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Set a bi-objectives model for suppliers selection with capacity constraint and reducing lead-time with meta-heuristic algorithms

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Abstract

Supplier evaluation and selection are some of the essential issues in organizational strategic planning between managers and Entrepreneurs. Nodaway, markets are in a situation where both buyers and suppliers are under the challenge. Supplier selection is a complex problem, and decision-makers need to use mathematical models to solve it. In this paper, we present a bi-objective supplier-selection model. The first objective is minimizing the total annual cost, and the second is minimizing lead times. Since supplier selection belongs to Np. The hard category of problems and the model objectives have conflict, and we used three different multi-objective meta-heuristic algorithms to solve the presented model and compare the results of these algorithms. The solving algorithms are multi-objective invasive weed optimization (MOIWO), Non-dominated Sorting Genetic Algorithm (NSGA-II), and Non-dominated ranked genetic algorithms (NRGA). The algorithm parameters were tuned using the Taguchi method, and for comparing the algorithms, the TOPSIS model has been used.

Keywords: Supplier selection, Lead-time, NSGA-II, NRGA, MOIWO, TOPSIS
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1 Introduction

Having an appropriate framework for supplier selection in an organization is one of the essential issues for researchers in this area. Nowadays, suppliers are faced with a new environment, and they must adapt to new methods, relationships, information systems, and people. They should challenge the worldwide companies which present many different services [12]. The supplier selection problem is very complex and leads the researchers to improve the mathematical model to solve it. Although in previous research, many different approaches have been developed for the supplier selection process, few researchers used improvement of quality approach in this area [12]. Ghodsypour and O'Brien [5] used a linear programming and analytic hierarchy process by considering tangible and non-tangible factors for supplier selection and maximized total purchase value. Some of the essential research in the supplier selection are presented in table 1.

By reviewing past research, we can find that almost no researcher tries to minimize the lead time in supplier selection models. In this paper, we work on a bi-objectives supplier selection model. The first objective is minimizing

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the system cost, and the other one is minimizing lead time. Also, we used three different multi-objective meta-heuristic algorithms to solve the presented model. And finally, for comparing these three algorithms together, we used the TOPSIS approach.

Table 1: Most essential researches in the related area

Researcher(s)	**Year published**	**Deterministic lead-time**	**Probabilistic lead-time**	**Single-objective model**	**Multi-objectives model**	**Exact solution**	**In-exact solution**	**Comparison between algorithm**
Baghalian et al. [2]	2013		*	*			*	
Govindan et al. [7]	2015		*		*		*	
Zhang et al. [16]	2016		*		*	*		
Kadambala et al. [8]	2016	*			*		*	*
Talaei et al. [11]	2016		*	*			*	
Kaya and Urek [6]	2016		*	*			*	
Zohal and Soleimani [17]	2016	*		*			*	
Diabat et. al [4]	2016		*	*		*		
Wei et al. [14]	2015		*	*		*	*	
Zoroofchi et al. [18]	2018	*		*		*		
Wu et al. [15]	2019		*	*		*		
Wang et al. [13]	2020	*			*		*	
Current research	2022	*			*	*		*

This paper is divided into five parts. The second part is the problem definitions. The third part deals with solving methods. Part four is the Evaluation of the Efficiency of Meta-heuristic algorithms, and the last part is the conclusion and further studies.

2 Problem Definition

In this paper, we consider the assumption of Ghodsypour and O'Brien [5] and present a new model for minimizing system total cost and lead time.

The main issue is to find an efficient mathematical model for a supplier selection problem, which aims to reduce the lead time and find the optimal value for decision variables. In this paper, two important issues are mentioned. The first one is the supplier's capacity considered as average annual long-term capacity. The average annual capacity means that the order quantity cannot exceed the annual capacity. And the second one is about the cyclic ordering policy. It means that an order to a supplier has been done at a certain time and period. Implementing a Cyclic Order Policy is easy, but it is not desirable for the buyer a fixed cost of the order at any time and place. Therefore, to reduce fixed order costs, if inventory costs do not increase, the buyer prefers to order a higher value in other periods instead of ordering in each period.

2.1 Model assumptions

- Order cost is fixed and for each order,
- Order policy is cyclic,
- Supplier capacity considered as the average of annual capacity,
- Orders from different suppliers at different times received when the inventory level is zero.

2.2 Nomenclatures

2.2.1 Indexes

i : Index of suppliers.

2.2.2 Parameters

D : The annual demand of buyer,

n : Number of suppliers,

r : Inventory holding cost rate,

A_i : Fixed order cost from i^{st} supplier,

P_i : The unit price for i^{st} supplier,

C_i : The annual capacity of i^{st} supplier,

q_i : The effective rate of i^{st} supplier,

q_a : The minimum acceptable, effective rate for input components.

2.2.3 Decision variables

l_i : Lead time (dependent decision variable)

X_i : Some percent of order allocated to i^{st} supplier,

Q_i : Order quantity of i^{st} supplier in each period.

2.3 Mathematical model

$$Z_1 = \min \sum_{i=1}^{n} \left(\frac{Q_i}{2} P_i X_i r + P_i X_i D + A_i \frac{X_i D}{Q_i} \right) \tag{2.1}$$

$$Z_2 = \min \sum_{i=1}^{n} l_i \tag{2.2}$$

such that

$$\sum_{i=1}^{n} X_i q_i \geq q_a \tag{2.3}$$

$$X_i D \leq C_i; \quad \forall i \in \{1, 2, ..., n\} \tag{2.4}$$

$$\sum_{i=1}^{n} X_i = 1 \tag{2.5}$$

$$\frac{Q_i X_i}{D} \leq l_i \tag{2.6}$$

$$Q_i \geq 0; \quad \forall i \in \{1, 2, ..., n\} \tag{2.7}$$

Equations (2.1) and (2.2) are objective functions that minimize total system cost and total lead time subsequently. Equation (2.3) defines the minimum acceptable, effective rates of each supplier constraint. Constrain (2.4) defines that the value of the amount of demand should not exceed the annual capacity. Equation (2.5) defines that the sum of the percentage of demand allocated to all suppliers must be equal to 100%, and finally, the constraint (2.6) controls the lead time of each supplier.

3 Solving Algorithms

Goossens et al. in 2007 proved that the supplier selection problem to minimize purchasing costs belongs to NP-hard problems [6]. They also proved that there is no approximate algorithm for solving this problem in polynomial time. This computational complexity reveals the need for the use of meta-heuristic algorithms in solving supplier selection problems. Given that the proposed model in this paper is the development of supplier selection models, NP-hardness can be concluded. So, we used three different meta-heuristic algorithms for solving the presented model. These algorithms are MOIWO, NSGA-II, and NRGA.

3.1 Multi-objectives invasive weed optimization

The invasive weed optimization algorithm is a numerical optimization algorithm based on the growth of invasive weeds. This algorithm was presented by Mehrabian and Lucas [10]. Invasive weeds are aggressive plants and are a restriction for crops. Invasive weeds are very stable and adaptable to environmental changes. So, by inspiring and simulating their properties, a robust optimization algorithm can be obtained.

Components and parameters of the invasive weed optimization algorithm

The Invasive weed optimization algorithm has important parameters that their selection has significant effects on the quality and accuracy of the method. These parameters are the number of the initial population, maximum iterations, the maximum number of invasive weeds, the maximum and the minimum number of grains, the nonlinear coefficient, and the initial and final values of standard deviation [10]. The flowchart of this algorithm is presented in figure 1.

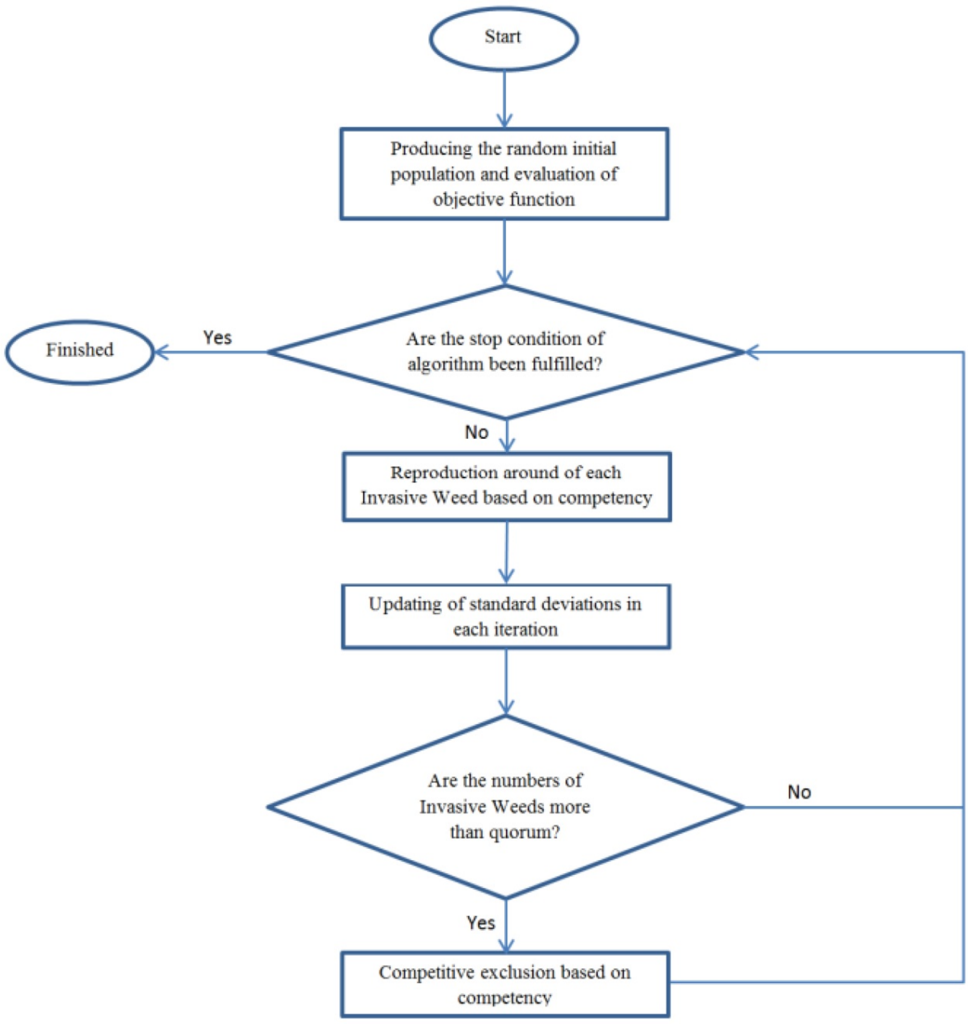

Figure 1: Flowchart of Invasive Weed Optimization algorithm.

3.1.1 Non-dominated sorting genetic algorithm

The NSGA-II algorithm is one of the most practical and powerful algorithms available for solving multi-objective optimization problems and has been proven to be effective in solving various problems. Deb et al. [3] introduced the NSGA-II optimization algorithm in 2000 to solve multi-objective optimization problems. The flowchart of this algorithm is presented in figure 2.

3.1.2 Non-dominated ranked genetic algorithms

In 2008, a new population-based multi-objective evolutionary algorithm called the genetic algorithm based on the ranking of non-dominants was successfully developed by Omar Al-Jadaan et al. [1] for optimizing non-convex, nonlinear, and discrete functions. They evaluated multi-objective algorithms that worked based on non-dominant sorting. The flowchart of this algorithm is presented in figure 2 too.

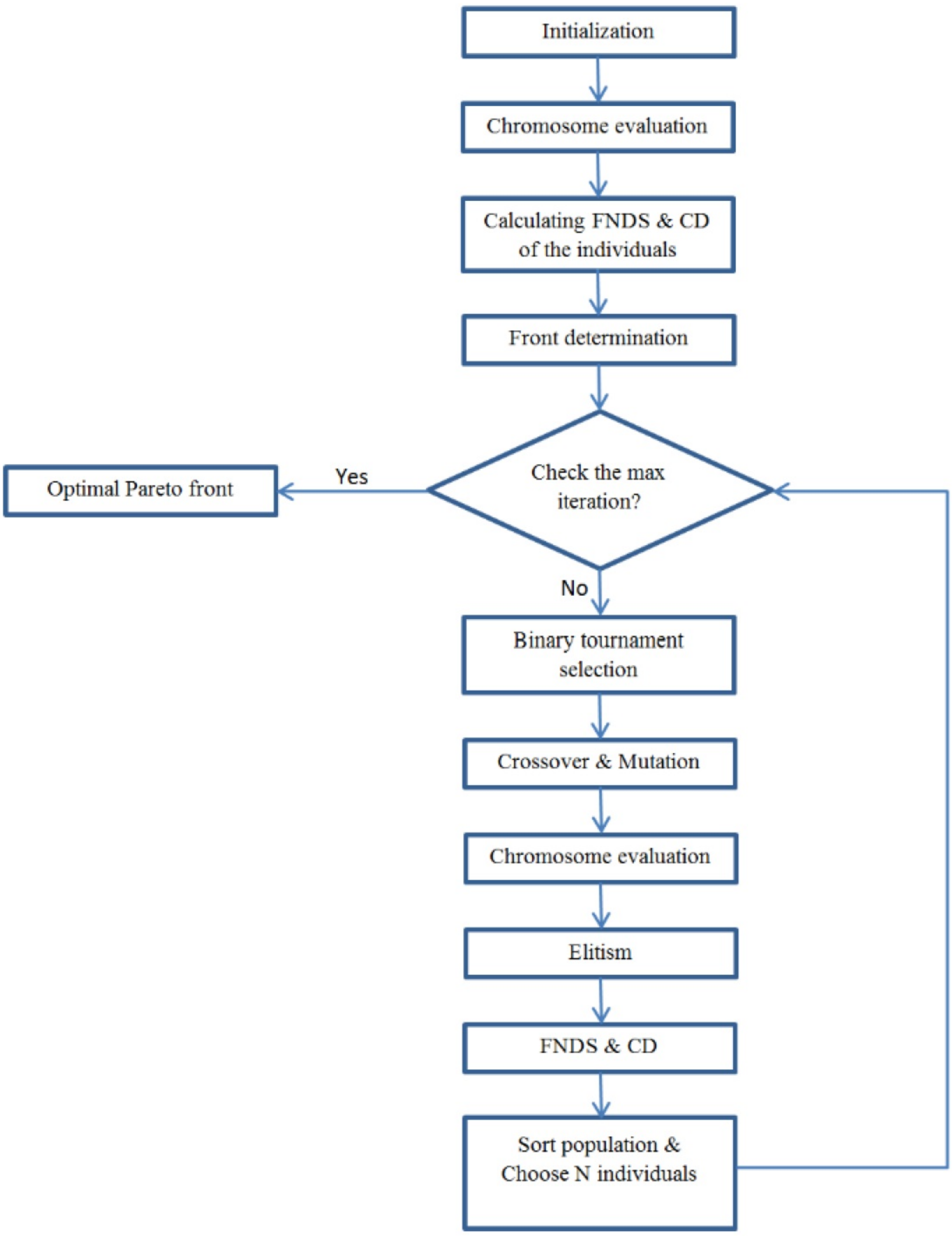

Figure 2: Flowchart of NSGA-II and NRGA.

3.2 Solution coding for all three algorithms

A set of cells that contain decision variables is called a solution. A solution represents a feasible or infeasible solution to a problem. A solution depending on the problem can be a string of discrete variables, binary values, and continuous values.

In this paper, we use a two-phase mechanism to define a solution. In the first phase, the solutions are generated in coded form, and then in the second phase, the encoded solutions are decoded and indicate the values of the decision variables. How to define the answer in the coding step is that we first create a matrix of dimensions. M is the number of suppliers. All the numbers of this matrix are random and between zero and one. For example, Figure 3 shows a solution encoded with ten suppliers.

0.952	0.920	0.053	0.738	0.269	0.423	0.548	0.943	0.418	0.983
0.301	0.701	0.666	0.539	0.698	0.667	0.178	0.128	0.999	0.171

Figure 3: Chromosome structure of NSGA-II and NRGA (Coded).

The first line represents the percentage of orders assigned to the ist supplier and the second line of the order quantity of the supplier. To decode this solution, first, the numbers in the first row are added to each other's, and then each of the numbers is divided into a sum. Thus, the sum of decoded numbers will be equal to 1. In other words, we have normalized the numbers in the first row. To decode the numbers in the second row, all of these numbers are first normalized. Then the normalized numbers will be multiplied by the total demand, and the order quantity will be determined by the supplier. Using this type of decryption, the values of decision variables Xi and Qi will be specified. Figure 4 shows the decoded mode of Figure 3, in which there are ten suppliers, and the total demand is 10,000 units.

0.152	0.147	0.008	0.118	0.043	0.068	0.088	0.151	0.067	0.157
597	1389	1320	1068	1383	1320	353	254	1979	339

Figure 4: Chromosome structure of NSGA-II and NRGA (Decoded).

Using this coding pattern, the solutions are guaranteed feasible. Given that the sum of the first row of the chromosome is equal 1, it can be concluded that the demand limitation is met. Also, the production of a random number is related to the percentage of the order of each supplier between zero and the maximum capacity of the supplier, thereby satisfying the supplier's capacity limitations.

3.3 Model validation

In this section, we plan to validate and solve the proposed model. For this purpose, we use two approaches. First, we create a random sample problem and solve it using the GAMS software. To this matter, using a weighting tool, we turn the problem into a single-objective problem. We then examine the performance of the model by changing the input parameters. Parameters of the sample problem are given in Table 2, and the results of this problem presented in table 3.

Table 2: Parameters of the initial problem.

Number of suppliers	1	2	3	4	5	6	7	8	9	10
Fixed order cost from i^{st} supplier	90	99	43	104	103	24	23	55	55	27
Unit price presented for i^{st} supplier	57	83	85	69	71	87	100	68	71	43
Annual capacity of i^{st} supplier	8690	5938	6810	6223	5383	7201	5661	9721	7348	8544
Effective rate of i^{st} supplier	0.903	0.721	0.850	0.968	0.912	0.842	0.646	0.807	0.912	0.842
The minimum acceptable, effective rate for input components	0.8									
Annual demand from the buyer	10000									
Inventory holding cost rate	10									

Table 3: Results of sample example

Supplier	1	2	3	4	5	6	7	8	9	10
Some percentage allocated to i^{st} supplies	0.094	0.048	0.042	0.171	0.176	0.133	0.011	0.109	0.039	0.176
Order quantity from i^{st} supplies in each period	260	1475	1697	1292	175	94	2118	383	1702	804

Now we set the cost of the fixed order cost from the first and the fifth supplier to a vast number, and we expect the order quantity from these suppliers turned to zero. The results presented in table 4 and showed that our expectations are satisfied.

Table 4: Results of sample example with predetermined conditions.

Supplier	1	2	3	4	5	6	7	8	9	10
Some percentage allocated to i^{st} supplies	0.000	0.048	0.142	0.271	0.000	0.193	0.011	0.109	0.039	0.190
Order quantity from i^{st} supplies in each period	0	1475	1697	1727	0	94	2118	383	1702	804

As expected, from the first and the fifth suppliers, we did not receive any product that indicates the correct performance of the model.

In the second method, using the comprehensive criteria method (LP metric), the problem is solved, and the problem-solution is compared with the solution of the problem solving with a simple genetic algorithm, the results are presented in Table 5.

Table 5: Comparison of the results of LP-Metric and GA.

Problem number	**Lp-Metric solution**	**GA solution**	**Gap**
1	1568729	1568729	0
2	1696361	1696361	0
3	1545668	1545668	0
4	1379852	1402125	0.016142
5	1597643	1597643	0
6	1799271	1799271	0
7	1796511	1812453	0.008874
8	1473282	1473282	0
9	1642658	1642658	0
10	1456132	1589245	0.091415
Average	1595611	1612744	0.011643

Based on the results, we can say that the genetic algorithm is only 0.011643 different from the optimal solution. However, we calculate the 95% confidence interval and based on Figure 5, and we can say that the efficiency of the two methods is statistically equal.

3.4 Algorithms parameters tuning

The Taguchi method has been used to set parameters for three algorithms. For the selection of an orthogonal array, the required degrees of freedom must be calculated. In this problem, there is one degree of freedom for the total mean and two degrees of freedom for each three-level factor. Therefore, the required degrees of freedom for the NSGA-II and NRGA algorithms are equal to $\{1 + (2 \times 4) = 9\}$ and for the MOIWO algorithm is equal to $\{1 + (2 \times 8) = 17\}$. Consequently, you must select an array that has at least 9 and 17 lines. Referring to the standard orthogonal arrays, it is determined that these conditions apply to orthogonal arrays of L27. The lower and upper limits of each parameter, along with its optimal value after tuning, are presented in table 6.

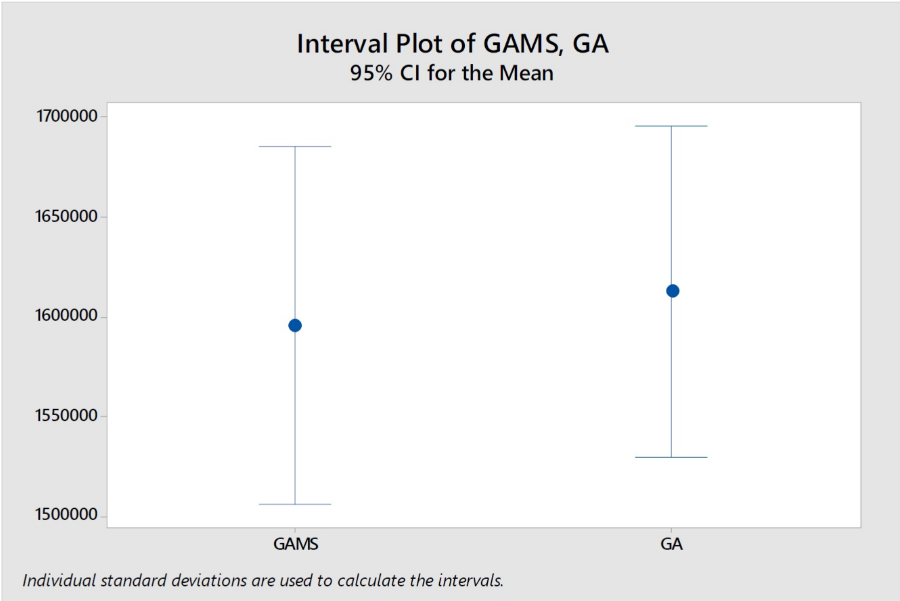

Figure 5: Interval plot for comparison of the results of GAMS and GA.

Table 6: Algorithms parameters levels and optimal values.

	Parameters	Level 1	Level 2	Level 3	Optimal values
NSGA-II	Popsize	50	100	150	150
	P_m	0.05	0.10	0.15	0.15
	P_c	0.5	0.6	0.7	0.6
	Iteration	50	200	300	300
NRGA	Popsize	50	100	150	100
	P_m	0.10	0.15	0.20	0.20
	P_c	0.4	0.5	0.6	0.5
	Iteration	150	250	350	250
MOIWO	MaxIt	100	200	300	300
	P_{init}	10	20	30	30
	$P_{\max}$	50	70	100	70
	m	1	2	3	3
	$sd_{\min}$	0.01	0.03	0.05	0.03
	$sd_{\max}$	1	3	5	5
	$S_{\min}$	1	2	3	1
	$S_{\max}$	5	7	10	5

4 Evaluation of the Efficiency of Meta-heuristic algorithms

After analyzing the structure of the proposed mathematical model and MOIWO, NSGA-II, and NRGA algorithms, this chapter analyzes the computational results of the proposed solving methods. To analyze the results, 30 different problems were implemented. Sample problems are created based on the number of suppliers in three categories of 10, 50, and 100 suppliers. In each category, ten problems are generated randomly. Table 7 shows the parameters needed to generate random sample problems.

4.1 Comparison criteria's

Then, for comparing the performance of the algorithms, four criteria are presented, and the performance of the proposed algorithms is compared with each other's based on these four criteria. These criteria are the mean ideal distance (MID), Diversity, the implementation time of the algorithm, and the number of Pareto solutions.

Table 7: Parameter values (randomly generated).

Number of suppliers	[10, 50, 100]
The annual demand of the buyer	[10000, 50000, 100000]
Fixed order cost from suppliers	Uniform (10,110)
Unit price presented to suppliers	Uniform (40,140)
The annual capacity of suppliers	Uniform (5000,50000)
The effective rate of suppliers	Uniform (0.6,1)
The minimum acceptable, effective rate for input components	0.8
Inventory holding cost rate	Uniform (10,15)

4.1.1 Mean ideal distance

This criterion is used to calculate the mean distance of Pareto solutions from source coordinates. The results obtained from solving the presented model with these three algorithms are presented in Table 8. Figure 6 shows the performance of the MOIWO algorithm is better than NSGA-II, and the performance of the NSGA-II algorithm is relatively better than the NRGA algorithm in the MID criterion.

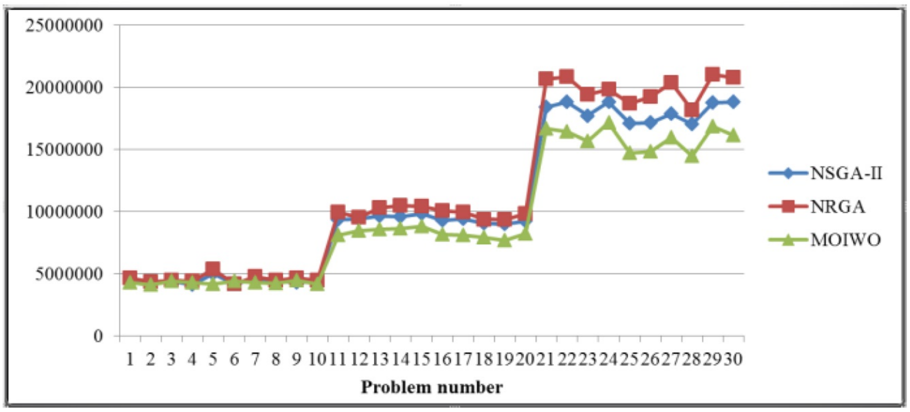

Figure 6: Comparison of performance of presented algorithms based on MID.

Table 8: The results of MID and its RPD.

Problem number	**MID**			**RPD**		
	NSGA-II	**NRGA**	**MOIWO**	**NSGA-II**	**NRGA**	**MOIWO**
1	4298543	4631997	4303753	0	7.757373	0.121204
2	4151772	4331471	4135925	0.383155	4.727987	0
3	4435145	4444240	4390710	1.012023	1.219165	0
4	4130411	4399505	4264198	0	6.514945	3.239072
5	5008254	5350443	4177016	19.90028	28.09247	0
6	4151602	4177932	4393395	0	0.634213	5.824089
7	4573896	4749518	4265020	7.242076	11.35981	0
8	4389744	4474246	4241890	3.485569	5.477653	0
9	4287395	4672873	4451258	0	8.990961	3.821971
10	4426520	4469162	4183572	5.807191	6.826463	0
11	9332815	9927631	8112577	15.04131	22.37333	0
12	9398311	9546615	8478184	10.85288	12.60212	0
13	9659780	10292480	8552090	12.95227	20.35046	0
14	9578462	10482402	8648125	10.75767	21.21011	0
15	9828910	10410884	8790532	11.81246	18.43292	0
16	9269617	10067965	8130869	14.00524	23.82397	0
17	9401298	9928814	8095200	16.13423	22.65063	0
18	9044125	9377430	7933658	13.99691	18.19806	0

19	9001213	9349059	7709673	16.7522	21.26401	0
20	9224178	9811088	8242248	11.91338	19.03413	0
21	18419039	20635756	16671249	10.48386	23.7805	0
22	18825461	20835561	16442494	14.49273	26.71777	0
23	17712291	19426971	15660549	13.10134	24.05038	0
24	18814497	19826506	17158924	9.648466	15.54632	0
25	17114268	18681732	14702908	16.40057	27.06148	0
26	17139448	19238880	14835525	15.52977	29.68115	0
27	17867917	20343957	15951881	12.01135	27.53328	0
28	17025595	18175701	14475340	17.61793	25.56321	0
29	18744982	21006128	16834149	11.35093	24.78283	0
30	18825847	20793056	16156665	16.52062	28.69646	0
Average	10602711	11462000	9479653	10.30688	17.83181	0.433545

4.1.2 Diversity

Table 9 and Figure 7 show the performance of MOIWO, NSGA-II, and NRGA algorithms in the diversity criterion. We can say that the MOIWO algorithm has better performance than other algorithms. Also, the performance of the NRGA and NSGA-II algorithms are similar.

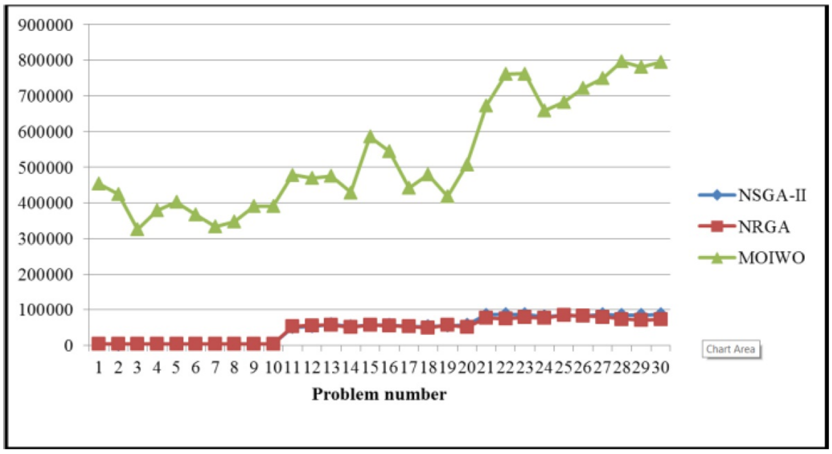

Figure 7: Comparison of the efficiency of presented algorithms based on maximum spread or diversity.

Table 9: The results of diversity and its RPD.

Problem number	MID			RPD		
	NSGA-II	NRGA	MOIWO	NSGA-II	NRGA	MOIWO
1	4031	3941	453992	99.1121	99.13192	0
2	3053	3180	423778	99.27958	99.24961	0
3	4129	4016	325327	98.73082	98.76555	0
4	3797	3788	378601	98.9971	98.99947	0
5	3278	3230	402516	99.18562	99.19755	0
6	3368	3460	366198	99.08028	99.05516	0
7	3797	3858	332587	98.85834	98.84	0
8	3443	3504	347775	99.00999	98.99245	0
9	3663	3805	390593	99.0622	99.02584	0
10	3646	3568	390742	99.0669	99.08687	0
11	51043	52636	478078	89.32329	88.99008	0
12	53548	56136	469779	88.60145	88.05055	0
13	59147	57501	475972	87.57343	87.91925	0
14	52400	52072	428836	87.78088	87.85736	0

15	56415	57435	585413	90.36321	90.18898	0
16	56948	55332	543344	89.51898	89.8164	0
17	53621	52527	441918	87.8663	88.11386	0
18	53793	50132	479798	88.78841	89.55144	0
19	55322	57905	418468	86.77987	86.16262	0
20	56359	51377	507018	88.88422	89.86683	0
21	85747	76179	672322	87.24614	88.66927	0
22	86530	74472	760845	88.62712	90.21194	0
23	87295	78831	762026	88.54435	89.65508	0
24	81197	76605	658000	87.66003	88.3579	0
25	85127	84806	681849	87.51527	87.56235	0
26	83042	83565	721422	88.48912	88.41663	0
27	86890	79868	749860	88.4125	89.34895	0
28	85147	74000	796861	89.3147	90.71356	0
29	83955	70157	780527	89.24381	91.01159	0
30	87047	73794	794799	89.04792	90.71539	0
Average	47892.6	45056	533974.8	91.9988	92.38415	0

4.1.3 Number of Pareto solutions

Table 10 and Figure 8 show the performance of MOIWO, NSGA-II, and NRGA algorithms in the number of Pareto solution criterion. Since the algorithm performance is better when this criterion is more, it can be concluded that the NSGA-II and NRGA algorithms have a much better performance than MOIWO and can produce more solutions in first Pareto's front.

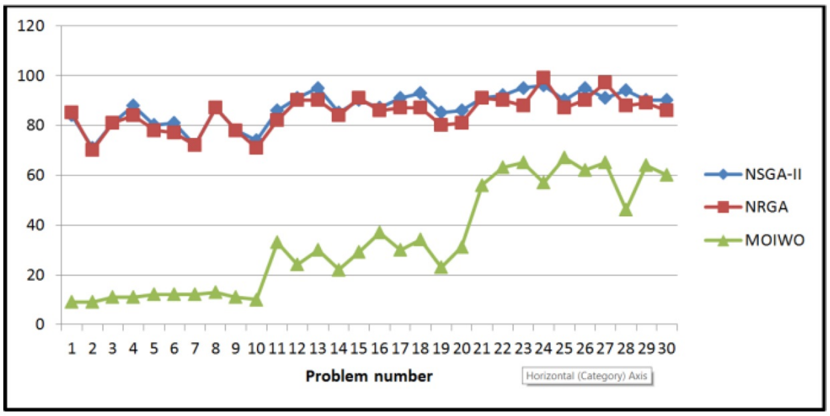

Figure 8: Comparison of the efficiency of presented algorithms based on NOS.

Table 10: The results of the number of Pareto solution (NOS) and its RPD.

Problem number	MID			RPD		
	NSGA-II	NRGA	MOIWO	NSGA-II	NRGA	MOIWO
1	84	85	9	1.176471	0	89.41176
2	71	70	9	0	1.408451	87.32394
3	81	81	11	0	0	86.41975
4	88	84	11	0	4.545455	87.5
5	80	78	12	0	2.5	85
6	81	77	12	0	4.938272	85.18519
7	72	72	12	0	0	83.33333
8	87	87	13	0	0	85.05747
9	78	78	11	0	0	85.89744
10	74	71	10	0	4.054054	86.48649
11	86	82	33	0	4.651163	61.62791

12	91	90	24	0	1.098901	73.62637
13	95	90	30	0	5.263158	68.42105
14	85	84	22	0	1.176471	74.11765
15	90	91	29	1.098901	0	68.13187
16	87	86	37	0	1.149425	57.47126
17	91	87	30	0	4.395604	67.03297
18	93	87	34	0	6.451613	63.44086
19	85	80	23	0	5.882353	72.94118
20	86	81	31	0	5.813953	63.95349
21	91	91	56	0	0	38.46154
22	92	90	63	0	2.173913	31.52174
23	95	88	65	0	7.368421	31.57895
24	96	99	57	3.030303	0	42.42424
25	90	87	67	0	3.333333	25.55556
26	95	90	62	0	5.263158	34.73684
27	91	97	65	6.185567	0	32.98969
28	94	88	46	0	6.382979	51.06383
29	90	89	64	0	1.111111	28.88889
30	90	86	60	0	4.444444	33.33333
Average	86.96667	84.86667	33.6	0.383041	2.780208	62.76449

4.1.4 Implementation time of the algorithm

The results of the algorithms implementation time presented model with these three algorithms are presented in Table 11. Figure 9 shows the superiority of the MOIWO algorithm over NSGA-II and NRGA based on implementation time. Through this figure, the MOIWO algorithm performs better than two other algorithms in small-size problems. Also, with the increase in the size of the problems, the performance of the MOIWO algorithm is highly increased so that it has a significant difference with the other two other algorithms, especially NSGA-II.

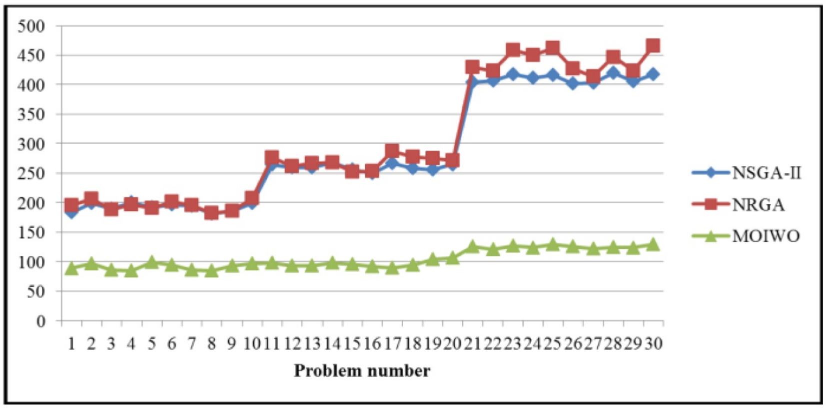

Figure 9: Comparison of the efficiency of presented algorithms based on Time.

Table 11: The results of time and its RPD.

Problem number	MID			RPD		
	NSGA-II	NRGA	MOIWO	NSGA-II	NRGA	MOIWO
1	184	196	89	106.7416	120.2247	0
2	199	207	97	105.1546	113.4021	0
3	190	189	86	120.9302	119.7674	0
4	200	197	85	135.2941	131.7647	0
5	192	191	99	93.93939	92.92929	0
6	197	202	95	107.3684	112.6316	0
7	194	196	86	125.5814	127.907	0

8	181	182	85	112.9412	114.1176	0
9	186	186	93	100	100	0
10	199	208	97	105.1546	114.433	0
11	264	277	98	169.3878	182.6531	0
12	260	262	93	179.5699	181.7204	0
13	260	267	93	179.5699	187.0968	0
14	268	268	98	173.4694	173.4694	0
15	256	252	96	166.6667	162.5	0
16	250	253	92	171.7391	175	0
17	267	287	90	196.6667	218.8889	0
18	258	278	95	171.5789	192.6316	0
19	256	275	104	146.1538	164.4231	0
20	265	272	107	147.6636	154.2056	0
21	404	429	126	220.6349	240.4762	0
22	407	423	121	236.3636	249.5868	0
23	418	458	127	229.1339	260.6299	0
24	412	450	124	232.2581	262.9032	0
25	416	462	129	222.4806	258.1395	0
26	402	427	126	219.0476	238.8889	0
27	403	414	122	230.3279	239.3443	0
28	420	447	125	236	257.6	0
29	405	423	124	226.6129	241.129	0
30	417	466	129	223.2558	261.2403	0
Average	287.6667	301.4667	104.3667	169.7229	181.6568	0

4.2 Evaluation of algorithms using the TOPSIS technique

To evaluate the quality of the proposed algorithms, we used the comparison criteria, although we know that the algorithms cannot be compared with the comparison criteria. For this purpose, the TOPSIS technique was used to determine the algorithm with better efficiency. Table 12 shows the decision matrix of the problem, which includes NSGA-II, NRGA, and MOIWO algorithms alternatives, along with the four criteria presented above. All numbers in the matrix are obtained from the mean of the 30 solved problems.

Table 12: Decision matrix.

Algorithm	MID	Diversity	Pareto solutions	Time
NSGA-II	10602711	47893	87	288
NRGA	11462000	45056	85	301
MOIWO	9479653	533975	34	104

The result of the TOPSIS technique is presented in Table 13. Based on the results of this table, it can be said that the MOIWO algorithm has the highest relative proximity to the ideal solution, and as the last step, the MOIWO algorithm is better than the NRGA and NSGA-II algorithms for this model.

Table 13: Comparative proximity of alternatives to the ideal solution

Comparative proximity of MOIWO to the ideal solution	0.5502
Comparative proximity of NSGA-II to the ideal solution	0.2304
Comparative proximity of NRGA to the ideal solution	0.2194

5 Conclusions and Further Studies

In this paper, we present a two-objective mathematical model for the supplier selection problem. The first objective is to minimize the total annual holding cost, including the fixed cost of the order, the cost of maintenance and the annual purchase price, and the second objective is to minimize the total lead-times of the suppliers. After describing the literature review in the field of supplier selection, the model presented as a mathematical model and MOIWO, NSGA-II, and NRGA algorithms have been used to solve the given model. Thirty numerical examples were designed, and the algorithms parameters tuned to achieve maximum performance. According to the results, it can be seen that the MOIWO algorithm is better than two other algorithms in all criteria except the number of Pareto solutions criterion. Since it is not possible to determine the best algorithms with the comparison criteria, the TOPSIS technique was used to define the better algorithm for solving the presented model, and the results of the TOPSIS technique showed that the MOIWO algorithm has better performance than other algorithms.

The proposal to other researchers for future work is as follows:

- Randomization of model parameters and solving by simulation technique,
- Adding production corruption constraint to model,
- Using Fuzzy parameters,
- Consider uncertainty at lead-time,
- Considering other levels of the supply chain like recycling and collection centers,
- Developing the problem by applying changes to assumptions, for example:
  - Consider different discount models,
  - Consider the backorder,
  - Consider the probability of failure of the transportation equipment,
  - ...

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