliers, on the other hand, are aware of this competitive environment and hence try to stay in the best condition for the customers. Following this line of reasoning, the suppliers try to increase their competitive power by offering discounts in return for more. This discount, however, affects the buyer’s order volume. In fact, they should establish a balance between the storage and transport costs and benefits before deciding on the value of the
purchase. Also, when supply chains have insufficient capacity to meet the demand for transportation, they should consider capacity constraints. Other problems with the supplier selection include the product quality, the number of defective items in the consignment, and the timing of the posts and receipts. Supplier selection must be performed properly before customer satisfaction can be attained by meeting the customer’s needs. The complexity and importance of deciding on the choice of suppliers according to different factors highlight the necessity of providing a comprehensive model. Under these preconditions and observing the research gap, we were motivated to investigate the supplier selection problem on a three-level supply chain. In the proposed model considering the transport discounts, product quality, and capacity constraints of the suppliers and manufacturers simultaneously. Here the objectives include the minimization of logistics costs and lead time. Another contribution of this paper is introducing a metaheuristic algorithm to solve the problem.

The rest of this paper is organized as follows. Section 2 gives a formal review of the related literature. Section 3 lays out the proposed model. The algorithm for solving the problem and the computational results are presented in Section 4. Section 5 draws the conclusions.

2. Research background. In a broad classification, Weber et al. [35] categorized quantitative approaches to supplier selection into three categories: linear weighted models, mathematical programming models, and statistical/probabilistic approaches. The linear weighted methods seek to determine the optimal vendors and assign the orders to them in such a way to minimize the purchase and inventory costs considering a set of constraints including the supplier capacity, the demand level, and the vendor’s quality of service [4, 32]. Since long ago, the mathematical programming models have been focused on vendor selection and order assignment. These models are used to formulate the supplier selection problem according to a single objective function that must be either maximized (e.g. profit) or minimized (e.g. cost). In 1974, Gaballa applied mixed integer programming to exploit the maximum discount offered by vendors [17]. Before Weber et al. [35], only 10 studies had suggested the use of mathematical programming techniques though many researchers elaborated on this approach since then [2].

Many researchers have used single-objective techniques, e.g. mixed or linear integer programming, in which a single criterion (usually the cost) is considered as the objective function and other criteria provide constraints. Single-objective models can be used to minimize the purchasing costs, inventory costs, or ordering costs, while multi-objective models enable the researchers to consider multiple criteria simultaneously, thus multiplying the target functions by maximizing or minimizing presentation [36]. Knowing that the present research is focused on mathematical programming, a brief review of the relevant literature is presented in this section.

Aguezzoul and Ladet presented a paper on the multi-purpose selection of suppliers and the integration of transport policies. In their paper, a nonlinear multi-objective programming model was presented to minimize total cost and order delivery time [1]. Liao and Rittscher presented a multi-objective programming model with stochastic demands. The authors sought to minimize total cost, product return rate, and delivery latency while maximizing the flexibility [24]. Demirtas and Ustun proposed a multi-objective decision-making approach to supplier selection where the analytic network process (ANP) was combined with multi-objective linear
programming [12]. Shaw et al. approached the supplier selection problem through an integration of the fuzzy analytic hierarchy process (AHP) and multi-objective linear programming to develop a carbon-free supply chain [33]. Amin and Zhang presented a multi-objective model for selecting suppliers in a closed-loop supply chain. In this model, a producer-managed closed-loop chain was assumed. The goals were maximizing the profit and weight of the suppliers and minimizing the rate of defective products [3]. Arikan presented a multiple-source problem in the scope of linear programming and considered three objective functions: (1) minimizing the incurred costs, (2) maximizing the quality, and (3) maximizing the timely deliveries [5]. Nazari Shirkouhi et al. introduced a fuzzy multi-objective linear programming model for the supplier selection and order assignment in a two-stage framework. The authors tried to minimize the purchasing and ordering costs, the number of defective units, and the delivery latencies simultaneously [31]. Kannan et al. introduced a fuzzy multi-criteria decision-making model for supplier selection and order assignment along a green supply chain, with the so-called multi-objective mathematical programming proposed for solving the model. Here the objective was to maximize the total value of the purchased products at the minimum total purchasing cost [22]. Deng et al. introduced an integrated problem of designing the production line and selecting suppliers following a multi-objective decision approach. The goals included maximizing the profit, the quality, and performance of the production line at the minimum possible cost of the production line [13]. Jadidi et al. presented a goal programming model for supplier selection, where minimum price, product return rate, and delivery time were the objectives [20]. Moghaddam introduced a fuzzy multi-objective model for selecting suppliers and assigning orders to them across a reverse supply chain [29]. Jazemi et al. proposed a three-objective model focused on cost, quality, and delivery time. In their work, maximizing the number of healthy products was set as the quality objective, and minimizing the delivery latencies was targeted as the objective focusing on the delivery time [21]. To the best of our knowledge, the mathematical model of the multi-objective supplier selection with transport discounts and capacity constraints is yet to be adequately addressed. In the following, relevant research works are classified for the two main focuses of the present study.

2.1. Supplier selection with transport discount. Xia and Wu considered multi-criteria supplier selection with volume discounts [36]. Tsao and Lu elaborated on the design of a supply chain network considering transportation cost discounts [34]. In their article, Mendoza and Ventura formulated two mixed-integer nonlinear programming models for supplier selection and allocation of order quantities while minimizing the annual ordering, inventory holding, and purchasing costs under supplier capacity and quality constraints [28]. Khosroabadi et al. proposed a mixed-integer linear programming model for the multi-period joint supplier selection and order lot-sizing problem concerning both the defective products rate and remanufacturable items; they assumed that not only the purchase price but also the transportation cost were subject to discounts according to the number of departure vehicles [23].

2.2. Supplier selection with capacity constraints. Ghodsypour and O’Brien presented a mixed-integer nonlinear programming model to solve the multiple sourcing problem. The model took into consideration the total cost of logistics, including net price and storage, transportation, and ordering costs [18]. Ekrici provided an
improved model for supplier selection from a pool of candidates with limited capacities according to multiple criteria [15]. Hu and Motwani developed a framework for minimizing the risks associated with suppliers and their capacities, order quantity and purchase, ordering time, and purchase and sales prices [19]. Mohammaditabar et al. presented a work where supplier selection and sell prices were analyzed on a decentralized supply chain [30].

A review of the relevant literature shows that discounts have been only rarely discussed. This is while the discounts are among the most important issues faced by organizations in the real world. A few researchers have focused on capturing the supplier capacity, which is, by the way, very important depending on the company’s type of activity.

3. Mathematical model of the problem. In the manufacturing systems of today, the manufacturer must be flexible enough to adapt to the customer demand changes in presence of various challenges including the limited production capacities, priorities of the demands, delivery time constraints, supplier and transportation capacity limitations, etc. Accordingly, the present research seeks to optimize two objectives concerning the supplier selection problem simultaneously: (1) minimizing the costs, and (2) minimizing the delivery time.

3.1. Assumptions. The following assumptions are made in this research:

- A three-level single-product supply chain is encountered (supplier, warehouse, and customer levels).
- Suppliers are selected based on three criteria: purchase and storage costs, product quality, and delivery time.
- Suppliers have limited production and storage capacities.
- Having discounts at the first level of the chain, the shipping costs differ among different carriers.
- Distribution centers are established at fixed and well-known locations.
- Transit between regional distribution centers and retailers incurs fixed and variable cost components, with the variable cost being dependent on the distance.
- Each retailer is assigned to a specific regional distribution center by which it is provided.

3.2. Problem formulation. The notations used in this research are as follows:

| Indices | Description |
|---------|-------------|
| $I$ suppliers | $v$ Supplier-to-warehouse carriers (carrier type-I) |
| $J$ warehouses | $v'$ Warehouse-to-customer carriers (carrier type-II) |
| $K$ customers | $m$ Price levels |
### Parameters

| Parameter | Description |
|-----------|-------------|
| $A_i$     | Cost of ordering from the supplier $i$ |
| $P_i$     | The per-unit cost of purchasing from the supplier $i$ |
| $r_j$     | The cost of storing goods at the warehouse $j$ |
| $B_m$     | The $m^{th}$ cost boundary for transportation costs from suppliers to warehouses for $m$ intervals related to price levels ($0 = B_0 < B_1 < \cdots < B_m < B_{m+1} = \infty$) |
| $T_{ijvm}$| The per-unit cost of transporting from supplier $i$ to the warehouse $j$ by the carrier $v$ at the price level $m$ |
| $F_v$     | The fixed cost of using the carrier $v$ |
| $F_v'$    | The fixed cost of using the carrier $v'$ |
| $C_{jkv'}$| The per-unit cost of transportation from warehouse $j$ to customer $k$ by the carrier $v'$ |
| $q_i$     | The quality of the goods procured by the supplier $i$, (measured based on product return rate). |
| $M$       | A very large number |

### Decision variables

| Decision Variable | Description |
|-------------------|-------------|
| $D_i$             | Total demand allocated to warehouse $j$ |
| $u_v$             | $\begin{cases} 1 & \text{If the carrier } v \text{ is utilized} \\ 0 & \text{otherwise} \end{cases}$ |
| $y_{ijvm}$        | The quantity of goods purchased from the supplier $i$ at the price level $m$ and dispatched to the warehouse $j$ by the carrier $v$ |

| Decision Variable | Description |
|-------------------|-------------|
| $u_v$             | $\begin{cases} 1 & \text{If the carrier } v \text{ is utilized} \\ 0 & \text{otherwise} \end{cases}$ |
| $x_{jkv'}$        | The amount of goods purchased from the warehouse $j$ by the customer $k$ to be carried by the carrier $v'$ |
| $y_{ijvm}$        | The quantity of goods purchased from the supplier $i$ at the price level $m$ and dispatched to the warehouse $j$ by the carrier $v$ |
The problem was formulated into a mathematical model as follows:

\[ \min, z_1 = \sum_i \sum_j \sum_m \sum_v y_{ijvm} \left( \sqrt{2A_i D_j P_i r_j} + D_j P_j \right) + \sum_i \sum_j \sum_m \sum_v y_{ijvm} T_{ijvm} \text{Dis}_{ij} \]

\[ + \sum_v F_v u_v + \sum_v F'_v u'_v + \sum_j \sum_k \sum_v x_{jkv} C_{jkv'} \text{Dis}_{jk} + \sum_i \sum_j \sum_v \sum_{m} q_{t} y_{ijvm} D_{ij} T_{B_{ij}} \]

(1)

\[ \min, z_2 = \sum_i \sum_j \sum_v \sum_m l_{ijv} y_{ijvm} \]

(2)

subject to

\[ \sum_j \sum_m \sum_v y_{ijvm} \leq EI_i \quad \forall i \]

(3)

\[ D_j = \sum_k d_k z_{jk} \quad \forall j \]

(4)

\[ \sum_i \sum_m \sum_v y_{ijvm} (1 - q_i) = \sum_k \sum_{v'} y_{jkv'} \quad \forall j \]

(5)

\[ \sum_j \sum_{v'} x_{jkv'} \geq d_k \quad \forall k \]

(6)

\[ \sum_k \sum_{v'} x_{jkv'} \leq EI_j \quad \forall j \]

(7)

\[ \sum_{v'} x_{jkv'} \leq M z_{jk} \quad \forall j, k \]

(8)

\[ \sum_{v'} x_{jkv'} \leq \text{CAP}_{v} u_{v} \quad \forall v, i \]

(9)

\[ \sum_{v'} x_{jkv'} \leq \text{CAP}_{v'} u_{v'} \quad \forall v', j \]

(10)

\[ \sum_j z_{jk} = 1 \quad \forall k \]

(11)

\[ B_{m-1} w_{ij} \leq \sum_v y_{ijvm} \leq B_m w_{ijm} \quad \forall i,j,m \]

(12)

\[ \sum_v w_{ijm} \leq 1 \quad \forall i,j,m \]

(13)

\[ x_{jkv'}, y_{ijvm}, D_j \geq 0, \quad z_{jk}, w_{ijm}, u_v, u_v' \in \{0, 1\} \quad \forall i,j,m \]

(14)

Equation (1) denotes the first objective function (i.e., cost minimization). In this equation, the first term represents the sum of purchasing, ordering, and storage costs, and the second term is the cost of transporting the goods from the supplier to
the warehouse considering some discount. The third and fourth terms are the fixed costs of utilizing the carriers from the supplier to the warehouse and then from the warehouse to customers, while the fifth term is the variable cost of shipment from the warehouse to the end user. The sixth term refers to the cost of returning the goods from the warehouse to the supplier. Equation (2), the second objective function, seeks to minimize the waiting time for receiving the goods from the supplier to the warehouse. Constraint (3) sets a limit on the supplier capacity. Constraint (4) calculates the total demand attributed to each of the warehouses used in the first objective function. Constraint (5) sets the total amount of goods received from suppliers to different warehouses equal to the sum of goods shipped to the customers. Constraint (6) ensures that the customer demand is satisfied. Constraint (7) captures the warehouse capacity limitations. Constraint (8) ensures that no commodity will be dispatched from a warehouse to a customer unless the customer is assigned to that warehouse. Constraints (9) and (10) guarantee that no good is sent through a carrier until the carrier is utilized and only within the capacity of the carrier. Constraint (11) requires that each customer be assigned to a single warehouse only. Constraint (12) defines the price levels and keeps the quantity of goods dispatched from a supplier to a warehouse within the predetermined intervals of the price range. Constraint (13) implies that only one price level is selected and, finally, Constraint (14) represents the signs of variables.

4. Proposed solution approach. Initially, a small-scale version of the mathematical model of the problem is subjected to the augmented epsilon-constraint method, an exact solution technique. Then the NSGA II metaheuristic algorithm is developed to solve the problem at medium and large scales within reasonable time intervals. In the following sections, comparisons are presented between the two approaches. The comparisons and sensitivity analyses are conducted to demonstrate the stability of the proposed model. By establishing the multi-objective decision-making model on a multi-level supply chain, it is easy to achieve a stable supplier selection.

4.1. Augmented epsilon-constraint method. Before the epsilon-constraint method can be properly applied, one should (1) constrain the range of the objective functions over effective solutions and (2) ensure the effectiveness of the solution. Determining a proper range for constraining the objective functions is not easy to achieve, because unlike the best values of the objective functions, which are easy to compute with a single-objective optimization, their worst values are difficult to obtain while remaining within the effective solution set. These values are most frequently obtained from the so-called balance table. However, in cases where there are multiple optimal solutions, there is no guarantee that all of the solutions from the set are effective. Mavrotas [26] proposed hierarchical optimization for each objective function to generate the balance table and hence overcome this ambiguity. When it came to estimating the worst values of the objective functions, he suggested taking the reservation value of each objective function as its lower bound (or upper bound for a minimization objective function).

If at least one of the objective functions leads to more than one optimal solution, the solution from the epsilon-constraint method will not be effective, but rather a weak effective solution. Mavrotas proposed auxiliary variables for converting the constraints of the objective functions to equations in an attempt to avoid the weak effective solutions; the sum of these auxiliary variables was considered as a second
term with less weight in the objective function, simultaneously. The conversion leads to a new problem of the form expressed in Equation (15), where $p$ is the number of objective functions, $r_p$ denotes the range of the $p$-objective function, and $\delta$ is a very small number that usually ranges between $10^{-6}$ and $10^{-3}$.

\[
\max \left( f_1(x) + \delta \left( \frac{s_2}{r_2} + \frac{s_3}{r_3} + \cdots + \frac{s_p}{r_p} \right) \right)
\]

subject to

\[
\begin{align*}
    f_2(x) - s_2 &= e_2 \\
    f_3(x) - s_3 &= e_3 \\
    \vdots \\
    f_p(x) - s_p &= e_2 \\
    x &\in S \text{ and } s_i \in \mathbb{R}^+
\end{align*}
\]

Mavrotas designated this technique as augmented epsilon-constraint and utilized it to get rid of the weak solutions and obtain strong feasible solutions. In addition, he further customized the technique in such a way that it would stop and jump out of the loop if the problem could not be justified for a combination of $e_i$. In this way, the strategy of restricting each objective function was started from a fully-released value (the lower bound for maximization and the upper bound for minimization objective function) and gradually approached towards the optimal value. Once an unfeasible point was encountered, the remaining runs of the loop were given up, saving much time, especially when the number of objective functions is large.

The augmented epsilon-constraint method aims to present and evaluate an improvement on the main epsilon-constraint method, so as to make it suitable for solving multi-objective integer programming problems. This method has been proven to be more effective in providing accurate Pareto solution sets in integer programming problems, as compared to the previous version and some other common methods. Mavrotas and Florios [27] proved that this method can be used to prevent the generation of poor solutions so that only robust and effective solutions would be generated.

4.2. **NSGA II metaheuristic algorithm.** As stated, the goal of multi-objective optimization is to find a set of quasi-optimal or Pareto-optimal solutions to a given problem. In a genetic algorithm (GA), each solution is represented as a chromosome with a set of genes. In the first step, a set of random solutions is generated. The non-dominated sorting genetic algorithm II (NSGA II) is based on the classification of alternatives to several quasi-optimal levels, so that the first-level solutions are non-dominated by the solutions across the entire search space, the second-level solutions are non-dominated by the solutions across the entire search space except for the first-level solutions, and so on. As an extra control factor, the crowded distance was used as a secondary criterion to classify and rate the solutions for the sake of elitism. Accordingly, the higher the number of alternatives existing in the neighborhood around an alternative, the lower is the goodness-of-fit of that alternative. Details of the algorithm developed for the considered problem are explained in the following subsection.

4.2.1. **Solution representation.** Representing each solution with a chromosome, each chromosome is expressed as a NCus $\times$ 5 matrix where NCus represents the number
of customers. In this matrix, the first column denotes the quantity of the goods shipped from the supplier to the warehouse, while the second through fifth columns indicate the numbers of suppliers, type-I carriers performing the shipment, warehouses, and type-II carriers performing the shipment, respectively. Each row in this matrix defines a route to the respective customer. An example of a chromosome is presented in Figure 1.

| 8.75 | 1 | 1 | 1 | 1 |
|------|---|---|---|---|
| 12.85| 1 | 2 | 2 | 1 |

**Figure 1.** Demonstration of a chromosome (i.e., a solution) in the proposed metaheuristic algorithm.

The number of rows in a chromosome indicates the number of customers. For instance, the chromosome shown in Figure 1 refers to only two customers, two suppliers, two warehouses, and two type-I and type-II carriers for shipments. Two price range levels are considered. The two suppliers have product return rates of 0.07 and 0.04. Given the demands raised by the first and second customer (8 and 12, respectively), this chromosome indicates that 8.57 unit items are dispatched from the first supplier to the first warehouse by the first carrier. Upon the product return, 8 items are shipped from the first warehouse to the first customer by the first carrier to address the customer’s demand.

**Figure 2.** Demonstration of the solution of the case study.

In order to generate random chromosomes, the value of the second column is randomly set to the number of suppliers; similarly, the third column is defined to indicate the number of type-I carriers for shipment, and the fourth column is set to store the number of warehouses. Finally, the number of type-II carriers for shipment is randomized along the fifth column. After assigning different values to the second to fifth columns, the values along the first column, namely $y$, are assigned in such a way to preserve the flow conservation constraints. Moreover, the penalty technique is used to comply with other constraints.
4.2.2. Calculating the fitness value. The value of $y_{ijvm}$ serves as a basis for calculating the discount intervals. To specify the value of $x_{jku'}$, one should consider different rows to cover the entire demand. In Figure 2, if the discount applies to purchases exceeding 15 while the $y$ value is below 15, then no discount becomes applicable and we have $y_{1221} = 12.85$ and $x_{221} = d_2 = 12.00$.

4.2.3. Initial population. Similar to other metaheuristic methods, the NSGA II algorithm needs an initial population of random solutions. In order to generate the initial population, chromosomes (solutions) are produced to the required population size. For this purpose, a cell structure is used to store the initial population, with each cell containing a single chromosome, the objective function value, the solution rank, and the crowded distance.

4.2.4. Genetic operators. Genetic operators are very important in a variety of genetic algorithms, as those lead to more effective guidance of the algorithm towards the optimal solutions in less time. Chromosomes are recombined to produce offsprings out of parent chromosomes. The operation by which one or two parents cooperate to produce one or more offsprings resembling the parent(s) is called the crossover operator. In contrast, the mutation operator produces offsprings differing from the parent(s) to avoid local optima by widening the search space.

- Crossovers operator

In the crossover operation, two parents of certain probability are selected and have one or more of their columns exchanged to generate two offsprings. The offsprings are then examined and adjusted in terms of the flow conservation constraints to address the infeasible solutions. The purpose of this operator is to assess customer demands and warehouse supplies. If the exchange of the columns interrupts the balance between the supply and demand, the amount of goods sent from the warehouse to the customer is redefined.

In Figure 3, the first column is selected for the exchange between the parents. If there are two or more similar paths (e.g., the second parent), the values are summed when decoding the solution; for example, the quantity of goods sent from the first supplier to the first warehouse would then be 21.42.

| 1 1 1 2 3.27 | 1 1 1 2 0 |
| 1 1 2 2 17.63 | 1 1 2 2 21.72 |
| 1 1 2 1 0 |
| 1 1 2 1 21.42 |

Parents

| 1 1 1 2 3.27 | 1 1 1 2 0 |
| 1 1 2 2 17.63 | 1 1 2 2 21.72 |
| 1 1 2 1 0 |
| 1 1 2 1 17.63 |

Offsprings

Figure 4. Demonstration of the mutation operator.

- Mutation operator
The mutation operator is used to induce variation into the pool of solutions. First, one of the solutions with a certain probability is selected. Then, the genes on each of the selected chromosome rows are either kept fixed or regenerated with a probability of 0.5. Next, the first column (i.e., the quantity of goods sent to the warehouses) is randomly regenerated according to the generated routes considering the flow conservation constraint.

|   |   |   |   |   |
|---|---|---|---|---|
| 1 | 2 | 1 | 1 | 8.57 |
| 2 | 1 | 1 | 1 | 12.85 |

|   |   |   |   |   |
|---|---|---|---|---|
| 1 | 1 | 2 | 1 | 17.79 |
| 2 | 1 | 2 | 2 | 3.54 |

**Figure 4.** Demonstration of the mutation operator.

Figure 4 assumes that the random number generated for both rows of this chromosome is greater than 0.5 and both rows are selected for mutation; thus, the genes of both rows are regenerated randomly. As shown in this example, there are cases where offsprings are identical to the parents. The values along the first column are regenerated randomly to meet the flow conservation constraints. This largely adds to the variation across the solution space, helping avoid local optima.

4.2.5. *Chromosome selection and stopping criterion.* To select the offsprings to form the next generation, the so-called elitism is used, as explained previously. In this way, superior non-dominated solutions are transferred to the new front. The maximum number of iterations is used as the stopping criterion in this research.

4.3. **Generating sample problems and parametrization.** The proposed algorithm was coded in MATLAB and run on a laptop powered by an Intel Core i5 @ 2.60 GHz processor and 6 GB of RAM. The proposed mathematical model was also solved using the BARON solver in GAMS software. A maximum total processing time of 7200 seconds and/or a per-iteration processing time of 600 seconds is considered for launching the augmented epsilon-constraint method.

A number of sample problems of different sizes are herein produced and investigated. The size-related parameters and the different levels of the supply chain are presented in Table 1. Due to the random nature of a metaheuristic algorithm, each sample problem is solved by the metaheuristic algorithm several times and average values are reported. In this regard, the algorithm is herein executed for five test instances for each sample problem.

Each supplier/warehouse is herein served by two vehicles for transporting goods to other nodes. In order to generate a random purchase, the per-unit costs of purchasing and ordering are assumed to be distributed uniformly from 40 to 50 and from 2 to 8, respectively. The storage cost of the warehouses is randomly selected from a uniform distribution in the range of 0.2-0.6. The quality of the goods shipped by the suppliers is randomly selected from the uniform distribution ranging from 0.02 to 0.10. In order to randomly generate the demand of each customer, a uniform distribution is used in the range of 5 - 15. The supplier and
Table 1. Details of the sample problems.

| Sample No. | No. of suppliers | No. of warehouses | No. of customers | No. of price levels |
|------------|------------------|-------------------|-----------------|-------------------|
| 1          | 2                | 2                 | 3               | 2                 |
| 2          | 2                | 2                 | 4               | 2                 |
| 3          | 2                | 3                 | 5               | 2                 |
| 4          | 3                | 3                 | 4               | 2                 |
| 5          | 3                | 4                 | 6               | 2                 |
| 6          | 3                | 5                 | 8               | 2                 |
| 7          | 4                | 4                 | 8               | 2                 |
| 8          | 4                | 6                 | 12              | 2                 |
| 9          | 4                | 8                 | 16              | 2                 |
| 10         | 20               | 30                | 40              | 2                 |
| 11         | 25               | 20                | 45              | 2                 |
| 12         | 30               | 25                | 50              | 2                 |
| 13         | 2                | 2                 | 4               | 4                 |
| 14         | 2                | 3                 | 5               | 4                 |
| 15         | 3                | 3                 | 4               | 4                 |
| 16         | 3                | 4                 | 6               | 4                 |

Warehouse capacities are taken from uniform distributions ranging from 70 to 100 and 20 to 50, respectively. The fixed costs of using the type-I and type-II vehicles are randomly extracted from uniform distributions in the ranges of 100 - 200 and 200 - 400, respectively. The price discount intervals are defined by identifying two intervals. For this purpose, firstly, a random value is extracted from a uniform distribution in the range of 25 - 50; considering this value, the cost of transporting goods from the supplier to the warehouse at the first level is then extracted from the uniform distribution in the range of 1-5; subsequently, the shipping cost at the second price level is set to be equal to that at the first level but reduced by a factor of 0.5. For the examples where more levels are considered, the higher price levels are calculated by decreasing the preceding-level price by a factor of 0.2. The cost of shipment from the warehouse to the customer is generated from a uniform distribution ranging from 2 to 7. The capacities of the type-I and type-II carriers are generated from uniform distributions in the ranges of 40-60 and 20-40, respectively. The cost of returning the goods is uniformly distributed from 1 to 3. The lead time was selected from a uniform distribution ranging from 5 to 15 days. The supplier-warehouse distances are taken from a uniform distribution in the range of 50-150, while the warehouse-customer distances are selected from a similar distribution but in the range of 50-100. The augmented epsilon-constraint
method is coded and implemented in GAMS, according to Mavrotas [30], to obtain Pareto-optimal solutions using the mathematical model.

In order to parameterize the algorithm (Table 2), three levels are considered for each parameter. The algorithm is then executed on a specific example with 7 nodes for different values of a particular parameter while keeping the other parameters constant. The results are shown in Figure 5. Finally, the values for which the algorithm returned the optimal performance in terms of the number of Pareto points and processing time are selected for the respective parameters (Table 3).

Table 2. Parametrization of the algorithm.

| Parameter                  | Level 1 | Level 2 | Level 3 |
|----------------------------|---------|---------|---------|
| The initial population     | 40-30-20| Mutation rate | 0.1-0.3-0.5 |
| Maximum No. of iterations  | 400-300-100| Crossover rate | 0.9-0.7-0.5 |

After examining different values of different parameters, the algorithm is parameterized as reported in Table 3.

In the proposed metaheuristic algorithm, the capacity constraints are satisfied by the penalty method for avoiding infeasible solutions. For this purpose, penalties for violation of the constraint are added to both objective functions.

Various criteria have been presented to evaluate the performance of multi-objective optimization. The following criteria are used to analyze the results of this research:

- **Comparison of boundary solutions**: This criterion compares the best values for different objectives.
**Table 3.** Results of the parametrization of the proposed metaheuristic algorithm.

| Parameter                          | Value  |
|------------------------------------|--------|
| The initial population            | 30     |
| Penalty for violation of storage capacity | 30000  |
| Maximum No. of iterations         | 300    |
| Penalty for violation of supplier capacity | 30000  |
| Crossover rate                    | 0.7    |
| Penalty for violation of type I carrier capacity | 30000  |
| Mutation rate                     | 0.3    |
| Penalty for violation of type II carrier capacity | 30000  |

**Run-time criterion:** This criterion takes into account the processing time of the algorithm for obtaining non-dominated solutions.

**The number of Pareto solutions:** This criterion focuses on the number of solutions obtained by each method.

**Spread criterion (D):** This criterion is computed through Equation (16), where $f_i^m$ indicates the intended $m$-th objective function for the $i$-th solution of the set of final non-dominated solutions, and $F_1$ is the set of solutions on the first front of the final population in the last iteration of the algorithm. For example, this criterion is equivalent to the Euclidean distance between two boundary solutions in the search space. Therefore, the larger this criterion, the higher is the performance of the implemented method [32].

$$D = \sqrt{\sum_{m=1}^{M} \left( \max_{i=1}^{\mid F_1 \mid} f_i^m - \min_{i=1}^{\mid F_1 \mid} f_i^m \right)^2}$$ (16)

**Diversity criterion ($\Delta$):** This criterion is calculated via Equation (17), where $d_i$ represents the Euclidean distance between successive solutions in the final set of non-dominant solutions, $\bar{d}$ is the average value over the Euclidean distances, and $d_f$ and $d_l$ are the distances between the boundary solutions obtained from the metaheuristic algorithm and those from the mathematical modeling, respectively. Clearly, a solution set with smaller $\Delta$ value represents a better solution, where the solutions are distributed more uniformly yet more diversely across the search space [33].

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{\mid F_1 \mid-1} |d_i - \bar{d}|}{d_f + d_l + (\mid F_1 \mid - 1) \bar{d}}$$ (17)

The values of the above-mentioned criteria for the mathematical modeling and the proposed algorithm are presented in Tables 4 and 5, respectively.

For robust comparison between two methods, average processing time and the number of Pareto solutions over test instances of each size are also reported in Tables 4 and 5.

As shown in Tables 4 and 5, the metaheuristic algorithm outperforms the mathematical model and the augmented epsilon-constraint method in terms of boundary solutions for most problem sizes, especially the medium- and large-scale cases.
Table 4. Sample problems with two price levels.

| Example number | Solutions of the mathematical model | Metaheuristic algorithm | The number of Pareto solutions | Solution time(s) |
|----------------|-------------------------------------|-------------------------|-------------------------------|-----------------|
|                | Total cost  | Lead time  | Total cost  | Lead time  | Mathematical model | Mathematical algorithm | Mathematical model | Mathematical algorithm |
| 1              | 68341.34    | 192.79    | 68341.34    | 192.79    | 5                  | 23                     | 5                  | 21                     |
|                | 38878.15    | 240.99    | 38878.15    | 240.99    |                    |                        |                    |                        |
| 2              | 121651.55   | 314.90    | 11737.38    | 314.90    | 5                  | 24                     | 8                  | 24                     |
|                | 64614.87    | 574.81    | 64614.87    | 574.81    |                    |                        |                    |                        |
| 3              | 75789.91    | 235.26    | 78716.08    | 235.23    | 6                  | 27                     | 782                | 21                     |
|                | 53963.32    | 318.05    | 52274.41    | 327.23    |                    |                        |                    |                        |
| 4              | 78533.08    | 209.05    | 78716.08    | 209.07    | 8                  | 27                     | 70                 | 21                     |
|                | 43011.82    | 303.94    | 42183.37    | 431.03    |                    |                        |                    |                        |
| 5              | 81203.42    | 291.36    | 87200.36    | 270.90    | 9                  | 38                     | 2713               | 22                     |
|                | 50979.63    | 531.78    | 49854.45    | 645.99    |                    |                        |                    |                        |
| 6              | 219299.25   | 556.65    | 221539.56   | 591.10    | 5                  | 38                     | 2471               | 18                     |
|                | 137964.35   | 1043.08   | 136235.26   | 991.28    |                    |                        |                    |                        |
| 7              | 150034.73   | 456.26    | 145148.71   | 454.95    | 2                  | 28                     | 1221               | 17                     |
|                | 121703.96   | 696.96    | 104719.58   | 738.18    |                    |                        |                    |                        |
| 8              | -           | -         | 197548.38   | 454.95    | 0                  | 59                     | 3600               | 17                     |
|                | -           | -         | 141281.50   | 1336.12   |                    |                        |                    |                        |
| 9              | -           | -         | 317966.30   | 1410.04   | 0                  | 63                     | 7200               | 9                      |
|                | -           | -         | 295530.83   | 1898.55   |                    |                        |                    |                        |
| 10             | -           | -         | 692358.54   | 3516.57   | -                  | 538                    | -                  | 15                     |
|                | -           | -         | 614931.40   | 5127.21   |                    |                        |                    |                        |
| 11             | -           | -         | 1395014.66  | 304484.07 | -                  | 436                    | -                  | 9                      |
|                | -           | -         | 1358331.99  | 305700.94 |                    |                        |                    |                        |
| 12             | -           | -         | 1319417.25  | 274612.41 | -                  | 693                    | -                  | 9                      |
Table 5. Sample problems with four price levels.

| Example number | Mathematical model solutions | Metaheuristic algorithm | The number of Pareto solutions | Solution time(s) |
|----------------|-----------------------------|-------------------------|-------------------------------|-----------------|
|                | Total cost                  | Lead time               | Total cost                    | Lead time       | Mathematical model | Metaheuristic algorithm | Mathematical model | Metaheuristic algorithm |
| 13             | 58818.69                    | 178.97                  | 55591.93                      | 178.97          | 12                | 37                      | 12                | 16                |
|                | 53372.19                    | 192.41                  | 48951.15                      | 438.95          |                   |                         |                   |                   |
| 14             | 85499.87                    | 351.63                  | 92925.05                      | 92925.05        | 2090              | 40                      | 5                 | 23                 |
|                | 62789.30                    | 492.64                  | 62935.46                      | 497.88          |                   |                         |                   |                   |
| 15             | 83856.96                    | 263.83                  | 99922.57                      | 253.48          | 2113              | 33                      | 9                 | 22                 |
|                | 53647.19                    | 605.75                  | 53384.45                      | 593.19          |                   |                         |                   |                   |
| 16             | 108712.51                   | 369.94                  | 100694.07                     | 394.24          | 2373              | 42                      | 6                 | 14                 |

Table 6 compares the proposed mathematical model and the proposed algorithm based on two criteria: spread and diversity. It shows the superiority of the mathematical model in terms of uniformity and diversity, while the proposed algorithm provided a larger spread across the solution space.

Table 7 signifies that average processing time for sample problems of any size is much less using the metaheuristic algorithm rather than the mathematical model. Note that the average processing time has been calculated only for the sample problems that could be solved via the mathematical model in less than 7200 seconds. Also, on average, the NSGA II produced more Pareto solutions than the augmented epsilon-constraint method.

A comparison between the results of the metaheuristic algorithm and those of the mathematical model reveals that the developed algorithm provides superior quality in much less processing time. Moreover, due to the relatively large number of constraints in the epsilon-constrained method, the mathematical model cannot handle large-scale problems in a reasonable time, while the metaheuristic algorithm can well solve the sample problems of all sizes in much less time and provides a non-dominated solution close to the Pareto optimality.

Figure 6 compares the Pareto results obtained from the metaheuristic algorithm and the mathematical model and their Pareto fronts for the sample problem No. 3. Figure 7 refers to the sample problem No. 9 as a large-scale example that could not be handled by the mathematical model in less than 7200 seconds.

5. Summary and conclusion. Efficient and effective procurement plays a vital role in the supply chain of organizations. The purchase activity has gained lots of
Table 6. Comparison of the proposed mathematical model and algorithm based on diversity and spread criteria.

| Example No. | Spread criterion | Diversity and uniformity criteria |
|-------------|------------------|----------------------------------|
|             | Mathematical model | Metaheuristic algorithm | Mathematical model | Metaheuristic algorithm |
| 1           | 29714.36         | 29463.23             | 0.97               | 1.43                  |
| 2           | 54007.81         | 52753.16             | 0.60               | 1.68                  |
| 3           | 19401.56         | 26441.83             | 0.65               | 0.85                  |
| 4           | 14492.95         | 25051.45             | 0.52               | 1.00                  |
| 5           | 25165.95         | 37347.79             | 0.24               | 0.78                  |
| 6           | 41666.65         | 85305.24             | 0.74               | 1.10                  |
| 7           | 28331.79         | 40430.12             | -                  | 1.00                  |
| 8           | -                | 29245.55             | -                  | 0.93                  |
| 9           | -                | 22440.79             | -                  | 0.74                  |
| 10          | -                | 77443.89             | -                  | 0.92                  |
| 11          | -                | 36702.85             | -                  | 0.80                  |
| 12          | -                | 220125.97            | -                  | 1.51                  |
| 13          | 5446.50          | 6645.87              | 0.68               | 0.99                  |
| 14          | 11106.65         | 2990.05              | 0.32               | 0.77                  |
| 15          | 28204.12         | 46539.36             | 0.24               | 0.97                  |
| 16          | 9979.74          | 15707.09             | 0.72               | 0.93                  |

Table 7. Comparison between different solution methods regarding average processing time and the number of Pareto solutions obtained for the small-sized problem.

| Methodology                     | Average processing time (in seconds) | The number of Pareto solutions |
|--------------------------------|--------------------------------------|-------------------------------|
| augmented epsilon-constraint method | 1897                                 | 6                             |
| Metaheuristic algorithm         | 38                                   | 19                            |

attention in the supply chain management thanks to the globalization phenomenon, increased value-added of this activity in the supply chain, and rapid technological evolutions. Supplier selection is the most important step of the purchase activity, largely contributing to the profitability of organizations. Proper evaluation andselection of the suppliers can provide organizations with competitive advantages over the competitors in terms of the product or service quality, production capacity, and delivery time. Various models and approaches have been developed to address the
supplier selection problem. In the present study, a capacity-constrained supplier selection problem is investigated considering price discounts at different levels. Two objectives were sought: (1) minimizing the transport cost, and (2) minimizing the lead time. In order to optimize the two objectives simultaneously, the augmented
epsilon-constraint method is utilized. A metaheuristic algorithm is further developed and numerical sample problems are explained and solved by GAMS software to validate the proposed model. The results indicate a conflict between the objective functions and the proper performance of the proposed model. In summary, the purpose of this paper is to help researchers and industries to easily access to a cohesive model of supplier selection considering transportation that are essential to the solution of many real-world challenging logistics issues.

Considering both the literature and the findings of the present study, the following directions are recommended for future research in the field of supplier selection:

- Formulating new multi-objective metaheuristic algorithms and comparing their results with those of the model proposed in this research;
- Considering diverse goals for the multi-objective supplier selection problem; examples of such goals include the development of green supply chains and incorporation of the customers’ and suppliers’ satisfaction levels into the model;
- Considering different levels of cooperation between suppliers (having multi-layer suppliers);
- Considering the effects of different uncertainties and risks in the model, such as the uncertainties associated with customer demand and delivery time, by handling robust optimization, stochastic optimal control, and chance-constrained optimization (see for example [6, 7, 9]);
- Considering multimodal transportation for handling the goods among suppliers, warehouses, and customers;
- Focusing on the Taguchi method [25] to compare the results with the results of a trial-and-error approach to further tune the parameters of the proposed algorithm;
- Evaluating the proposed method in real cases.

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