Finally, which meta-heuristic algorithm is the best one?

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Abstract: This paper is conducted to rank the six meta-heuristic algorithms such as the genetic, ant colony optimisation, tabu search, particle swarm optimisation, imperialist competitive, and simulated annealing algorithm and choose the most efficient algorithm among them, concerning collected information. Accordingly, three multi-criteria decision-making methods, including the analytical hierarchy process (AHP), TOPSIS, and AHP-TOPSIS methods are used. Criteria for comparing algorithms are selected based on the capability of each algorithm and the issues that are necessary to solve each problem. The result of the TOPSIS method indicates the superiority and efficiency of the tabu search algorithm. However, the analytical hierarchy process presents the ant colony algorithm as the best algorithm. Also, in the AHP-TOPSIS method, the best meta-heuristic algorithm is genetic. Finally, according to the results obtained from all three methods and the use of the combined compromise solution method (CoCoSo), the genetic algorithm is selected as the best algorithm.

Keywords: meta-heuristic algorithms; TOPSIS; analytical hierarchy process; AHP; multi-criteria decision-making; combined compromise solution method; CoCoSo.

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1 Introduction

Today, meta-heuristic algorithms and operation research science are used for optimisation in solving various problems.

Because of the wide-spread dimensions of real-world problems and the fact that the exact methods cannot solve these problems, the meta-heuristic algorithms are widely used to find the near optimal solution. Therefore, choosing the appropriate algorithm among the existing abundant algorithms is an important decision.

Given that, each of the meta-heuristic algorithms is applicable and efficient in a particular problem, comparing these algorithms is difficult and requires a lot of research. In answer to the question posed in the title of the article, it should be said:

> "No meta-heuristic is better than all the rest to solve all the problems. So, the best meta-heuristic does not exist. What exists are differences between meta-heuristics when applied to a particular problem. However, the average performance of some meta-heuristic algorithms can be examined in some problems."

There are many similar papers in the field of comparing meta-heuristic algorithms, which can be referred to Shadkam and Bijari (2014), which examined and compared the meta-heuristic algorithms of the cuckoo optimisation algorithm, firefly algorithm, and artificial bee colony algorithm on the Rastrigin function in different dimensions. There are also many papers on practical problems such as portfolio selection (Shadkam et al., 2015), production planning (Akbarzadeh and Shadkam, 2015), project portfolio optimisation problems (Shakhsi-Niaei et al., 2015), machine scheduling problems (Yazdani et al., 2017, 2016) multi-objective problem (Borhanifar and Shadkam, 2016; Gorjestani et al., 2015; Khalili et al., 2016; Shadkam and Jahani, 2015).

All research on determining the best meta-heuristic algorithm is specific to a particular problem. So far, no research has been done on identifying the best meta-heuristic algorithm in general and simultaneously on several practical problems. In fact, the main novelty of this article is the comparison between meta-heuristic algorithms in general and wide range of optimisation problems.

In this paper, the best meta-heuristic algorithm is identified for the first time, using multi-criteria decision-making methods and considering different criteria. According to the collected information, the best meta-heuristic algorithm was identified among the six mentioned algorithms. The final purpose of this paper is to determine the meta-heuristic algorithm with the highest score according to the weight of the criteria.

Subsequently, in Section 2, a brief overview of the studies carried out to compare the meta-heuristic algorithms in various fields has been presented, and in Section 3, there is a brief discussion of six meta-heuristic algorithms. Section 4 involves the presentation of the decision matrix for meta-heuristic algorithms. In Section 5, the results of the implementation of the analytical hierarchy process (AHP), TOPSIS and AHP-TOPSIS methods on the decision matrix will also be presented. In the continuation of the paper, to obtain the final result, the combined compromise solution method (CoCoSo) new method will be introduced. Finally, the results of this paper and the conclusions are examined in Section 6.

2 Literature review

In this section, the related researches to the meta-heuristic algorithms and the capabilities of each one are examined and summarised. The results of the reviewed papers are shown in Table1.

Table 1 The applications and results of the meta-heuristic algorithms

Problem	*No.*	*Authors*	*Year*	*Applied algorithm*
Portfolio selection	1	Yang et al.	(2011)	Genetics, simulated annealing, tabu search
	2	Cura	(2009)	Genetics, simulated annealing, tabu search, particle swarm optimization
	3	Fernández and Gómez	(2007)	Genetics, simulated annealing, tabu search
	4	Branke et al.	(2009)	Multi-objective evolutionary algorithm
	5	Rahmani et al.	(2019)	Artificial bee colony, portfolio optimization, genetic algorithm, ant colony algorithm
	6	Kalayci et al.	(2020)	Ant colony optimization, artificial bee colony, genetic algorithms
	7	Mokhtari and Imamzadeh	(2019)	Genetic algorithms
	8	Kalayci et al.	(2020)	Ant colony optimization, genetic algorithms
	9	Abbasi et al.	(2020)	Genetic algorithm, particle swarm optimization
	10	Alfieri et al.	(2020)	Tabu search algorithm
Job shop scheduling	1	Kumar and Mishra	(2020)	Genetic algorithm, simulated annealing, particle swarm optimization
	2	Li et al.	(2020)	Artificial bee colony algorithm
	3	Yuan et al.	(2020)	Co-evolutionary genetic algorithm
	4	Wu et al.	(2019)	Simulated annealing algorithm
	5	Wang et al.	(2019)	Particle swarm optimization
	6	Wang and Peng	(2020)	Multi-objective evolutionary algorithm
Travelling salesman problem	1	Küçükoğlu et al.	(2019)	Hybrid simulated annealing/tabu search algorithm
	2	Yoshikawa and Otani	(2010)	Ant colony, genetics, simulated annealing
	3	Thamilselvan and Balasubramanie	(2009)	A genetic algorithm with a tabu search
	4	Osaba et al.	(2018)	Ant colony optimization
	5	Ebadinezhad	(2020)	Ant colony optimization
	6	Silva et al.	(2020)	Ant colony algorithm
	7	Abdrashitova et al.	(2018)	Genetic algorithm and simulated annealing
	8	De Moraes and De Freitas	(2019)	Genetic algorithms

Table 1 The applications and results of the meta-heuristic algorithms (continued)

Problem	*No.*	*Authors*	*Year*	*Applied algorithm*
Location and allocation	1	Yaghoubi and Akrami	(2019)	Ant colony optimization algorithm and particle swarm optimization algorithm
	2	Aly and White	(1978)	Queuing theory and meta-heuristics algorithm
	3	Arostegui et al.	(2006)	Tabu search, simulated annealing, and genetic algorithms
	4	Grillanda et al.	(2020)	Predator algorithm (PPA), particle swarm optimization, firefly agorithm and suitable genetic algorithm
	5	Li and Yeh	(2005)	Genetic algorithm, simulated annealing and neighbourhood search methods
	6	Fontalvo et al.	(2017)	Genetic algorithm
	7	Mohammadi et al.	(2016)	NSGA-II and PAES algorithms.
	8	Seifi and Soroush	(2020)	Genetic algorithm, grey wolf optimization, whale optimization algorithm and artificial neural networks
Facility layout	1	Tongur et al.	(2019)	Migrating bird optimization, tabu search (TS) and simulated annealing (SA)
	2	Liu and Liu	(2019)	Ant colony optimization
	3	Chen et al.	(2019)	Genetic algorithm
	4	Liu et al.	(2020)	Multi-objective evolutionary algorithms
	5	Liu et al.	(2018)	Multi-objective particle swarm optimization
	6	Allahyari and Azab	(2018)	Simulated annealing
	7	Pourhassan and Raissi	(2017)	Non-dominated sorting genetic algorithm
	8	Safarzadeh and Koosha	(2017)	Genetic algorithm

3 Meta-heuristic algorithms

This section gives a brief overview of each of the algorithms discussed in this paper.

3.1 Genetic algorithm

The original idea of this algorithm is inspired by Darwinian evolution theory and its application is based on natural genetics. The basics of the genetic algorithm (GA) were presented by John Holland et al. at the University of Michigan from 1962 to 1965.

The GA is one of the most important meta-heuristic algorithms used to optimise the defined functions in a limited domain. In this algorithm, the past information is extracted according to the inheritance of the algorithm and is used in the search process. The concepts of the GA were developed by Goldberg in 1989.

3.2 Ant colony optimisation algorithm

This algorithm inspired by the behaviour of ants in finding a route between the nest and the food was introduced in 1992 by Marco Dorigo in his doctoral dissertation.

The ant colony algorithm is inspired by studies and observations on an ant colony. These studies have shown that ants are social insects that live in colonies and their behaviour is directed towards saving the colonies rather than the survival of one part of it. One of the most important and interesting behaviours of the ants is their food-finding specifically how to find the shortest route between food and nest supplies. This kind of behaviour of the ants has a kind of mass consciousness that has recently attracted the attention of scientists. In the real world, ants wander in different directions to find food. They then go back to the nest and leave a track of pheromone. Such marks become white after the rain. Other ants stop wandering and follow it. Then, if they reach the food, they return home and leave the other way behind them; in other words, they highlight the previous path.

3.3 Tabu search algorithm

It was introduced by Glover (1986) for the first time. In 1997, the first book on tabu search (TS) algorithm was published by Glover and Laguna.

To get an optimal solution to an optimisation problem, the TS algorithm first starts with an initial solution. Then the algorithm chooses the best neighbour solution among neighbours of the current solution. If this solution is not in the tabu list, the algorithm moves in the neighbouring solution; otherwise, the algorithm will check the criteria called the aspiration criterion. Based on the aspiration criterion, if the neighbour's solution is better than the best-found a solution, it moves towards it even if that solution is on the forbidden list. After moving the algorithm to the neighbouring solution, the tabu list is updated; in that sense, the previous move by which the neighbouring response is found is placed in the tabu list to prevent the algorithm from returning to that response and creating a cycle. In fact, the tabu list is a tool in the TS algorithm, which prevents the algorithm from being trapped in a local optimum. After placing the previous move on the tabu list, a number of moves that were previously on the tabu list are removed from the list. The duration of placing the solutions in the tabu list is determined by a parameter that is called the tabu time. Moving from the current solution to the neighbour's solution continues until the condition ends.

3.4 Particle swarm optimisation algorithm

The particle swarm optimisation (PSO) algorithm was first presented by Russell Ebert and James Kennedy in 1995. PSO is an evolutionary algorithm inspired by nature and based on repetition. The source of inspiration for this algorithm is the social behaviour of animals such as the swarm movement of birds and fish. A bunch of birds randomly searches for food in a specific range. There is only one piece of food in this area and the birds are unaware of it, but they know their distance from food at any moment. Since the PSO also starts with an initial random population matrix, it is similar to many other evolutionary algorithms, such as continuous genetic and imperialist competition algorithms (ICAs).

3.5 Imperialist competition algorithm

The ICA is a method in the field of evolutionary computing that addresses the optimal solution to various optimisation problems. This algorithm offers an algorithm for solving mathematical optimisation problems by mathematical modelling of the socio-political evolution process. In terms of application, this algorithm is placed in the category of evolutionary optimisation algorithms such as genetic, PSO, ant colony, and simulated annealing (SA) algorithms. Like all algorithms in this category, the ICA forms an initial set of possible solutions.

3.6 SA algorithm

It is a simple and effective meta-heuristic algorithm for solving optimisation problems. The origin method of the SA algorithm was the works of Kirkpatrick et al. in 1983 and 1985. Kirkpatrick et al. were experts in statistical physics. They proposed a method based on a gradual annealing technique for solving difficult optimisation problems. The gradual annealing technique is used by metallurgists to achieve a state in which the solid material is well regulated and its energy minimised. This technique involves placing the material at high temperature and then reducing the temperature gradually.

4 The decision matrix of meta-heuristic algorithms

In order to compare meta-heuristic algorithms, five practical optimisation problems have been selected, which include facility layout, portfolio selection, job shop scheduling, location/allocation, and travelling salesman problems. A brief description of each of these problems is provided below:

Placing facilities (machines) in the factory space is often referred to as the facility layout problem. A proper arrangement of facilities in the factory can affect the efficiency of the entire factory production process. Apart from its cost perspective, the arrangement of facilities from various other dimensions such as the impact on product quality, impact on safety and working conditions, flexibility in production, optimal use of available space and etc. is also very important.

Portfolio optimisation or optimal portfolio selection is one of the most important issues in the field of financial science and investment, and has many applications in financial planning and decision-making. The set of shares purchased by the investor is called the stock portfolio. In fact, a portfolio refers to the problem that you have to divide your capital between several different financial assets in order to reduce your investment risk.

Job shop scheduling is a computer science optimisation and operations research problem in which ideal jobs are assigned to resources at specific times.

The location-allocation problem is one of the broad areas of mathematical modelling in the real world, in which several new facilities (supply facilities) serve a range of existing customers according to their requirements. Facility location issues determine the location of a set of facilities (resources) in order to minimise the cost of supplying sets of demands (customers) due to a number of constraints.

Table 2 The first decision matrix (meta-heuristic algorithms/criterion)

Algorithm	*Execution time (seconds)*				*Solution quality (percent)*				
	Facility layout	*Portfolio selection*	*Job shop scheduling*	*Location and allocation*	*Facility layout*	*Portfolio selection*	*Job shop scheduling*	*Location and allocation*	*Travelling salesman*
GA	8.4	660	472	1,796	0.7863	0.9808	0.7863	0.976	0.4083
ACO	15.6	2,122.67	2,382.56	1,601.67	0.9533	0.9423	0.9533	0.9679	0.9495
TS	30	2,122.67	276	2,322	0.8379	0.9423	0.8379	0.9896	0.5819
PSO	15.6	5,400	515.5	1,601.67	0.9473	0.8654	0.956	0.9679	1
ICA	15.6	308	2,382.56	1,601.67	0.7503	0.9806	0.7503	0.9679	0.3024
SA	8.4	2,122.67	8,266.73	687	0.99	0.9423	0.977	0.9381	0.9295

Algorithm	*Memory*	*Approach type*			*Application type*		*Probabilistic*
		Evolutionary	*Learning*	*Optimisation*	*Complex*	*Hybrid*	
GA	1	1	0	0	1	1	1
ACO	1	0	1	0	1	1	1
TS	1	0	0	1	1	0	0
PSO	1	1	0	0	1	0	1
ICA	1	1	0	0	1	1	1
SA	0	0	0	1	1	1	1

Algorithm	*Size of the problem*	*Multi-objective problem*	*Problem type*				
			Continuous		*Discrete*		
			Nonlinear	*Linear*	*Integer*	*Binary*	*Mixed*
GA	0.2	1	1	1	1	1	0
ACO	0.8	1	1	1	0	0	0
TS	0.8	0	0	0	0	0	1
PSO	0.2	1	1	0	1	1	1
ICA	0.8	0	1	1	1	1	1
SA	0.2	1	0	0	0	0	0

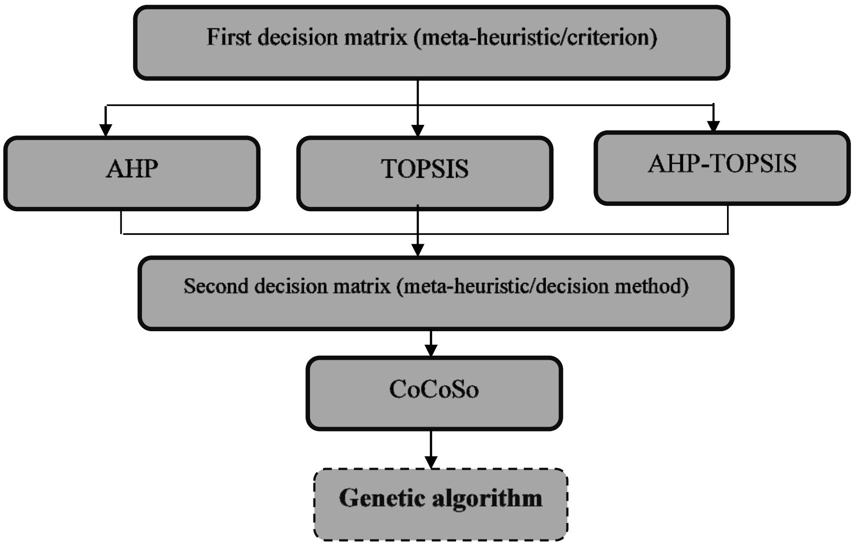
The problem of the travelling salesman is one of the most fundamental problems of routing and transportation planning. The purpose is to find the shortest route through a series of cities (nodes), so that each city meets only once and then returns to the original city from which it started.

Table 2 is obtained according to the criteria and mentioned algorithms in this paper. The criteria used in this matrix include the solution quality, execution time, problem dimension, problem type, approach type, memory, ability to solve the multi-objective problem, application type, and transitional rules. The data of the decision matrix in Table 2 is based on the mentioned papers in Table 1. In some matrix cells, zero and one numbers are used that the zero indicates that the algorithm does not cover the desired criterion and 1 indicates that the algorithm covers the criterion.

5 Identifying the best meta-heuristic algorithm

The general structure and used methods in this paper are shown in Figure 1. First, the best meta-algorithms for each method are identified using three methods AHP, TOPSIS, and AHP-TOPSIS and the first decision matrix. Then, according to the results of all three methods, a second decision matrix was generated and using the CoCoSo method, which is one of the newest decision-making methods, the best meta-algorithm is identified. The advantage of the combined structure of the article is the use of the advantages of all the mentioned methods simultaneously.

Figure 1 The hybrid structure of the paper to determine the best meta-heuristic optimisation algorithm



In the following, first a brief overview of the AHP, TOPSIS and AHP-TOPSIS are discussed and then, the CoCoSo method is described, which will be used to determine the final best meta-heuristic algorithm.

Figure 2 The hierarchical structure diagram for best meta-heuristic algorithm

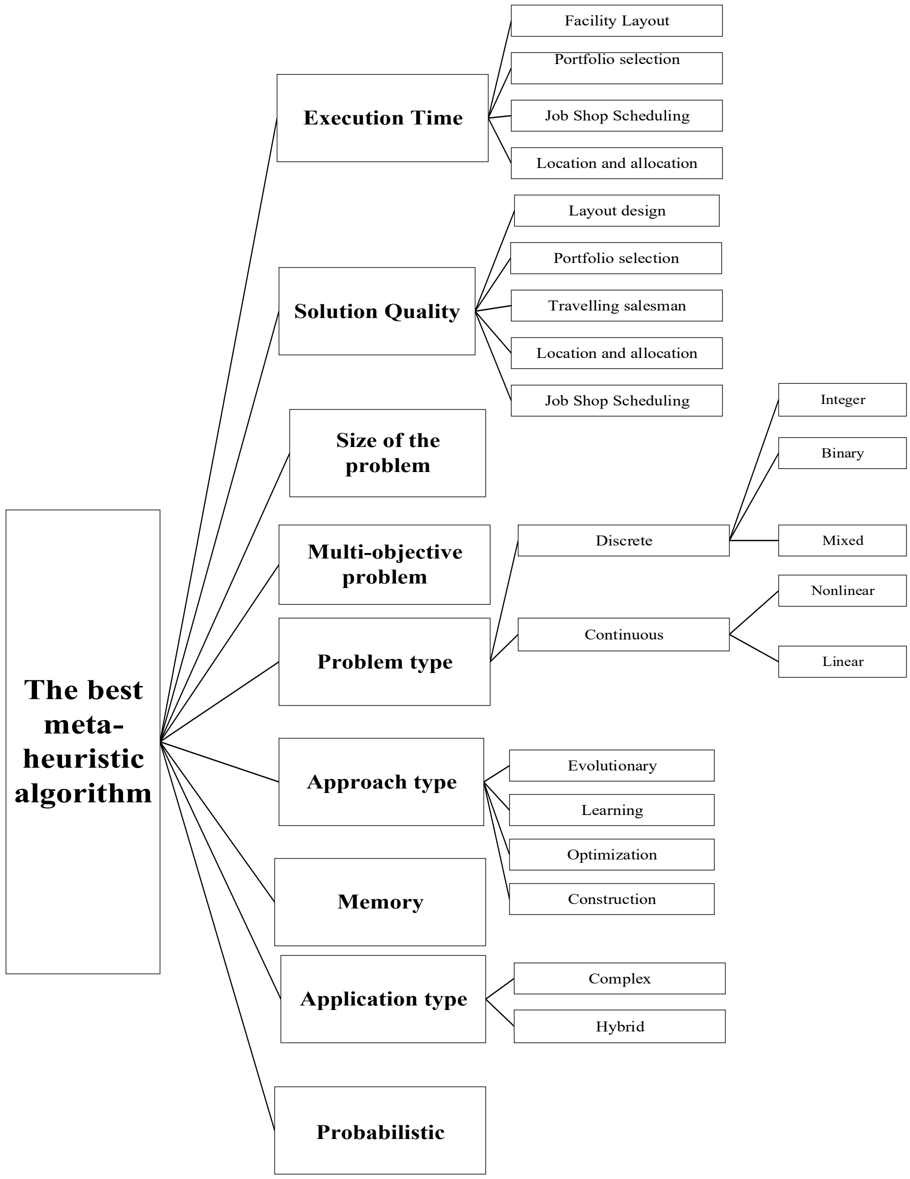


Table 3 The pairwise comparison matrix (first level)

Objective	*The best meta-heuristic algorithm*
The best meta-heuristic algorithm	1

Table 4 The pairwise comparison matrix (second level)

	Execution time	*Solution quality*	*Size of the problem*	*Multi-objective problem*	*Problem type*	*Approach type*	*Memory*	*Application type*	*Probabilistic*
Execution time	1	0.2	0.1	0.3	0.9	0.8	0.6	0.5	0.2
Solution quality	5	1	0.4	0.2	0.1	0.5	0.15	0.2	0.4
Size of the problem	10	2.5	1	0.1	0.4	0.3	0.25	0.3	0.1
Multi-objective problem	3.333	5	10	1	0.1	0.2	0.4	0.5	0.3
Problem type	1.111	10	2.5	10	1	0.9	0.1	1	0.4
Approach type	1.25	2	3.333	5	1.111	1	0.4	0.5	0.7
Memory	1.666	6.6666	4	2.5	10	2.5	1	0.7	0.8
Application type	2	5	3.333	2	1	2	1.42857	1	0.4
Probabilistic	5	2.5	10	3.3333	2.5	1.42857	1.25	2.5	1

The AHP was proposed by Tomas L. Saati in 1980 and resolved the problems associated with decision-making problems due to ambiguity in understanding the problem and the relative concepts. This approach is one of the most comprehensive multiple attribute decision-making (MADM) models. AHP method has many applications in various researches (Das et al., 2012; Nivolianitou et al., 2015). By providing a hierarchical structure for organising and evaluating the importance of different criteria and preferences of options for decision makers, this approach makes it easy to make decisions. Today, this method is widely used in decision-making problems. It is used in fields such as economics, production planning, energy management, material supply, project selection, forecasting, budget allocation, etc. The steps of this method are as follows:

Step 1 Forming a hierarchical structure.

Step 2 Generating the pairwise comparison matrices.

Step 3 Calculating the weights.

Step 4 Calculating the score of each alternative.

Subsequently, Figure 2 presents the hierarchical structure of the problem of this paper.

Table 5 The pairwise comparison matrix (third level)

Solution quality	*Facility layout*	*Portfolio selection*	*Job shop scheduling*	*Location and allocation*	*Travelling salesman*
Facility layout	1	0.3	0.2	0.6	0.8
Portfolio selection	3.333	1	0.4	0.4	0.3
Job shop scheduling	5	2	1	0.2	0.6
Location and allocation	1.666	2.5	5	1	0.9
Travelling salesman	1.25	3.333	1.666	1.1111	1

Table 6 The pairwise comparison matrix (fourth level)

Discrete	*Integer*	*Binary*	*Mixed*
Integer	1	0.3	0.6
Binary	3.3333	1	09
Mixed	1.6667	1.1111	1

Table 7 The pairwise comparison matrix (fifth level)

Time-facility layout	*GA*	*ACO*	*TS*	*PSO*	*ICA*	*SA*
GA	1	0.5384	0.28	0.5384	0.5384	1
ACO	1.8574	1	0.52	1	1	1.8572
TS	3.5714	1.9231	1	1.9228	1.9228	3.5711
PSO	1.8574	1	0.52	1	1	1.8572
ICA	1.8574	1	0.52	1	1	1.8572
SA	1	0.5384	0.28	0.5384	0.5384	1

Table 8 The obtained weights from the pairwise matrices of the AHP method

Criterion	*Weights*	*Criterion type*
Facility layout	0.0089	–
Portfolio selection	0.0262	–
Job shop scheduling	0.0516	–
Location and allocation	0.0046	–
Location and allocation	0.0003	+
Facility layout	0.0005	+
Travelling salesman	0.0075	+
portfolio selection	0.0001	+
Job shop scheduling	0.0005	+
Size of the problem	0.0172	+
Multi-objective problem	0.0368	+
Nonlinear	0.0368	+
Linear	0.0629	+
Integer	0.0629	+
Binary	0.0629	+
Mixed	0.0629	+
Evolutionary	0.0629	+
Learning	0.1625	+
Optimisation	0.0996	+
Memory	0.0165	+
Complex	0	+
Hybrid	0.0368	+
Probabilistic	0.179	+

Table 9 The AHP scores

	TS	*ACO*	*ICA*	*GA*	*PSO*	*SA*
Score	0.075	*0.419*	0.157	0.203	0.17	0.142

Some pairwise comparison matrixes are presented in Tables 3 to 9 for calculating weights. Preferences for these matrices have been obtained from operations research experts. It is necessary to mention, that the positive and negative symbols in the last column of Table 8 indicate the type of criterion that can be profit (positive) or cost (negative).

Finally, the ant colony algorithm was selected as the best algorithm with higher score based on the result of the AHP method (Table 9).

The TOPSIS method was proposed by Huang and Yun in 1981. This model is one of the best MADM models. This technique is based on the notion that the choice should have the least distance from the positive ideal alternative (best possible condition) and the maximum distance with the negative ideal (worst possible condition). TOPSIS method has many applications in various researches (Nivolianitou et al., 2015). Solving the problem with this method involves six steps:

Step 0 Obtaining the decision matrix.

Step 1 Normalising the decision matrix.

Step 2 Weighting the normalised matrix.

Step 3 Identifying the positive and negative ideal alternative.

Step 4 Calculating the distance measure.

Step 5 Calculating the relative proximity to the ideal alternative.

Step 6 Ranking alternatives.

Table 10 The distance measure between each alternative from the positive and negative ideal alternatives and the results of the TOPSIS method

Algorithm	S^{-}	S^{+}	*Score*
GA	0.087465	0.064595	1.064595
ACO	0.082852	0.062183	1.062183
TS	0.065681	0.073317	*1.073317*
PSO	0.078889	0.060589	1.060589
ICA	0.08614	0.042808	1.042808
SA	0.061682	0.072769	1.072769

The results of the TOPSIS method are presented in Table 10. Assuming the same importance of the criterion, the weight of each criterion is considered to be $\frac{1}{23}$ (23 criteria).

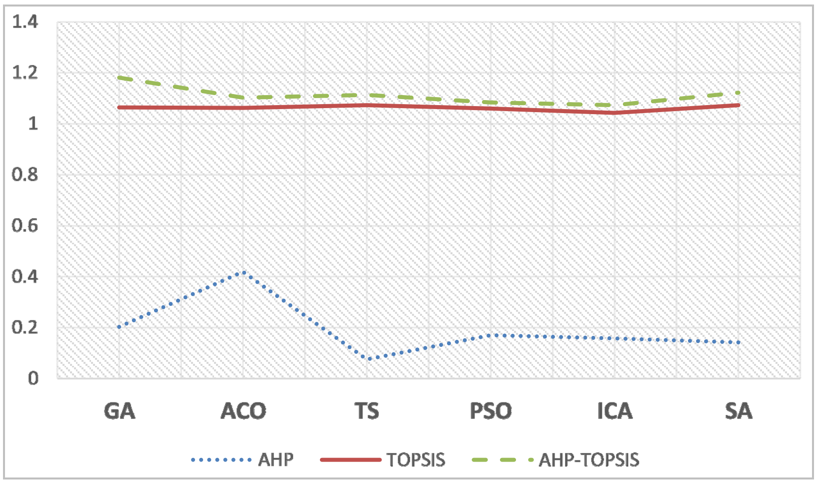
The TS algorithm was selected as the best algorithm based on the result of the TOPSIS method.

The AHP-TOPSIS method is exactly the same as the TOPSIS method, except that the weights obtained from the AHP method are used. The results of the AHP-TOPSIS method are shown in Table 11, and as can be seen, the GA is the best.

Table 11 The results of the AHP-TOPSIS method

Algorithm	s^{-}	s^{+}	*Score*
GA	0.123075	0.180964	*1.180964*
ACO	0.19129	0.102168	1.102168
TS	0.093144	0.113042	1.113042
PSO	0.12011	0.084172	1.084172
ICA	0.123921	0.07286	1.07286
SA	0.110666	0.122359	1.122359

Figure 3 The final results of three methods (see online version for colours)



According to the different results of all three methods (Figure 3), a new (second) decision matrix is generated according to Table 12, and using the CoCoSo method, which is described below, the best final meta-heuristic algorithm is identified.

Table 12 The different results of three methods

Algorithm	*AHP*	*TOPSIS*	*AHP-TOPSIS*
GA	0.203	1.064595	1.180964
ACO	0.419	1.062183	1.102168
TS	0.075	1.073317	1.113042
PSO	0.17	1.060589	1.084172
ICA	0.157	1.042808	1.07286
SA	0.142	1.072769	1.122359

The CoCoSo is one of the new multi-criteria decision-making techniques that were presented in Yazdani et al. (2019). In this method, a compromise combined solution is provided for ranking alternatives. This method is an integrated method of simple average weighted (SAW) and weighted product model (WPM), the steps of the CoCoSo method are given below:

Step 1 Obtaining the decision matrix.

Step 2 Normalising the decision matrix through equations (1) and (2):

$$r_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{ for benefit criterion} \tag{1}$$

$$r_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{ for cost criterion.} \tag{2}$$

Step 3 Calculating the value of SAW and WPM by equations (3) and (4):

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij} \right) \tag{3}$$

$$P_i = \sum_{j=1}^{n} \left(r_{ij} \right)^{w_j}. \tag{4}$$

Step 4 Determining the evaluation score of the alternatives based on three strategies using the relations (5) to (7). In this relation λ is determined by the decision maker but in 0.5 mode, it has a lot of flexibility

$$k_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m} (S_i + P_i)} \tag{5}$$

$$k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \tag{6}$$

$$k_{ic} = \frac{\lambda S_i + (1-\lambda) P_i}{\lambda \max S_i + (1-\lambda) \max P_i}; 0 \le \lambda \le 1. \tag{7}$$

Step 5 Determining the final score and rank the alternatives using equation (8). In fact, this relationship represents the sum of the geometric mean and arithmetic mean of the three strategies of the previous stage.

$$K_i = \left(k_{ia} k_{ib} k_{ic} \right)^{\frac{1}{3}} + \frac{1}{3} \left(k_{ia} + k_{ib} + k_{ic} \right). \tag{8}$$

The second decision matrix (Table 12) is intended to implement the CoCoSo method. Also, the weights required for this method are extracted from the paper of Sharma et al. (2020). In their paper, three methods AHP, TOPSIS, and AHP-TOPSIS are compared. In the end, the best method was AHP-TOPSIS and the worst method was TOPSIS. According to the results of this paper, the following weights (Table 13) are considered for each of them according to the superiority of the method.

Table 13 The weight of three methods AHP, TOPSIS, and AHP-TOPSIS

Method	*AHP*	*TOPSIS*	*AHP-TOPSIS*
Weight	0.335	0.225	0.44

Table 14 The results of the CoCoSo method

Algorithm	S_i	P_i	k_a	k_b	k_c	K_i
GA	0.725328	2.645112	0.238803	13.35935	1	*6.338167*
ACO	0.597176	2.465984	0.217032	11.46495	0.908831	5.509521
TS	0.388547	1.646969	0.144221	7.528271	0.603932	3.627576
PSO	0.269689	1.905825	0.15414	6.458322	0.645469	3.28223
ICA	0.079855	0.618558	0.049484	2	0.207217	1.025954
SA	0.487674	2.28315	0.196319	9.798108	0.822096	4.770552

As can be seen, the best meta-heuristic algorithm is Genetic to the results of the CoCoSo method (Table 14). Also, the worst algorithm is the imperialist competition. In fact, this algorithm was identified as the best meta-heuristic optimisation algorithm according to the four methods of AHP, TOPSIS, AHP-TOPSIS, and CoCoSo.

6 Conclusions

In this paper, according to abundant meta-heuristic and their applicability in various problems, six meta-heuristic algorithms are considered, including genetic, ant colony optimisation (ACO), TS, PSO, imperialist competitive, and SA algorithms. These algorithms were compared based on comparison criteria, including the execution time, the solution quality, dimensions of the problem, problem type, and so on, using the TOPSIS, AHP, and AHP-TOPSIS methods.

Based on the decision matrix of algorithms, it is observed that each algorithm is effective in a specific problem. In the proposed approach, which is a combination of meta-heuristic algorithms and various criteria the computational results of using the TOPSIS method suggest that the TS algorithm is ranked first among other algorithms. However, the ranking of algorithms using the AHP method indicates that the ant colony algorithm is the superior algorithm. The AHP-TOPSIS method has identified the GA as the best algorithm.

Due to the different results obtained from these three methods, the CoCoSo method was the basis for selecting the best algorithm. Finally, the GA was selected as the best meta-heuristic algorithm.

According to the collected information, the best meta-heuristic algorithm was identified among the six mentioned algorithms. However, it is not possible to finally answer the question in the title of the article in general. A specific algorithm is the best for any specific problem. Also, due to the rapid generation and development of new algorithms, it is very difficult to make a definite statement on this claim.

Also, the advantages of using newer methods of performance evaluation in this field can be used. So, it is hoped that in future studies, a more detailed analysis of other meta-heuristic algorithms with more criteria for selecting the best algorithm will be performed. Also, the best algorithm can be examined in more detail for each specific problem separately.

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