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Applying A Multi-Objective Genetic Optimization Algorithm to Select Automotive Parts Suppliers

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Abstract

This paper proposes a multi-objective mathematical model to select the best suppliers of parts and products to improve vehicle quality and reduce costs. The results are presented in two sizes, and a sensitivity analysis of the demand parameter has been performed. For each of the medium and large sizes, the indices of the Unconstrained Non-Dominated Sorting Genetic Algorithm II (NSGA-II), including computational time, Maximum Spread Index (MSI), metric distance index, and the number of efficient solutions, have been calculated. The results show that the number of efficient solutions increases with problem size, indicating the high efficiency of the undefeated NSGA-II in finding efficient solutions for the supplier selection problem.

Keywords: Supplier selection, Automotive industry, Multi-objective genetic algorithm, Non-dominated sorting genetic algorithm II .

1 | Introduction

The supplier selection problem is complex, and numerous quantitative and qualitative performance criteria, such as quality, price, flexibility, and delivery time, must be considered to determine the most appropriate supplier. In this regard, multi-criteria decision-making methods in a fuzzy environment have been used for supplier selection, and a method for calculating weights and ranking alternatives using the fuzzy TOPSIS technique has been proposed [1]. The Pareto algorithm leads to weak convergence; therefore, the NSGA-II algorithm is considered a suitable alternative for solving such problems [2]. Chita and Subbaraj [3] studied the

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reverse flow of materials from consumers to producers for material recycling. In reverse logistics, parameters such as facility capacities, demand, cost, quality, and others are uncertain. Considering these issues, this research presents a probabilistic mixed-integer linear programming model for designing a reverse logistics network. To solve this type of model, it was first converted into a deterministic model. The proposed model is multi-product and multi-echelon, simultaneously incorporating transportation costs and facility establishment costs.

An efficient method based on a genetic algorithm with priority-based encoding was proposed to solve the model. Razaei Kallaj [4] noted that, because suppliers play a fundamental role in cost, quality, service, and other criteria in achieving supply chain objectives, they are vital components of an organization and can significantly affect organizational performance. Since supplier selection problems in the real world face uncertainty and various constraints for both buyers and suppliers, the supplier selection process under multiple sourcing in an uncertain environment has been studied. Ghasemi and Abolghasemian [5] investigated the development of an optimal order quantity determination model with appropriate supplier selection using a multi-objective genetic optimization algorithm. In this study, the model was solved using the multi-objective NSGA-II metaheuristic, and, for validation, using the particle swarm optimization metaheuristic, with the results compared to those obtained from the first method.

Focusing solely on economic performance to optimize costs or return on investment cannot lead to the development of a sustainable supply chain. The impacts of supply chain activities on social life and environmental issues that contribute to sustainable development must also be considered. However, among the three dimensions of sustainability, economic, social, and environmental, the economic dimension has the greatest influence [6]. Given the complexities of the supplier selection process for automotive parts, a multi-sourcing approach is necessary [7]. Supplier selection in supply chain management is a group multi-criteria decision-making problem. The degree of data uncertainty, the number of decision-makers, and the nature of the criteria are among the issues that must be considered in such problems [8]. In the first stage, the supplier selection problem in the automotive industry is modeled. To develop a comprehensive supplier selection model, four issues must be incorporated: which parts to purchase from which suppliers, in what quantities, and during which time periods. Additionally, the criteria considered in the model for supplier selection, including the objective functions and existing constraints, are particularly important.

After preparing the model, an appropriate algorithm is required to solve it, one that provides an acceptable, efficient solution that meets the defined objectives and constraints. The multi-objective mathematical model was initially solved by treating each objective separately using a genetic algorithm. Subsequently, since the supplier selection problem involves multiple objective functions and an optimal solution for one objective may not be suitable for others, it leads to Pareto-optimal (efficient) solutions. Therefore, the NSGA-II algorithm, one of the most widely used and powerful algorithms for solving multi-objective optimization problems, was employed. Its efficiency has been proven in various applications.

To model the supplier selection problem in the automotive industry, certain assumptions must be established first. Then, objective functions are formulated based on the defined criteria for supplier selection. Finally, the constraints within which the obtained solution must be valid are specified [9]. After completing the modeling process, an appropriate algorithm is used to find the optimal solution. The selection of the algorithm depends on the characteristics of the developed model and must be capable of providing optimal solutions considering the objectives and constraints. The mathematical model of supplier selection involves different and conflicting objectives. Therefore, in multi-objective problems, there is no absolute optimal solution. In such cases, an optimal solution for one objective may yield poorer outcomes for others, leading to Pareto-efficient solutions. Taguchi introduced an engineering method for product or process design aimed at minimizing variability and sensitivity to noise factors [10]. In the Taguchi method, appropriate factors are first identified, then the levels of each factor are selected, and finally a suitable experimental design is determined for these control factors. After defining the experimental design, experiments are conducted and analyzed to identify the optimal parameter combination [3].

2 | Modelling

Modeling assumptions are as follows:

I. Rework cost is applied separately for each part produced by each manufacturer.

II. The developed model is multi-objective and linear.

III. The designed model is a multi-period model that allocates orders across the specified periods.

IV. The ordering cost of item p from supplier s is independent of the quantity ordered.

V. Lots received from suppliers are transferred to a temporary warehouse and inspected. These lots contain an average number of defective items, q, that are identified during inspection and replaced by the supplier.

VI. Holding items after the end of the first period incurs inventory holding costs. These costs are calculated for each part based on the available information.

VII. Since inventory levels for each part do not usually reach zero at the end of the planning horizon, the initial inventory for each part at the beginning of the next planning period is treated separately.

VIII. All suppliers have limited capacity, and each supplier's capacity is fixed in each period.

IX. Given fixed setup costs for the supplier's production line and the policy of sourcing not all required items from a single supplier, minimum and maximum limits for each item in each period must be considered.

The indices used in modeling the problem are as follows:

p	Index representing the required part types.
s	Index representing the suppliers under consideration.
t	Index representing the time periods.

The parameters of the model are defined as follows:

C_{pst}	Purchasing cost of product type p from supplier s in time period t.
CO_{pst}	Ordering cost of product type p from supplier s in time period t.
D_{pt}	Demand for product type p in time period t.
H_{pst}	Holding cost of product type p from supplier s in time period t.
Tr_{pst}	Transportation cost of one unit of product type p from supplier s in time period t.
QR_{pst}	Quality level of product type p received from supplier s in time period t, based on the defect (return) rate.
QRW_{pst}	Quality level of product type p received from supplier s in time period t, based on the rework rate of the supplier.
QS_{pst}	Overall quality level of suppliers for producing product type p in time period p.
TD_{pst}	Production lead time of product type p by supplier s in time period t.
CAP_{ps}	The maximum production capacity of suppliers for the product type.
EF_{ps}	Initial inventory of product type p at supplier s at the beginning of the planning horizon.
EN_{ps}^{max}	Maximum allowable inventory level of product type p at supplier s at the end of the time period.
NSU_{ps}	The maximum required quantity from suppliers for producing the product type.

NSL_{ps}	Minimum required quantity from suppliers for producing the product type.

The decision variables of the model are defined as follows:

X_{pst}	The quantity of product type P that must be supplied from suppliers in the time period t.
Y_{pst}	If supplier s supplied product p in time period t, it takes the value 1; otherwise, it takes the value 0.
I_{pst}	Supplier's inventory of product in time period t.
EN_{ps}	Ending inventory of supplier s' warehouse of product p.

The objective function of the model is defined as follows:

First objective function: Minimize the total cost, which consists of five components: purchasing cost, fixed ordering cost, holding cost, and transportation cost.

Purchasing cost: equals the total purchasing cost of selected healthy items from selected suppliers during the planning time periods. The aforementioned cost is calculated as follows:

$$\sum_{p}\sum_{s}\sum_{t} C_{pst}\, X_{pst}\left(1 - QR_{pst}\right). \tag{1}$$

Ordering cost function:

$$\sum_{p}\sum_{s}\sum_{t} CO_{pst}\, Y_{pst}. \tag{2}$$

Holding cost function:

$$\sum_{p}\sum_{s}\sum_{t} H_{pst}\, I_{pst}. \tag{3}$$

Transportation cost function:

$$\sum_{p}\sum_{s}\sum_{t} Tr_{pst}\, X_{pst}. \tag{4}$$

Finally, the total cost function is as follows:

$$\begin{aligned} \mathrm{Min}Z_1 = {} & \sum_{p}\sum_{s}\sum_{t} C_{pst}\, X_{pst}\left(1 - QR_{pst}\right) + \sum_{p}\sum_{s}\sum_{t} CO_{pst}\, Y_{pst} + \sum_{p}\sum_{s}\sum_{t} H_{pst}\, I_{pst} \\ & + \sum_{p}\sum_{s}\sum_{t} Tr_{pst}\, X_{pst}. \end{aligned} \tag{5}$$

Second objective function: Minimization of waiting time as follows:

$$\mathrm{Min}Z_2 = \sum_{p}\sum_{s}\sum_{t} TD_{pst}\, X_{pst}. \tag{6}$$

Third objective function: Minimize the number of returned items as follows:

$$\mathrm{Min}Z_3 = \sum_{p}\sum_{s}\sum_{t} QR_{pst}\, X_{pst}. \tag{7}$$

Fourth objective function: Minimize the amount of rework as follows:

$$\mathrm{Min}Z_4 = \sum_p \sum_s \sum_t \mathrm{QRW}_{pst} X_{pst}. \tag{8}$$

Fifth objective function: Maximizing quality as follows:

$$\mathrm{Max}Z_5 = \sum_p \sum_s \sum_t \mathrm{QS}_{pst} X_{pst}. \tag{9}$$

The constraint equations of the model are defined as follows:

$$\sum_s X_{pst} + T_{pst-1} - I_{pst} = D_{pt} \quad \text{for all p, t,} \tag{10}$$

$$I_{pst} = EF_{ps}, \quad \text{for all p, s, t = 1,} \tag{11}$$

$$I_{pst} = EN_{ps}, \quad \text{for all p, s, t = T,} \tag{10}$$

$$EN_{ps} = EN_{ps}^{max}, \quad \text{for all p, s,} \tag{13}$$

$$X_{pst} \leq CAP_{ps} Y_{pst}, \quad \text{for all p, s, t,} \tag{14}$$

$$\sum_s Y_{pst} \leq NSU_{ps}, \tag{15}$$

$$\sum_s Y_{pst} \geq NSL_{ps}. \tag{16}$$

Constraint (10) of the supplier selection model concerns satisfying the total customer demand over the planning horizon, which is calculated using the following relationship. Under this constraint, the inventory accumulated at the end of one period is carried over to the beginning of the next. *Constraint (11)* represents the initial inventory level at the beginning of each period. *Constraints (12)* and *(13)* specify the maximum allowable level of remaining inventory at the end of the planning period for each supplier. *Constraint (14)* indicates the maximum permissible production capacity and ensures that a supplier cannot initiate production unless it has been selected. *Constraints (15)* and *(16)* define the minimum and maximum number of suppliers required for the production and supply of products.

3 | Results

In tuning the parameters of the Non-dominated Sorting Genetic Algorithm-II (NSGA-II), three levels were considered for each factor. Each experiment was repeated 5 times, and the average of the resulting values was used for the final evaluation. *Table 1* presents the parameter settings for the proposed algorithms. *Table 2* shows the optimal parameters obtained after parameter tuning using the Taguchi method.

The first problem was defined with five products, eight suppliers, and 6 time periods, while the second problem was defined with 10 products, 12 suppliers, and 9 time periods. Accordingly, in this section, the aforementioned problems were solved using a multi-objective genetic optimization algorithm, and *Tables 3* and *4* present the efficient solutions obtained from the algorithm outputs, respectively. The dispersion of efficient solutions relative to one another for medium and large problem sizes is illustrated in *Fig 1*. and *2*, respectively.

In an efficient parameter design, the primary objective is to identify and adjust the factors that minimize the variation in the response variable, while the subsequent objective is to distinguish between controllable and uncontrollable factors. The ultimate goal of this method is to determine the optimal combination of controllable factor levels. The method of defining and examining all possible conditions in an experiment involving multiple factors is known as the Design of Experiments (DOE). In some publications, this approach is referred to as a factorial design. In this study, three levels are considered for each factor. For each algorithm, the experimental design is determined by the number of factors and their corresponding levels, and the design is then implemented. It should be noted that each experiment is repeated an average of five times, and the mean values obtained are used for the final analysis. *Table 2* presents the parameter tuning levels of the proposed algorithms, and *Table 3* shows the optimal parameters obtained after parameter tuning using the Taguchi method.

Table 1. NSGA-II parameters level.

Level 3	Level 2	Level 1	Parameters
100	500	200	Population
200	100	80	Max-Iteration
0.6	0.4	0.2	Cross over
0.9	0.7	0.5	Mutation

Table 2. Optimum NSGA-II parameters.

Cross over	Mutation	Max-Iteration	Population	Parameters
0.5	0.6	100	200	Optimum value

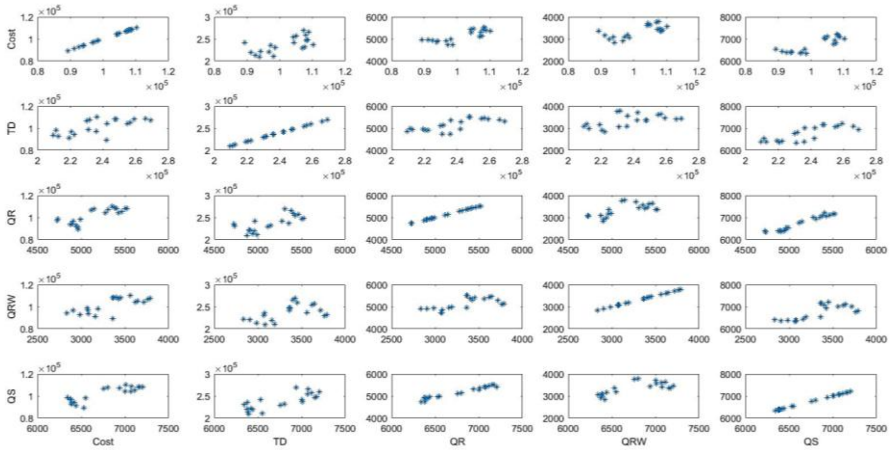

Fig. 1. Scatterplot of efficient solutions of problem objectives relative to each other at average size.

Table 3. An efficient solution to the medium-sized supplier selection problem.

Efficient Solution	Objective Function 1	Objective Function 2	Objective Function 3	Objective Function 4	Objective Function 5
1	93799.36	209448.02	4871.39	3067.98	6391.4
2	94123.44	222326.17	4900.21	3564.24	6420.92
3	89343.67	242151.19	4964.13	3077.37	6530.84
4	98629.25	230853.93	4727.62	3427.98	6341.47
5	110269.85	236265.87	5356.83	3789.03	7012.77
6	97255.42	235713.55	4725.58	3454.25	6381.97
7	107299.38	269007.55	5307.44	3369.16	6935.95
8	107676.98	231532.56	5147.01	3644.87	6802.54
9	108014.06	259023.47	5406.94	3359.92	7205.57
10	108478.83	247866.63	5521.82	3621.1	7172.08
11	105012.29	256459.91	5462.06	2904.83	7112.22
12	108116.54	247250.96	5506.24	3717.46	7152.43
13	104225.54	254862.94	5427.58	3401.01	7066.81
14	96651.07	220727.11	4908.56	2982.46	6370.43
15	104380.32	242399.74	5277.71	3763.8	7006
16	108778.33	265904.08	5376.66	3191.17	7077.39
17	92584.01	212685.4	4940.01	3161.47	6387.29
18	106841.69	229854.94	5110.67	3067.98	6755.2
19	98131.14	211120.02	4988.17	3564.24	6545.92
20	91172.85	219140.11	4956.8	3077.37	6437.72

Table 4. Efficient solution to the large-scale supplier selection problem.

Efficient Solution	Objective Function 1	Objective Function 2	Objective Function 3	Objective Function 4	Objective Function 5
1	206267.64	533487.28	11249.11	6800.068	14173.94
2	218482.09	559670.48	10711.9	7155.47	14492.9
3	220115.28	464155.86	11382.12	6831.42	14544.21
4	214116.74	487885.22	11227.23	6171.08	14291.49
5	202013.68	512117.89	11445.05	7451.05	14456.89
6	235697.77	531780.61	12046.3	8162.1	15629.09
7	255152.19	600796.23	11621.42	7445.19	15774.19
8	245430.58	628858.19	12184.4	7277.09	16055.77
9	246946.88	616193.35	12360.71	7240.59	16137.03
10	243384.56	624660.38	12099.71	7225.95	15944.47
11	227243.42	544064.76	11654.79	7367.94	14974.9
12	228734.75	490092.93	11492.29	7397.44	14896.59
13	238698.4	572351.9	11885.67	6843.8	15607.19
14	213371.8	481881.24	11332.05	6657.18	14369.81
15	222266.41	500590.66	10987.22	6304.47	14664.98
16	247472.62	553031.68	11982.48	7878.41	15751.63
17	239724.31	582637.92	11809.32	7002.5	15494.25
18	235168.77	532252.2	12005.51	8035.3	15486.14
19	243098.08	575826.33	11908.2	7019.81	15674.23
20	230145.04	528061.62	11575.71	7622.53	15259.01
21	222927.1	517004.54	11716.37	7580.62	15022.13
22	209181.03	551293.94	10817.97	7205.68	14334.21
23	240950.98	569335.95	11962.86	7760.13	15698.09

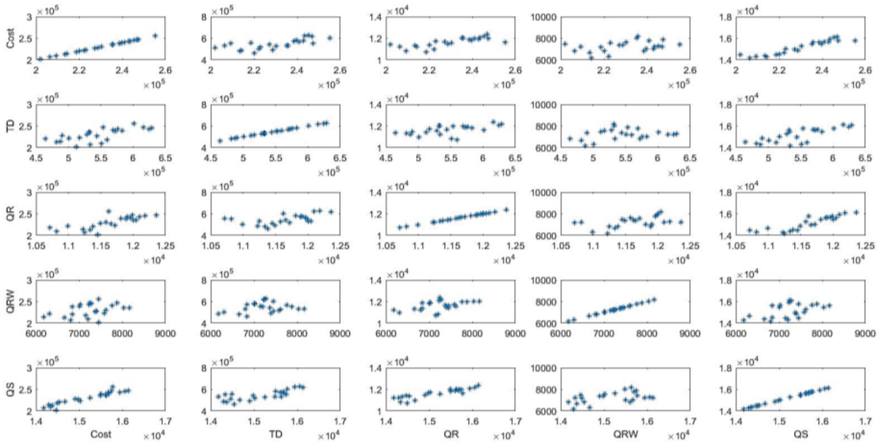

Fig. 2. Scatterplot of efficient solutions of the problem objectives relative to each other on a large scale.

4 | Conclusion

Table 5. summarizes the performance indices for the medium- and large-sized problems. According to Table 5, lower CPU time and SM values indicate better algorithmic performance. Therefore, as the problem size increases, computational time increases, while the SM value decreases compared to the medium size due to the greater number of efficient (Pareto-optimal) solutions. In addition, the MSI value increases with problem size and the number of efficient solutions, demonstrating the high efficiency of the multi-objective genetic optimization algorithm for larger problem sizes.

Table 5. Review of comparison indices of the NSGA II algorithm.

Index					Scale
NPF	MSI	SI	SM	CPU time	
20	63146.18	3039.85	0.37	79.75	Medium
23	173093.05	7814.65	0.50	112.16	Large

In this study, the problem of selecting parts suppliers in the automotive industry is investigated as a multi-objective, multi-period problem under real-world supply chain constraints. To achieve an efficient decision, a mathematical model is developed that simultaneously considers total cost, lead time, the rate of returned items, the level of rework, and quality performance. Given the conflicting nature of the objective functions and the problem's computational complexity, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is employed to solve the model. The results from solving the model for medium- and large-sized problem instances indicate that the NSGA-II algorithm is highly effective at generating a diverse and comprehensive set of Pareto-efficient solutions. The increase in the number of efficient solutions in the larger instance demonstrates the algorithm's scalability and effectiveness in addressing large, complex problems in the automotive industry.

Moreover, the appropriate dispersion of solutions in the objective space enables decision-makers to select the most desirable solution according to managerial priorities. An evaluation of the algorithm's performance indicators, including Computational Time (CPU time), Spacing Index (SI), Maximum Spread Index (MSI), Solution Distribution Metric (SM), and the Number of Pareto Front Solutions (NPF), reveals that although computational time increases with problem size, the quality of solutions improves in terms of diversity and coverage of the Pareto space. The reduction in the SM value for the larger problem size, due to the increased number of efficient solutions, indicates a more uniform distribution of solutions and enhanced search capability of the algorithm. Furthermore, the increase in the MSI value reflects an improvement in the extent of objective space coverage and the algorithm's ability to identify more diverse solutions.

Overall, this research demonstrates that the multi-objective genetic optimization algorithm NSGA-II can be used as an efficient and reliable tool for decision-making in supplier selection and order allocation in the automotive industry. In addition to cost reduction, the proposed model contributes to quality improvement, reduced lead times, and better control of defective items, and it can serve as a suitable basis for supply chain managers' decisions under real, complex conditions. It is recommended that future research explicitly incorporate parameter uncertainty using fuzzy or robust optimization approaches and compare the performance of NSGA-II with other advanced metaheuristic algorithms.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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