



Parameter setting of meta-heuristic algorithms: a new hybrid method based on DEA and RSM

Elham Shadkam¹

Received: 2 September 2021 / Accepted: 31 October 2021 / Published online: 17 November 2021
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Abstract

The parameter setting of meta-heuristic algorithms is one of the most effective issues in the performance of meta-heuristic algorithms and is usually done experimentally which is very time-consuming. In this research, a new hybrid method for selecting the optimal parameters of meta-heuristic algorithms is presented. The proposed method is a combination of data envelopment analysis method and response surface methodology, called DSM. In addition to optimizing parameters, it also simultaneously maximizes efficiency. In this research, the hybrid DSM method has been used to set the parameters of the cuckoo optimization algorithm to optimize the standard and experimental functions of Ackley and Rastrigin. In addition to standard functions, in order to evaluate the performance of the proposed method in real problems, the parameter of reverse logistics problem for COVID-19 waste management has been adjusted using the DSM method, and the results show better performance of the DSM method in terms of solution time, number of iterations, efficiency, and accuracy of the objective function compared to other.

Keywords Meta-heuristic algorithms · Parameter setting · Cuckoo algorithm · Response surface methodology · Data envelopment analysis · Waste management · COVID-19

Introduction and literature review

Many real-world problems can be modeled by operation research techniques and then optimized in a variety of ways. The goal of optimization is to find the best acceptable solution, given the constraints and assumptions of the problem. In each optimization problem, there are decision variables that are limited by a set of constraints or conditions. If the decision variables are discrete in nature, such problems are called combinatorial optimization problems. Because many potential solutions must be considered to solve combinatorial optimization problems, these problems are known as NP-hard problems. In many real-world problems, the solution time is increased non-linearly using exact optimization methods. To solve this problem, regardless of the accuracy of the solution, it is possible to create an acceptable solution

in a much shorter and more logical time by using approximate optimization methods. Therefore, optimization methods and algorithms are divided into two categories: exact and approximate methods. Exact methods are able to find the optimal solution accurately but are not efficient enough in NP-hard optimization problems. Thus, heuristic algorithms were first developed, which are a set of approximate algorithms, but these algorithms are generally designed for a specific problem and often cannot be used for other problems. Therefore, meta-heuristic algorithms were proposed that are independent of a specific problem. The performance of these algorithms is highly dependent on their parameters. In order for these algorithms to work optimally, it is necessary to find specific values for each parameter. Therefore, the problem of parameter setting of meta-heuristic algorithms has been raised. Adjusting the parameters of meta-heuristic algorithms is an effective factor in the performance of these algorithms, so this problem has been considered in many previous studies and various methods have been proposed for it (Lobo et al., 2007; Yazdani, et al., 2017a, 2017b). The importance of the parameters of any optimization algorithm, especially meta-heuristic algorithms, is inevitable (Yazdani et al., 2016). The optimal values of these parameters, which

Responsible Editor: Philippe Garrigues

✉ Elham Shadkam
e.shadkam@khayyam.ac.ir

¹ Department of Industrial Engineering, Faculty of Engineering, Khayyam University, Mashhad, Iran

generally depend on the characteristics of the parameter and the problem, have a significant impact on the performance of these algorithms and better search of the solution space (Najafi & Behnoud, 2015; Yazdani, et al., 2017a, 2017b). One of the recently introduced meta-heuristic algorithms is the cuckoo optimization algorithm (COA). The use of the COA has many applications in various engineering sciences. This algorithm, like other meta-heuristic algorithms, is sensitive to parameter setting. In using the COA, precise adjustments must be made in the execution of the algorithm, determination of the appropriate combination of parameters, final execution of the algorithm, and validation of the solutions. Previous research has used methods such as trial and error, experimental design, and Taguchi method to adjust the parameters of this algorithm (Azadeh et al., 2013). The problem of setting the parameters of meta-heuristic algorithms is so important and noteworthy that an article entitled *Why Tuning the Control Parameters of Meta-heuristic Algorithms Is So Important for Fair Comparison?* has been proposed in this regard (Kazikova et al., 2020). In a study, Cheng and Chang (2007) proposed a genetic algorithm to optimize the scheduling problem and proposed a hybrid method for optimizing the genetic algorithm parameters using the design of Taguchi experiments. They tested and optimized seven algorithm parameters including initial solutions, selection method, intersection approach, mutation rate, initial population size, algorithm velocity, and mutation method. Naderi et al. (2009) used the Taguchi method to adjust the parameters of the simulated annealing (SA) algorithm. They considered parameters such as initial solutions, coding pattern, and local search structure as controllable factors of SA and different levels for each factor. They then considered and optimized these factors using the Taguchi method. In a study, Bartz-Beielstein and Markon (2004) proposed a method for parameters setting of complex real-world optimization problems. This method is a combination of statistical design of experiment methods, regression analysis, design and analysis of computer experiments, and regression tree that has been used to set the parameters of the SA and evolutionary algorithm. In a paper, Ridge and Kudenko (2007) set the parameter of the ant colony optimization algorithm by designing experiments to solve the traveling salesman problem, which used the response surface methodology to evaluate the quality and time of the solutions. In their research, Fallahi et al. (2014) examined the parameters of the ant colony algorithm for traveling salesman problem, which were performed in five stages: parameter profile screening, clustering, parameter screening, response procedure methodology, and finally optimization. In a paper, solving the problem of vehicle routing using the Memetic algorithm, Saremi et al. (2007) considered setting the desired parameters using experimental design method and analysis of variance to investigate the interactions. Xu et al. (1998) examined the

parameter setting in the Tabu search algorithm using statistical tests and experimental design. In this study, the decision tree minimization problem is considered by explaining three types of neighbor structure selection methods. This method has been used by other researchers to adjust the parameters of the Tabu search algorithm to solve the problem of vehicle routing. Beielstein et al. (2002) examined the parameters of the particle swarm optimization algorithm using experimental design techniques and analyzed their important parameters and interactions. In an article, Ridge (2007) adjusts the parameters of one type of the ant colony algorithms to solve the traveling salesman problem, and the results show the better performance of the mentioned algorithm with standardized parameters. In a research, Šilc et al. (2015) proposed a data mining approach to set the performance of meta-heuristic algorithms. In this paper, the idea of learning, a model for algorithm behavior using data mining is presented as the results obtained in parameter setting. A paper presented by Veček et al. (2016) includes a method called the chess ranking system. This approach has been used to compare and score evolutionary algorithms. In that method, the desirability and performance of a combination of parameters are obtained by comparing with other structures based on their score, deviation from the score, and the distance of the score. During the performance and in each iteration, the bad structures are significantly eliminated and new structures are obtained through mutations and combinations of existing structures. The results of this method show that there is not always a significant difference in the assumption of zero statistical tests, but the method mentioned in the paper shows better performance when using similar parametric structures. Also, parameter setting with this method has been faster than other methods such as the competitive method, and there is no limit in setting absolute parameters. The researches done in this field are very diverse and extensive (Table 1), and the studies done in this field are reviewed.

One of the methods used for parameter setting of meta-heuristic algorithms is response level methodology (RSM). RSM is a combination of mathematical and statistical techniques that is widely used for modeling and data analysis. In this method, response variables (outputs) are influenced by several independent variables (inputs), and the goal is to obtain the best values of inputs in order to optimize outputs (Hinkelmann & Kempthorne, 1994). One of the first researches to determine the parameters of meta-heuristic algorithms using RSM is Wang and Wu's (1999) research, in which a six-step RSM-based process for identifying and optimizing the SA algorithm with computational time constraints has been performed. In a paper, Najafi and Behnoud (2015) presented a combined algorithm of RSM and data envelopment analysis (DEA) to adjust the parameters of meta-heuristic algorithms. Using the RSM, they set the parameters of a genetic algorithm to optimize the machine

Table 1 Review of the papers on parameter setting of meta-heuristic algorithms

No	Authors (year)	Meta-heuristic algorithm	Methods applied
1	Xu et al. (1998)	Tabu search algorithm	Statistical tests and experiments design
2	Beielstein et al. (2002)	Particle swarm optimization algorithm	Experiment design
3	Bartz-Beielstein and Markon (2004)	Simulated annealing algorithm	Experimental design, regression analysis, design and analysis of computer experiments, and regression tree
4	Ridge (2007)	Ant colony optimization algorithm	Design of experiments and response surface methodology
6	Joshi and Bansal (2020)	Ant colony optimization algorithm	Parameter specification screening, clustering, parameter screening, RSM, and optimization
7	Saremi et al. (2007)	Memetic algorithm	Design of experiments and variance analysis
8	Šilc et al. (2015)	Meta-heuristic algorithm	Data mining
9	Veček et al. (2016)	Evolutionary algorithms	Comparison and scoring
10	Najafi and Behnoud (2015)	Genetic algorithm	RSM and DEA
11	Saeheaw (2020)	HCSCROCF0-3Opt algorithm	A random manner
12	Odili and Fatokun (2020)	African buffalo optimization algorithm	Mathematical modeling
13	Gomes and de Almeida (2020)	Sunflower optimization	Statistical method of mixture design
14	Joshi and Bansal (2020)	Gravitational search algorithm	Topological characteristics of the given optimization problem
15	Do Ngoc Luu and Anh (2021)	Deep belief networks to predict time series data	Harmony search algorithm
16	Özakın and Kaya (2020)	Air-based PVT system	Taguchi method and ANOVA
17	Walker and Craven (2020)	Evolutionary multi- and many-objective optimization	A visualization approach
18	Phan et al. (2020)	Evolutionary algorithms and swarm intelligence algorithms	Dynamic parameter setting techniques
19	Thirumalai et al. (2021)	Non-dominated sorting genetic algorithm	Technique for order preference by similarity to ideal solution
20	Črepinšek et al. (2019)	Multi-objective evolutionary algorithms	A novel MOCRS-tuning method
21	Cheng et al. (2021)	Genetic algorithm and particle swarm optimization	Auto-tuning symbiotic organisms search algorithm
22	Alavi et al. (2021)	A variable neighborhood search meta-heuristic method	Conventional sequential optimization method
23	Devarapalli and Bhattacharyya (2021)	Power system stabilizer	Sine–cosine algorithm
24	Mergos and Yang (2021)	Flower pollination algorithm	A simple non-iterative, single-stage sampling tuning method
25	Tien Bui et al. (2021)	Neural computing	Whale optimization algorithm

scheduling problem assuming sequence-dependent preparation times. In their method, in order to optimize the parameters of the algorithm, only the optimization of the objective function has been considered and the solution time of the algorithm has not been addressed. The use of the DEA method in optimization problems is very common and can be referred to Shadkam (2021a, 2021b, 2021c) that in a two-phase algorithm using DEA to optimize the objective function and maximize the efficiency of the problem simultaneously. Also, Shadkam and Bijari (2015) in a research have used the combination of RSM and DEA in order to optimize multi-objective problems for bank branches. For the first time in a review paper, Phan et al. (2020) have reviewed and classified the various methods of parameter setting of evolutionary algorithms. These methods are divided into

two groups: parameter tuning and parameter control methods. Parameter tuning techniques are used to select offline parameters before the optimization algorithm is executed, but online parameter control techniques are used in dynamic optimization problems during an algorithm execution or after each algorithm execution. According to this classification, one of the most widely used and popular methods in the field is the experimental design of experiments method (DOE). In this method, the parameters are adjusted to create the best solution for the objective function. The Taguchi method is mostly used in this field. In fact, because only one solution can be examined, the value of the objective function is usually considered, and if we want to consider other response such as the number of iterations and the execution time of the algorithm, this process must be repeated

separately for each response. Finally, the parameters created will not perform well at all responses because each response is optimized separately.

In our study, by combining DEA and RSM methods, a hybrid method called DSM is presented. The name of the proposed hybrid method is taken from the methods used in it. This method has various applications that will be discussed in future research by the authors of this paper. In principle, this method is presented to optimize multi-objective problems and another application is to parameterize the meta-heuristic algorithm, which has been used in this paper to optimize the parameters of the COA. The COA is one of the newest and most powerful meta-heuristic algorithms that has the ability to solve discrete and continuous problems. The parameter setting process of this algorithm is performed by the proposed DSM method, with the help of data obtained from the design of experiments and the implementation of the algorithm for both standard and real-time functions. In the hybrid DSM method, first, a number of decision-making units (DMUs) are selected, and the values of their inputs and outputs are determined. Then, the efficiency values of the DMUs are calculated using the DEA method. Then, with the RSM method, the response surfaces are made, which includes an efficiency surface and the response surfaces to the number of output variables. The efficiency surface is optimized, and the values of the optimal independent variables are obtained, then according to the optimal independent variables, the optimal response variables are obtained. The obtained independent variables and the optimal response variables are considered as a suitable configuration for the COA. Similarly, two tools, DEA and RSM, have been used for optimizing multi-surface problems in power plants of IRAN (Shadkam, 2021a, 2021b, 2021c). The proposed method of the paper overcome the shortcoming of DOE method and Najafi and Behnoud (2015) algorithm. In this method, in order to set the parameters, in addition to the value of the objective function, other responses (execution time and number of iterations) are also examined. Also, all three responses are optimized simultaneously, which ultimately leads to a better configuration for the algorithm.

In order to implement the proposed method in the real world, the medical waste management problem is examined. Medical wastes are one of the most important hazardous wastes and carry a large number of pathogenic bacteria (Sangkham, 2020). This issue has special importance and place in research, and many articles on the design of medical wastes logistics networks have been presented (Kargar et al., 2020b). The problem of waste disposal in hospitals is a very important problem that has been the subject of much research, including Wang et al. (2020), Fletcher et al. (2021), Adu et al. (2020), and Homayouni and Pishvae (2020). Due to the global outbreak of the

coronavirus, the volume of medical wastes and the dangers posed by it have increased dramatically (Ozkaya et al., 2020). In this regard, Shadkam (2021a, 2021b, 2021c) has presented a mixed integer model for the management of COVID-19 wastes, especially its vaccine. The purpose of this model is to design a reverse supply chain model for safe and optimal disposal of medical wastes (focusing on corona vaccine wastes). Due to the containers and equipment used in COVID-19 vaccine packaging for easy transportation and maintenance, this model can be a great help in returning these containers to the factory and recycling them, saving you money and time. Therefore, the proposed model directs non-recyclable wastes to disposal and returns recyclable wastes such as COVID-19 vaccine containers to the plant after disinfection. Many researches have been done in the field of medical waste management, an example of which can be seen in Table 2.

In this paper, the parameter setting of inverse logistics problem of corona waste management has been investigated. Today, reverse logistics is one of the main activities of supply chain management that covers all physical activities related to returned products (such as collection, recovery, recycling, and destruction) (Julianelli et al., 2020). In this regard, proper design and implementation of reverse logistics, in addition to increasing customer satisfaction, reduce inventory and shipping costs. In this paper, the parameter setting of a mixed integer linear programming model for the design of an integrated direct and reverse logistics network is investigated. Due to the prevalence of coronavirus (COVID-19) and the increase in medical waste, the need for a reverse logistics system for waste management is strongly felt. For this purpose, the inverse logistics model in the field of coronavirus waste management, especially vaccine waste, has been investigated. This model was introduced by Shadkam (2021a, 2021b, 2021c). This model is solved using the cuckoo optimization algorithm, and before solving using the proposed DSM method, the cuckoo algorithm parameter will be adjusted for the inverse logistics problem. In the following research, in the next section, the COA is described, then the proposed DSM method is presented, and how to implement it to set the parameters of meta-heuristic algorithms will be examined. In the next section, the parameters of the COA are adjusted with the help of the Ackley and Rastrigin functions. The verification of the proposed method is examined through four approaches, and the results will be reviewed and interpreted. These approaches include the Taguchi method, RSM, and Najafi and Behnoud (2015) method. In the next section, the cuckoo algorithm parameter is adjusted to solve the inverse logistics problem of COVID-19 waste and is compared with the experimental approach of parameter setting.

Table 2 Recent research in medical waste (Shadkam, 2021a, 2021b, 2021c)

No	Authors	Multi-objective	Multi-period	Multi-product	Uncertainty	Case study	Approach	Software
1	Shih and Lin (2003)	*	*			China	MILP Dynamic programming	Lingo GIS
2	Kargar, et al. (2020a, 2021b)	*	*	*	*	Iran	MILP Fuzzy goal programming Robust possibility Programming	Lingo
3	Osaba et al. (2019)		*	*		Spain	MILP Bat algorithm Firefly algorithm	Matlab
4	Gergin et al. (2019)	*	*	*		Turkey	MILP Artificial bee colony	Microsoft Visual C#
5	Vickers (2017)		*			Greece	MILP Genetic algorithm Monte Carlo simulation	Evolver Crystal Ball
6	Alshraideh and Qdais (2017)	*	*		*	Jordan	MILP Genetic algorithm	Matlab
7	Budak and Ustundag (2017)		*			Turkey	MILP	Fico Xpress IVE
8	Nolz et al. (2014)	*	*	*		France	MILP	Adaptive large neighborhood search
9	Almeida (2010)				*	Portugal	MILP	GAMS
10	Shi et al. (2009)		*			China	MILP Genetic algorithm	Matlab
11	Shadkam (2021a, 2021b, 2021c)					Coronavirus	MILP COA	Matlab Lingo

Introduction of the COA

This algorithm was proposed by Rajabioun (2011) and is inspired by the life of a cuckoo bird. In various papers, the performance of this algorithm has been compared with other similar algorithms, which can be referred to (Kahramanli, 2012) and (Shadkam & Bijari, 2014) for more information in this regard. This algorithm has been used in various fields, such as production planning (Akbarzadeh & Shadkam, 2015), portfolio selection (Shadkam et al., 2015), supplier selection (Shadkam & Bijari, 2017), and solving multi-objective optimization problems (Gorjestani et al., 2015; Shadkam & Jahani, 2015; and Borhanifar & Shadkam, 2016), supply chain problem (Shadkam et al., 2021), and resource leveling in control project management (Shadkam, 2021a, 2021b, 2021c). Due to the good performance of this algorithm, improved versions of this algorithm have also been presented (Shadkam & Bijari, 2020). The flowchart of this algorithm is presented in Fig. 1. In the COA algorithm, similar to other evolutionary algorithms, it starts with a random population of initial cuckoos. Each cuckoo has positions called a habitat (relation 1), which indicates the array of the problem-solving variables.

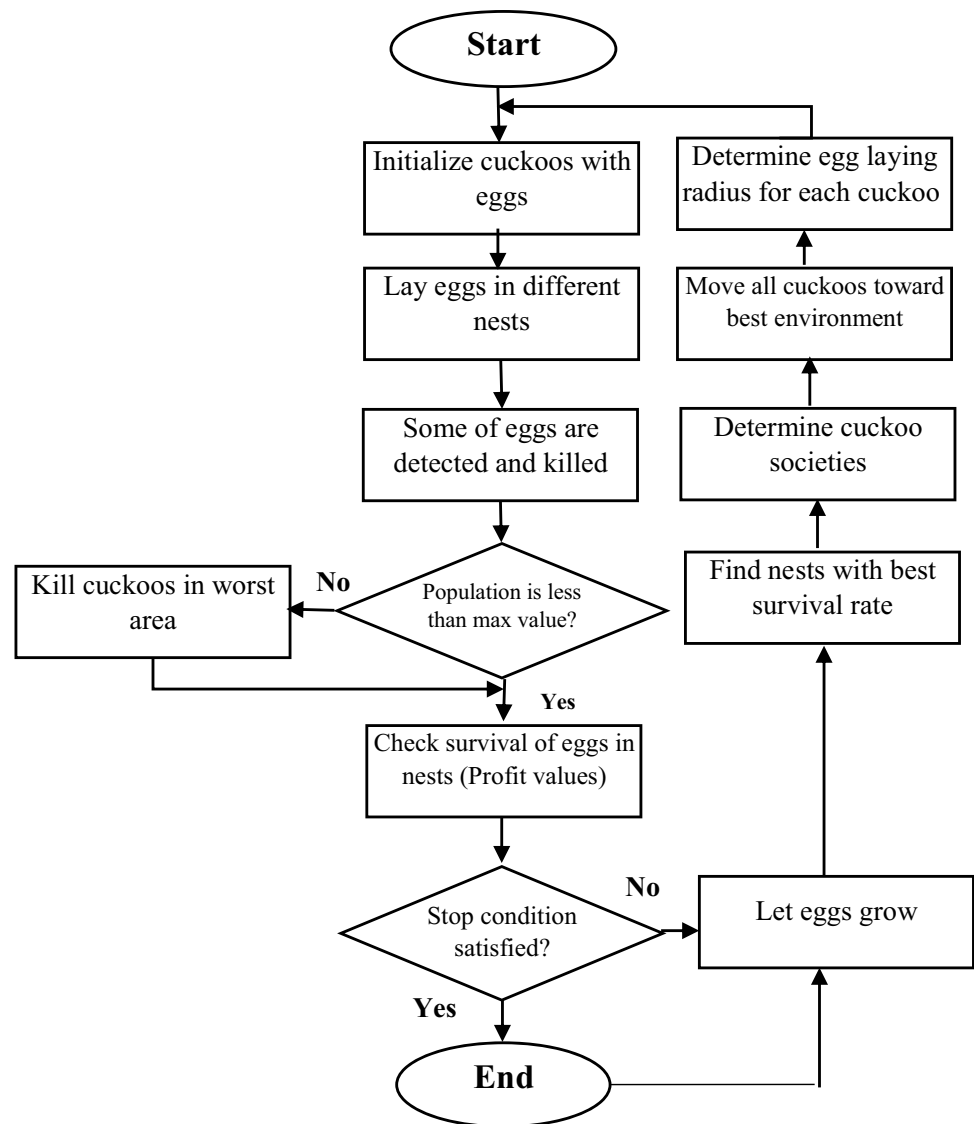
$$\text{Habitat} = [x_1, x_2, \dots, x_{Nvar}] \quad (1)$$

Each cuckoo lays a number of eggs according to its assigned egg-laying radius (relation 2). Some of these eggs are destroyed, and some of the eggs remain and become adult cuckoos. Adult cuckoos look for places where they have a better chance of survival or where the average value of the objective function is optimal in those areas. After identifying the optimal location, each cuckoo migrates with some deviation from the optimal location and starts laying eggs. Due to dietary restrictions, only a few cuckoos can survive. Therefore, cuckoos with inappropriate values of the objective function are removed, and only the more efficient cuckoos will be transferred to the next iteration of the algorithm. This process is repeated in the same order as mentioned to establish the stop condition.

$$\text{ELR} = \alpha \times \frac{\text{Number of current Cuckoos eggs}}{\text{Total number of eggs}} \quad (2)$$

× (Cuckoos eggs and upper bound – Cuckoos eggs and upper bound)

Fig. 1 The flowchart of the COA (Rajabioun, 2011)



Introducing the proposed DSM method

In most real-world problems, we have more than one response or output and optimizing multiple responses at the same time is one of the major problems in problems. Through design of experiments of data, the response surfaces is obtained, which is an equation between a response variable and independent (input) variables. In such cases, it is difficult to optimize several response surfaces simultaneously in order to obtain the best independent variables. Various methods have been proposed to solve such problems, which include constraining the problem using other objectives, the utility function, and the least-cost response surface. Since the proposed method includes two methods DEA and RSM, it is called DSM method. This proposed algorithm combines the RSM as one of the optimization methods. In order to make the optimization process more efficient, in addition to the RSM, the DEA

method has been used and a hybrid model of both is presented. The main advantage of the DSM algorithm is to create an efficiency surface instead of generating multiple surfaces for each of the output or objective functions. In DSM algorithm, first, a suitable experimental design is selected to generate the experiments, then the simulation process is performed for the designed experiments and the inputs and outputs generated from the simulation are analyzed using DEA and RSM tools. Finally, using the surface obtained for efficiency, the input parameters of the system can be determined in such a way that the system under review has the highest value of efficiency, and according to these input values, the corresponding outputs can be output from the response surfaces obtained for each output. The main advantage of the proposed model is its applicability to an unlimited number of objective functions and simultaneous attention to efficiency maximization along with optimization of problem outputs. The DSM method steps

include design of experiment, data normalization, DEA model (for efficiency), and RSM model (for response efficiency). Also, the pseudo-code of this method is as follows:

1. Design of experiment or data collection: Control factors and response variables of problem are determined.
2. Data normalization: To reduce the effect of different scales on the data, the collected data have been normalized.
3. Determination of efficiency for each experiment by DEA: Using the input and output values of step 2, the efficiency value of each experiment is calculated.
4. Making efficiency surface by RSM: Using the input values of step 2 and the efficiency values obtained from step 3, an efficient surface is created using the RSM.
5. Calculate optimal inputs: The optimal values of input variables or control factors are obtained.
6. Calculate optimal outputs: The optimal values of outputs variables or responses are obtained.

Input and output variables are determined by previous research and expert opinion. This data is collected for a number of specific decision-making units. Normalizations are performed to reduce the effect of different scales on the data. In this study, the Euclidean norm mentioned in Eq. 3 is used.

$$y'_{ij} = \frac{y_{ij}}{\sqrt{\sum_j^n y_{ij}^2}} \quad (3)$$

Measuring the efficiency in the field of performance evaluation in companies and organizations is very important. DEA is a non-parametric method in performance evaluation. There are several models in the field of DEA. The CCR method in model 4 is a basic model that is used in this study to evaluate the efficiency of decision-making units.

$$\text{Max } E_u = \frac{\sum_y u_y O_{ty}}{\sum_x u_x I_{tx}}$$

S.t.

$$\frac{\sum_y u_y O_{wy}}{\sum_x u_x I_{wx}} < 1 \quad (4)$$

$w = 1, \dots, L, u_y > 0, u_x > 0$

The purpose of using the RSM (Eq. 5) is to determine the best variables (inputs) that can create the best values for the objective function (system output). The main advantage of the proposed method is in this section. In fact, instead of generating multiple response surfaces for the outputs separately, an efficiency surface according to Eq. 5 is presented to calculate the optimal level of parameters.

$$\text{Max efficiency} = f(x) \quad (5)$$

In fact, to construct the efficiency surface, we use normalized inputs as independent variables, as well as the functions calculated as response variables. After setting the efficiency surface by the Minitab software, the surface is optimized by the Lingo software, and we introduce the resulting solutions as optimal system inputs. It then sets a separate surface for each output, except that here each output is placed as a response variable. Then, the optimal independent variables are placed in the response surfaces, and the optimal response variables are obtained which are considered as the optimal outputs of the system.

Parameter setting of COA using the proposed DSM hybrid method

In this section, in order to investigate the proposed DSM method, the optimal parameters of the COA are set. The details of the implementation of the proposed approach for setting the algorithm parameter are shown in Fig. 2.

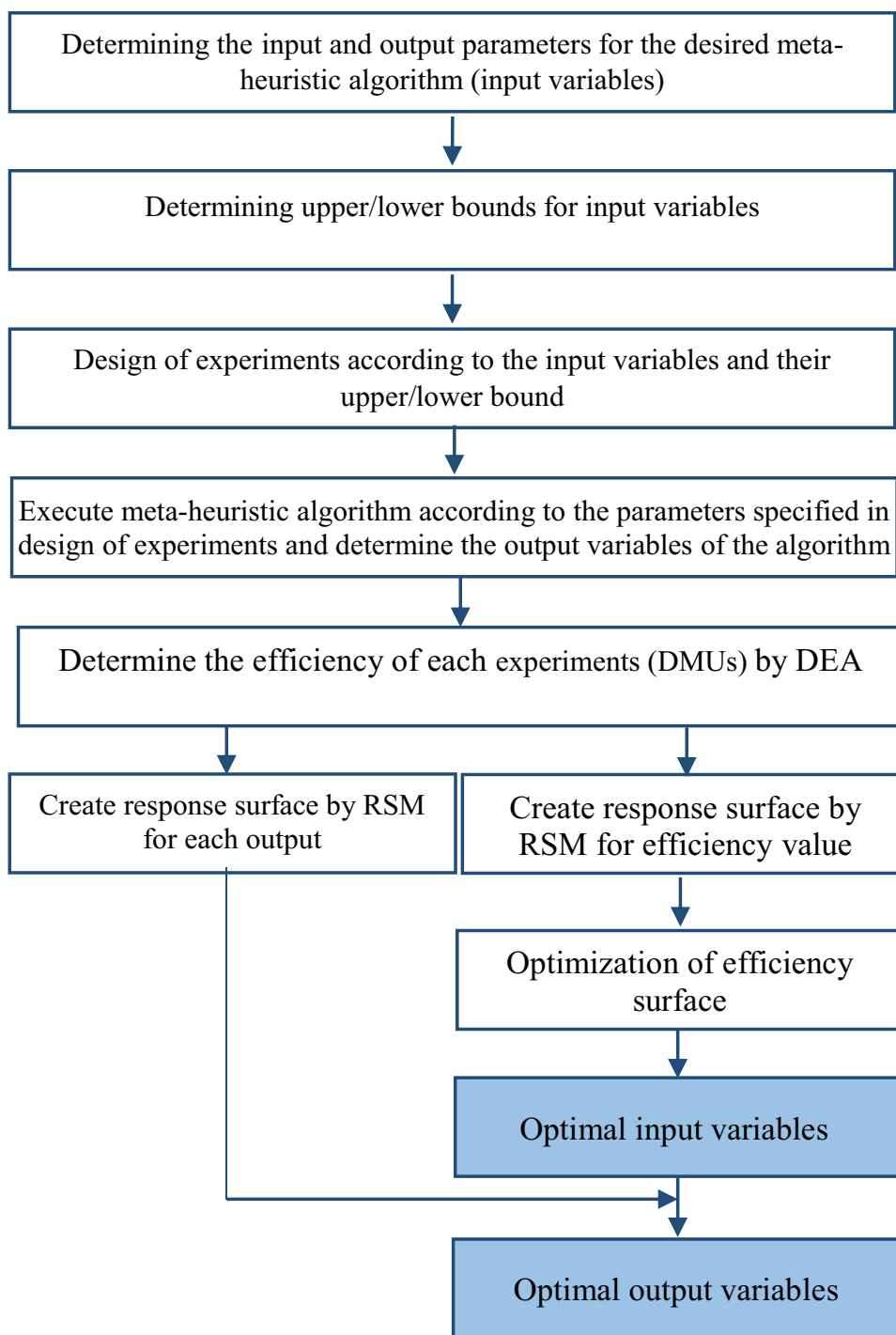
Implement the proposed DSM method for standard functions

The Ackley and Rastrigin functions are common non-convex functions used as a performance test problem for optimization algorithms. These functions are typical examples of non-linear multimodal functions. The Ackley function was proposed by David Ackley in his 1987 PhD Dissertation (Ackley 1987). Also, the Rastrigin function was presented in 1974 by Rastrigin as a 2-dimensional function (Rastrigin, 1974) and has been expanded by Rudolph (Rudolph, 1990). The Ackley and Rastrigin functions are expressed as relations 6 and 7, respectively. Also, the diagrams of the Ackley and Rastrigin functions are shown in Fig. 3. As can be seen, these functions have many local minimum, and therefore, it is difficult to find the global minimum. However, the cuckoo algorithm can find as well the optimal solution for these two functions. Also, n indicates the number of variables or dimensions of the problem, which is equal to 2 in Fig. 3, but we consider 100 to implement the DSM method and set the parameter.

$$\text{Min}F(x) = -20 \exp \left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n x_i^2} \right) - \exp \left(\frac{1}{n} \sum_{i=1}^n \cos(2\pi x_i) \right) + 20 + e \quad (6)$$

$$\text{Min}F(x) = An + \sum_{i=1}^n [x_i^2 - A \cos(2\pi x_i)] \quad (7)$$

Fig. 2 Diagram of the DSM method to parameter setting meta-heuristic algorithms



Step 1: Determine the problem variables

In this step, the independent variables (inputs) of the COA, which are the parameters of the algorithm, are determined, which are as follows:

1. The number of initial cuckoos (5–20)
2. The minimum number of eggs (2–4)

3. The maximum number of eggs (3–5)
4. Number of clusters (2–5)
5. Maximum number of cuckoos in each repetition (10–50)

The response variables (outputs) are as follows:

1. The value of the problem objective function
2. Execution time to solve the problem

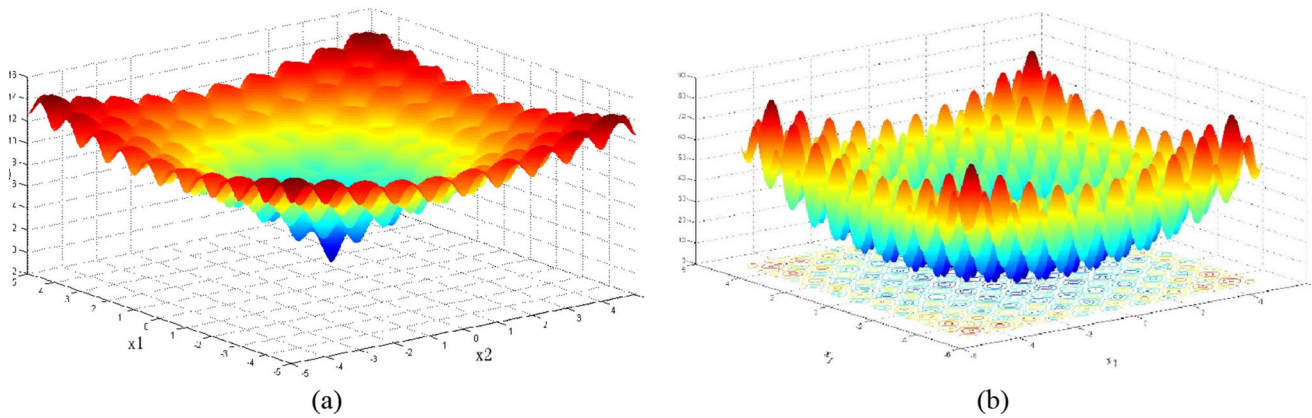


Fig. 3 The diagrams of functions. **a** Ackley. **b** Rastrigin

3. Number of iteration to solve the problem

Step 2: Design of experiments

By specifying the upper and lower bounds for each of the input variables (these bounds are written in front of the input parameters in parentheses), the design of experiments is performed using the Minitab software, the output of which is 32 test designs. In fact, each experiment is a configuration for the parameters of the meta-heuristic algorithm and consider as a DMU. Then, by placing each of these configurations of parameters in the COA, the optimization of Ackley and Rastrigin functions is performed with a number of variables equal to 100, and the values of the output variables determined in the previous step are measured, and the results for Ackley and Rastrigin functions are shown in Table 3.

Step 3: Data normalization

According to previous statements, the data are normalized with Euclidean norm. It should be noted that the type of the outputs values are cost, and Eq. 6 is used to normalize them (Eq. 8).

$$y_i' = 1 - \left(\frac{y_i}{\sum_{i=1}^n y_i^2} \right) \quad (8)$$

Step 4: Calculate efficiency by DEA

Each of the experiments or configurations of the previous step is considered as a DMU, and the efficiency values for each algorithm configuration in both functions are calculated using the DEA method and Lingo software according to last columns of Table 3. The calculation of efficiency values is done with the CCR approach.

Step 5: Efficiency surface and response surfaces by RSM model

In this step, using the information obtained from steps 4 and 5, the surfaces for efficiency and output variables are constructed. Surfaces are created using the Minitab software, inputs are considered as independent variables, and efficiency calculated in step 5 is considered as a response or dependent variable. The efficiency surface for the Ackley and Rastrigin functions is in accordance with Eqs. 9 and 10.

$$\begin{aligned} \text{Maxe} = & -0.83051 + 0.00409814x_1 + 0.178639x_2 + 0.153667x_3 + 0.0912142x_4 \\ & + 0.0005852x_5 - 2.24079E - 4x_1x_2 - 2.20808E - 4x_1x_3 - 9.77674E - 5x_1x_4 \\ & - 5.59514E - 7x_1x_5 - 5.59514E - 7x_2x_3 - 0.00549792x_2x_4 - 3.14486E - 05x_2x_5 \\ & - 0.00559131x_3x_4 - 3.09067E - 05x_3x_5 - 1.38115E - 5x_4x_5 \end{aligned} \quad (9)$$

$$\begin{aligned} \text{Maxe} = & 1.45733 + 0.00155771x_1 - 0.106527x_2 - 0.0891887x_3 + 0.0263433x_4 \\ & - 2.60030E - 4x_5 - 1.36606E - 4x_1x_2 + 8.01367E - 5x_1x_3 - 1.37235E - 4x_1x_4 \\ & + 3.86481E - 7x_1x_5 + 0.0154681x_2x_3 - 0.00284819x_2x_4 + 4.48567E - 5x_2x_5 \\ & + 0.000478417x_3x_4 - 2.33423E - 5x_3x_5 + 1.34745E - 5x_4x_5 \end{aligned} \quad (10)$$

Also, for the three mentioned outputs, separate procedures are considered in which the inputs are considered as independent variables and the outputs as the response variable. The Ackley function response surfaces are in the form of relations 11, 12, and 13. Also, the response functions of the Rastrigin function are in the form of 14, 15, and 16 relations.

The objective function surface for the Ackley function (y_1) is as follows:

$$\begin{aligned} y_1 = & 2.87342 + 0.000230282x_1 + 0.00919271x_2 + 0.00825863x_3 + 0.00982920x_4 \\ & + 7.13368E - 06x_5 + 1.82222E - 05x_1x_2 - 4.05556E - 05x_1x_3 - 1.10617E - 05x_1x_4 \\ & + 7.80556E - 08x_1x_5 - 2.75000E - 04x_2x_3 - 0.00159722x_2x_4 + 2.18750E - 06x_2x_5 \\ & + 0.000227778x_3x_4 - 4.23437E - 06x_3x_5 + 3.33333E - 07x_4x_5 \end{aligned} \quad (11)$$

Table 3 The input and output values for the Ackley and Rastrigin functions

Number of experiment	Inputs					Output			Efficiency
	Number of cuckoos	Min number of eggs	Max number of eggs	Number of clusters	Maximum number of cuckoos	Objective function	Execution time	Number of iteration	
Ackley function									
1	20	4	5	2	10	2.9914	0.948	18	0.99938
2	20	2	3	2	50	2.9838	1.107	18	1
3	5	2	3	5	50	2.9879	1.067	17	0.99982
4	20	4	3	5	50	2.986	1.413	16	1
5	5	4	3	5	50	2.9856	0.941	17	1
6	5	4	3	2	10	2.9863	0.92	17	1
7	20	4	3	2	50	2.9847	1.33	18	0.999871
8	20	4	3	2	10	2.9829	0.925	16	1
9	20	4	5	5	10	2.9839	0.966	17	0.999871
10	20	4	5	5	50	2.985	1.806	17	0.5999
11	5	2	3	2	50	2.9852	1.026	17	1
12	20	2	3	5	50	3.0095	1.195	16	1
13	20	2	3	2	10	2.9904	0.934	17	1
14	5	2	5	2	10	2.9855	0.907	17	1
15	5	4	5	5	10	2.9861	0.935	17	0.99996
16	5	2	3	5	10	2.9984	0.91	16	1
17	5	2	5	5	50	3.001	1.316	16	1
18	5	2	3	2	10	2.9878	0.925	17	1
19	5	4	3	2	50	2.985	1.244	18	1
20	5	2	5	5	10	3.0337	0.934	19	0.996539
21	5	4	3	5	10	2.982	0.911	18	1
22	20	2	5	2	50	2.986	1.313	18	0.999843
23	5	4	5	5	50	2.9858	1.653	18	0.999733
24	20	2	5	5	10	2.9877	0.922	17	0.999853
25	20	4	5	2	50	2.983	1.614	17	0.9999
26	5	4	5	2	50	2.9897	1.6	17	1
27	5	2	5	2	50	2.9875	1.236	18	0.999835
28	20	2	5	5	50	2.9886	1.428	17	0.999773
29	20	2	3	5	10	2.986	0.928	17	1
30	20	4	3	5	10	2.9822	0.946	16	1
31	20	2	5	2	10	2.9894	0.937	18	0.99972
32	5	4	5	2	10	2.9914	0.917	18	0.999576
Rastrigin function									
1	20	4	5	2	50	3.1538	1.712	34	1
2	5	2	3	5	10	2.6724	0.98	34	1
3	5	2	5	2	10	3.3072	0.962	34	1
4	5	4	3	5	10	0.35279	0.945	31	1
5	5	4	3	5	50	19.3691	1.267	37	1
6	20	2	5	5	50	2.9032	1.333	35	1
7	5	2	3	5	50	22.6083	1.114	33	0.916667
8	20	2	5	2	10	12.2647	0.916	35	1
9	20	4	5	5	10	2.6991	0.972	36	0.989076
10	5	2	5	2	50	5.4416	1.232	36	0.628767
11	5	4	5	2	50	32.8557	1.552	34	1
12	5	4	5	5	10	6.5067	0.97	30	0.946179
13	5	2	5	5	50	7.813	1.229	32	1

Table 3 (continued)

Number of experiment	Inputs					Output			Efficiency
	Number of cuckoos	Min number of eggs	Max number of eggs	Number of clusters	Maximum number of cuckoos	Objective function	Execution time	Number of iteration	
14	20	4	5	2	10	5.3067	1.125	33	1
15	20	4	3	2	50	2.3753	1.233	38	1
16	20	2	3	5	50	4.6461	1.138	34	1
17	20	4	3	5	50	14.716	1.289	34	0.9967
18	20	2	5	5	10	13.8605	1.045	30	1
19	20	2	5	2	50	1.1338	1.293	36	1
20	20	4	3	5	10	9.0523	0.942	32	0.941176
21	5	2	3	2	10	18.366	0.92	33	0.942857
22	5	4	5	5	50	14.0465	1.621	37	1
23	5	2	5	5	10	3.0532	0.922	33	0.962345
24	20	4	3	2	10	12.3225	0.952	43	1
25	20	2	3	5	10	0.116	1.265	32	1
26	20	2	3	2	50	4.4028	1.24	33	0.953243
27	20	2	3	2	10	0.6687	1.097	36	1
28	5	4	3	2	10	19.591	1.145	32	0.838342
29	5	4	5	2	10	7.224	1.042	35	1
30	20	4	5	5	50	1.053	1.83	32	1
31	5	2	3	2	50	1.9087	1.136	32	1
32	5	4	3	2	50	9.9196	1.1409	31	0.885714

The time execution surface for the Ackley function (y_2):

$$\begin{aligned}
 y_1 = & 3.19427 - 9.64494E - 04x_1 - 0.248918x_2 - 0.260315x_3 + 0.00982920x_4 \\
 & - 0.00220977x_5 + 0.000213333x_1x_2 - 2.21111E - 04x_1x_3 + 0.000149136x_1x_4 \\
 & + 1.35556E - 06x_1x_5 + 0.0283750x_2x_3 - 0.00336111x_2x_4 + 0.000143906x_2x_5 \\
 & + 0.00816667x_3x_4 + 0.000201250x_3x_5 + 1.07639E - 05x_4x_5
 \end{aligned}
 \tag{12}$$

The number of iteration surface for the Ackley function (y_3):

$$\begin{aligned}
 y_3 = & 11.5064 + 0.0201019x_1 + 0.512674x_2 + 0.559201x_3 - 0.211343x_4 \\
 & + 0.00434028x_5 - 0.00333333x_1x_2 + 0.00111111x_1x_3 - 0.00148148x_1x_4 \\
 & + 2.77778E - 06x_5 - 0.0625000x_2x_3 + 0.0277778x_2x_4 + 0.000156250x_2x_5 \\
 & + 0.0277778x_3x_4 - 4.68750E - 04x_3x_5 - 2.08333E - 04x_4x_5
 \end{aligned}
 \tag{13}$$

The objective function surface for the Rastrigin function (y_1):

$$\begin{aligned}
 Y_1 = & 38.5052 + 0.0296916x_1 + 8.45343x_2 + 3.47633x_3 + 3.01223x_4 \\
 & - 0.0229248x_5 - 0.0188956x_1x_2 + 0.00478616x_1x_3 + 0.00731104x_1x_4 \\
 & - 1.03883E - 04x_1x_5 - 0.288790x_2x_3 - 0.487949x_2x_4 + 0.00295977x_2x_5 \\
 & - 0.315704x_3x_4 - 2.05134E - 04x_3x_5 + 0.00231603x_4x_5
 \end{aligned}
 \tag{14}$$

The time execution surface for the Rastrigin function (y_2):

$$\begin{aligned}
 Y_2 = & 4.26218 + 0.000353820x_1 - 0.439723x_2 - 0.426627x_3 + 0.00826078x_4 \\
 & - 0.00226608x_5 - 2.55500E - 04x_1x_2 + 0.000104389x_1x_3 + 8.09630E - 05x_1x_4 \\
 & + 4.83472E - 07x_1x_5 + 0.0583781x_2x_3 - 0.00410972x_2x_4 + 0.000151867x_2x_5 \\
 & + 0.000165278x_3x_4 + 0.000198133x_3x_5 + 1.38924E - 05x_4x_5
 \end{aligned}
 \tag{15}$$

The number of iteration surface for the Rastrigin function (y_3):

$$\begin{aligned}
 Y_3 = & 14.7940 + 0.117650x_1 + 2.27370x_2 + 2.67040x_3 - 0.191397x_4 \\
 & - 0.0120052x_5 + 0.00611111x_1x_2 - 0.0105556x_1x_3 - 0.00567901x_1x_4 \\
 & - 1.52778E - 05x_1x_5 - 0.343750x_2x_3 + 0.0138889x_2x_4 + 7.81250E - 05x_2x_5 \\
 & - 0.0138889x_3x_4 + 0.000859375x_3x_5 + 0.000798611x_4x_5
 \end{aligned}
 \tag{16}$$

Step 6: Optimize efficiency surfaces and response surfaces

To find the optimal parameters of the COA, the surfaces obtained for efficiency (Eqs. 7 and 128 are optimized with Lingo software and the values of the independent variables are determined in Table 4 (Input).

Then, to calculate the values of the corresponding response variables, the obtained values of the independent

Table 4 The optimal values of independent variables and responses from DSM method

Input	Independent variables	Optimal values of Ackley	Optimal values of Rastrigin
Number of cuckoos	X_1	2.086 \approx 3	1.234 \approx 2
Min number of eggs	X_2	4.58 \approx 4	1.234 \approx 2
Max number of eggs	X_3	6.128 \approx 6	5.1167 \approx 5
Number of clusters	X_4	2.08 \approx 2	1.234 \approx 1
Maximum number of cuckoos	X_5	1.2 \approx 2	1.234 \approx 2
Output	Response variables	Optimal values of Ackley	Optimal values of Rastrigin
Objective function	Y_1	2.966	65.9
Execution time	Y_2	1.2	1.05
Number of iterations	Y_3	15.72 \approx 16	10.1 \approx 10

variables (input of Table 4) are placed in the output surfaces and the values of the response variables are calculated according to Table 4 (output).

Validation of the proposed DSM method compared to similar approaches

In this section, the proposed DSM method is compared with similar methods through different approaches including numerical results, Najafi and Behnoud (2015) method, Taguchi method and general comparison of all methods.

Comparison of analytical and numerical results of DSM method (validation I)

In this step, using the optimal configuration obtained from the proposed algorithm of the paper, the COA is executed 10 times with the help of the MATLAB software. This process is performed separately for both the Ackley and Rastrigin functions. It should be noted that because the independent variables (inputs) must be integers, the previously obtained optimal variables are rounded out according to Table 4. After executing the COA, the average of each response variable is calculated in Table 5. This process is to validate the results of the proposed DSM method with the results of the actual implementation of the algorithm. In fact, the results of the analytical approach are compared with numerical results. To facilitate the comparison of the results of both methods, the absolute value of the difference of the response variables in both approaches is calculated according to last column of Table 5.

As can be seen, the difference between the optimal values obtained from the DSM method and the values obtained from the implementation of the algorithm is very

small, and this indicates the optimality of the proposed DSM method.

Comparison of numerical and analytical results of the Najafi and Behnoud method (validation II)

In this section, the results of the proposed method are compared with the method of Najafi and Behnoud (2015) that were observed in the literature review. In this method, first, a central composite design was created, and then using the data related to this design, the complete second-order model was fitted. Then the optimal values of the parameters are determined by solving the non-linear model. Then, the efficiency of the problems solved by the algorithm is measured by considering the obtained parameters as inputs of the DEA method and the most efficient configuration of the genetic algorithm is determined. In this section, in order to validate the proposed DSM method, Najafi and Behnoud's (2015) method are implemented for the Ackley and Rastrigin functions. As can be seen from the process of this method, the algorithm parameter setting dose only pays attention to the response value of the objective function, and other important outputs such as execution time and number of iterations are not considered. The process of the Najafi and Behnoud (2015) methods are as follows.

Step 1: Determine the problem variables

Input variables (parameters affecting the performance of the algorithm) are identified, which are the same as input variables of the DSM method. Also, the output is the value of the objective function of the problem. Unlike the proposed DSM method, only one response is considered that is the value of the objective function of the problem, and the execution time and number of iterations are ignored.

Table 5 Tables of validation of the proposed DSM method compared to similar approaches

Comparison of numerical and analytical results from DSM method					
Function	Response variables	DSM method (analytical)	Algorithm execution (numerical)	Difference	
Ackley	Y_1	2.966	2.9932	0.0272	
	Y_2	1.2	0.9291	0.16	
	Y_3	16	18	2	
Rastrigin	Y_1	65.9	43.85	22.05	
	Y_2	1.9	0.89	1.01	
	Y_3	29	30	1	
The optimal values of independent variables and responses from Najafi and Behnoud method					
Input	Independent variables	Ackley function	Rastrigin function		
Number of cuckoos	X_1	20	5		
Min number of eggs	X_2	2	2		
Max number of eggs	X_3	3	3		
Number of clusters	X_4	2	2		
Maximum number of cuckoos	X_5	50	50		
Output	Response variables	Ackley function	Rastrigin function		
Objective function	Y_1	2.657	65.71		
Execution time	Y_2	1.91	2.38		
Number of iteration	Y_3	14.10	24.9		
Comparison of numerical and analytical results from Najafi and Behnoud method					
Function	Output	Response variables	Najafi and Behnoud method (analytical)	Algorithm execution (numerical)	Difference
Ackley	Objective function	Y_1	2.657	2.96	0.303
	Execution time	Y_2	19.1	1.36	17.74
	Number of iteration	Y_3	14	17	3
Rastrigin	Objective function	Y_1	65.71	8.1456	57.56
	Execution time	Y_2	2.38	1.04	1.34
	Number of iteration	Y_3	25	34	9

Step 2: Calculate the values of the variables

The values of the inputs and the corresponding value of the objective function are determined for the COA similar to the DSM method (Table 3).

Step 3: Surface of objective function by RSM

In order to implement the RSM method for the step 2 data, the response surface is created according to the values of the inputs for the output of the value of the objective function. Similarly, the response surface is the value of the objective function for the Ackley and Rastrigin functions according to Eqs. 9 and 12.

Step 4: Optimization of objective function surface

In order to determine the input parameters, the response surface of the value of the objective function (Eqs. 9 and 12) is considered, and the constraints related to the boundaries of the

parameters of meta-heuristic are considered. Finally, the mathematical model of parameter setting related to the Ackley and Rastrigin functions is 17 and 18, respectively. These models are optimized with the Lingo software, and the optimal values obtained for both functions are shown in Table 5 (input).

$$y_1 = 2.87342 + 0.000230282x_1 + 0.00919271x_2 + 0.00825863x_3 + 0.00982920x_4 + 7.13368E - 06x_5 + 1.82222E - 05x_1x_2 - 4.05556E - 05x_1x_3 - 1.10617E - 05x_1x_4 + 7.80556E - 08x_1x_5 - 2.75000E - 04x_2x_3 - 0.00159722x_2x_4 + 2.18750E - 06x_2x_5 + 0.000227778x_3x_4 - 4.23437E - 06x_3x_5 + 3.33333E - 07x_4x_5$$

S.t.

$$\begin{aligned} 5 &\leq x_1 \leq 20 \\ 2 &\leq x_2 \leq 4 \\ 3 &\leq x_3 \leq 5 \\ 2 &\leq x_4 \leq 5 \\ 10 &\leq x_5 \leq 50 \end{aligned} \quad (17)$$

$$y_1 = 38.5052 + 0.0296916x_1 + 8.45343x_2 + 3.47633x_3 + 3.01223x_4 - 0.0229248x_5 - 0.0188956x_1x_2 + 0.00478616x_1x_3 + 0.00731104x_1x_4 - 1.03883E - 04x_1x_5 - 0.288790x_2x_3 - 0.487949x_2x_4 + 0.00295977x_2x_5 - 0.315704x_3x_4 - 2.05134E - 04x_3x_5 + 0.00231603x_4x_5$$

S.t.

$$\begin{aligned} 10 &\leq x_5 \leq 50 \\ 5 &\leq x_1 \leq 20 \\ 2 &\leq x_2 \leq 4 \\ 3 &\leq x_3 \leq 5 \\ 2 &\leq x_4 \leq 5 \\ 10 &\leq x_5 \leq 50 \end{aligned} \tag{18}$$

The optimal values obtained for the COA parameters are placed in the response surfaces (Eqs. 11, 12, 13, 14, 15, and 16), and the values are calculated according to Table 5 (output).

Step 5: Comparison of the results

In this step, using the input variables obtained in step 4, the COA for both the Ackley and Rastrigin functions, with the help of the MATLAB software, is executed 10 times, and the average of the obtained response variables (numerical) to compare with the result obtained in step 4 (analytical). For ease of comparison, the absolute value of the difference in the results is calculated in Table 5. According to the results, it can be seen that Najafi and Behnoud’s (2015) methods have a big difference in terms of numerical and analytical, while in the proposed method (Table 5), this difference was small.

Comparison of the results of the Taguchi method with DSM (validation III)

As mentioned in the literature review, one of the most common tools used to parameter setting of meta-heuristic algorithms is the Taguchi method. In the following, the Taguchi and RSM methods are implemented for both of the Ackley and Rastrigin functions, and for each function, responses are considered separately, and the results are shown in Fig. 4. As mentioned earlier, this method only optimizes one response. Figure 4 (a) shows that considering the response value of the objective function, the best values for the input parameters are 20, 4, 3, 2, and 50. But if the execution time is examined (b), these optimal values change to 5, 2, 3, 2, and 10. Also, considering the results of response, the number of iterations (c) in Taguchi method are 20, 2, 3, 2, and 10. According to the different results of Taguchi method, the DSM method is implemented and the efficiency response is considered (d). To determine the most important factor, RSM method was implemented, the results of which can be seen in Fig. 4. When the value of the objective function is considered as the

response, the most important parameter is mini number of egg (e), and considering the execution time and the number of iterations as the response (f and g), the most important input variables will be maximum number of cuckoo and number of clusters, respectively. Here, too, the efficiency response is used because of the different results, and as can be seen (h), all inputs are of almost equal importance. This process is performed similarly for the Rastrigin function, and the results are shown in Fig. 4 (i–p).

Comparison of DSM, Taguchi, and Najafi and Behnoud methods (validation IV)

Figure 5 is based on the results obtained from the previous sections. As can be seen, the proposed DSM method performs better than other methods in all three responses of the value of the objective function, the execution time and the number of iterations of the algorithm. In the Ackley function, it was much better in terms of execution time, and in Rastrigin function, it was much better in terms of number of iteration. It should be noted that according to the different results of Taguchi method, the average of these values has been considered.

In order to compare the entire configuration created by the proposed DSM method with the Najafi and Behnoud and Taguchi methods in terms of both input and output values, the configuration efficiency obtained from the DSM method is compared with the configuration efficiency of other methods. The values for the DSM method, Najafi and Behnoud (2015) method, and Taguchi on the Ackley function are, 45.3779, 3.64499, and 2.78653, respectively. Also for the Rastrigin function are 48.8649, 2.13645, and 2.03467. In order to better compare the three methods, we allow the DEA model to have an efficiency value of more than one. It can be seen that the configuration created by the DSM method in both Ackley and Rastrigin functions is more efficient than other methods, and this indicates the superiority of the DSM method. Due to the importance of parameter setting, the proposed method can be used in various problems such as repairs’ scheduling (Al-Refaei & Al-Hawadi, 2021), supply chain network design (Hasani et al., 2021; Hosnavi et al., 2019; Khalili et al., 2017), and vehicle routing (Khalili et al., 2016; Latorre-Biel et al., 2021).

Implementation of the proposed DSM method for the inverse logistics problem of COVID-19 waste

In this section, the reverse logistics model of COVID-19 waste presented by Shadkam (2021a, 2021b, 2021c) is reviewed. After describing the model, it will be optimized using the proposed method of DSM and cuckoo optimization algorithm.

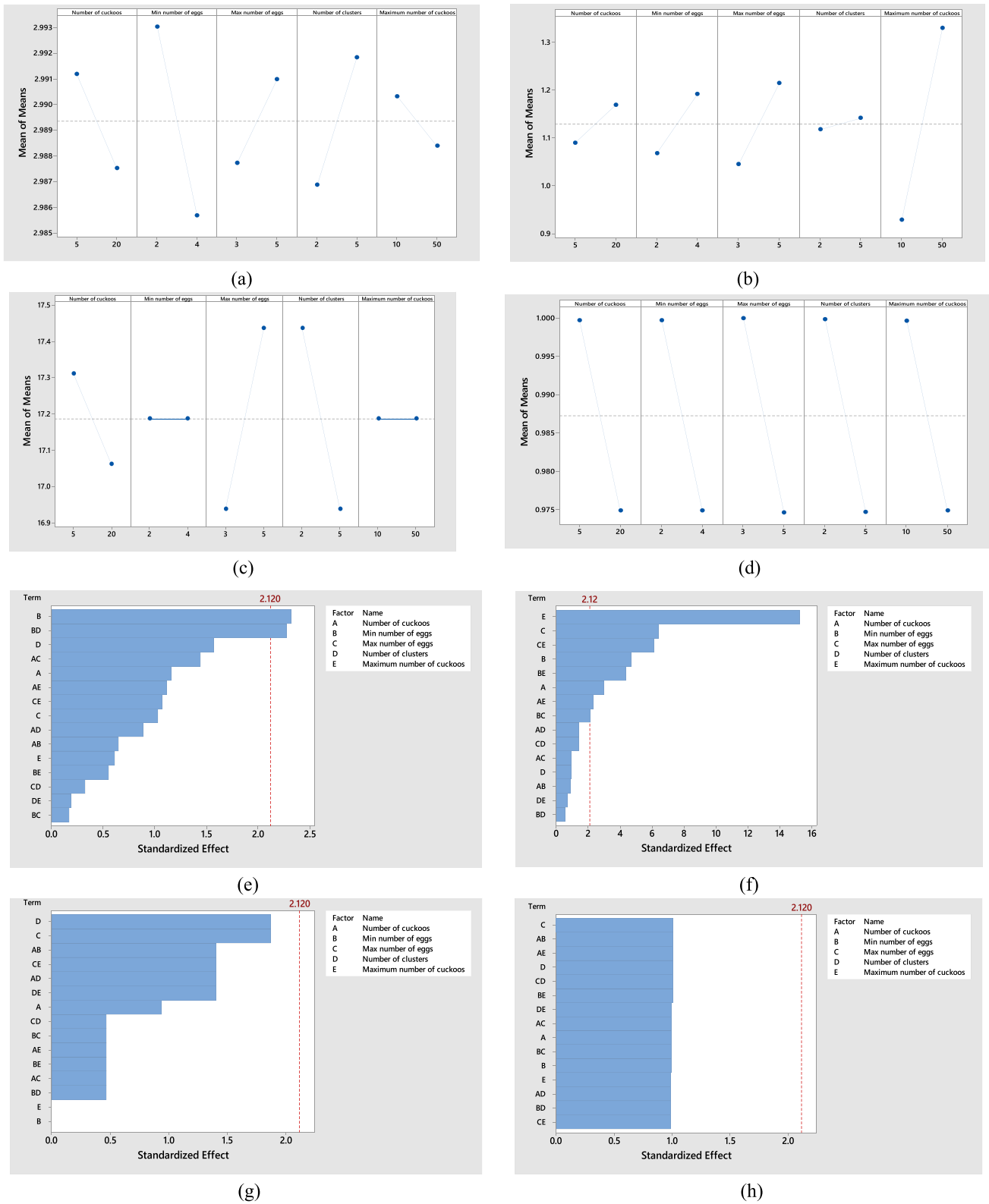
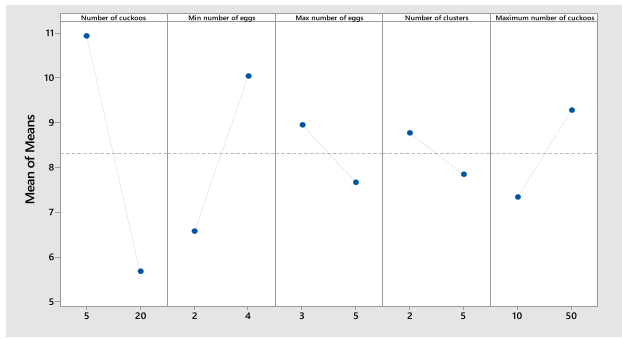
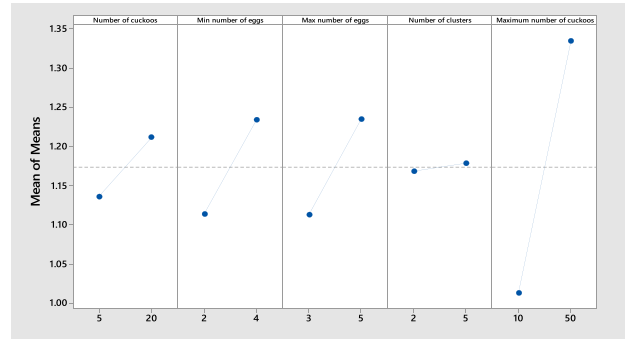


Fig. 4 The main effects plot for the means of the Ackley function. **a** Objective function. **b** Execution time. **c** Number of iterations. **d** Efficiency and Pareto chart of the standardized effects of the Ackley function. **e** Objective function. **f** Execution time. **g** Number of iterations. **h** Efficiency and main effects plot for the means of the Ras-

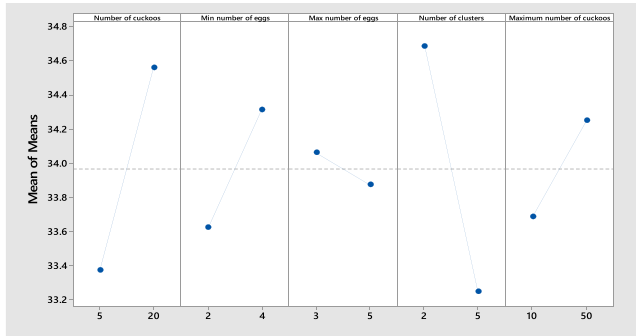
trigin function. **i** Objective function. **j** Execution time. **k** Number of iterations. **l** Efficiency and Pareto chart of the standardized effects of the Rastrigin function. **m** Objective function. **n** Execution time. **o** Number of iterations. **p** Efficiency



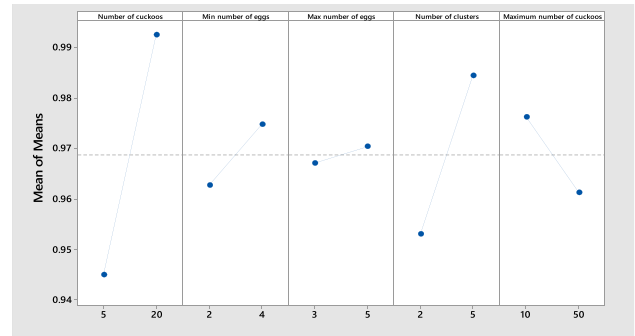
(i)



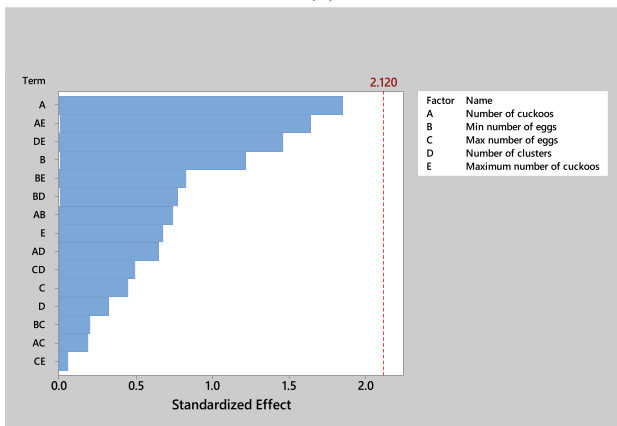
(j)



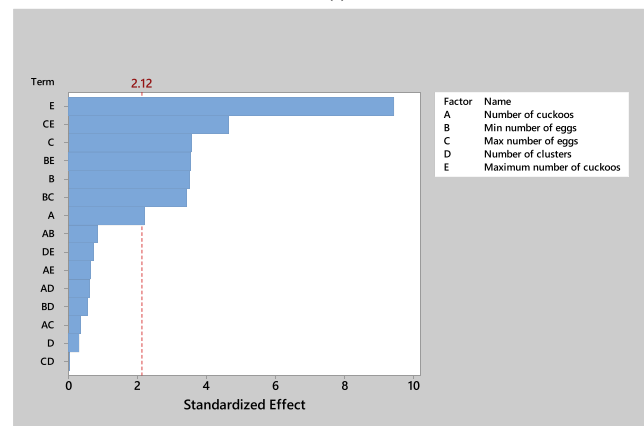
(k)



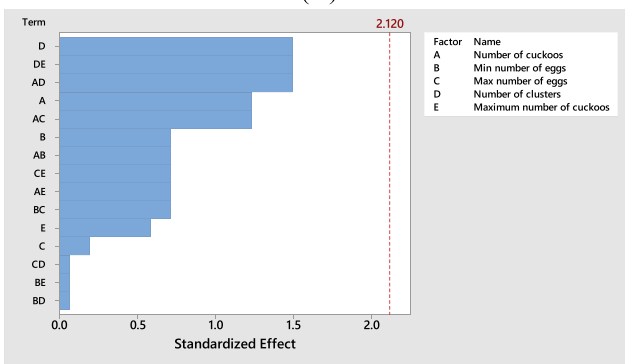
(l)



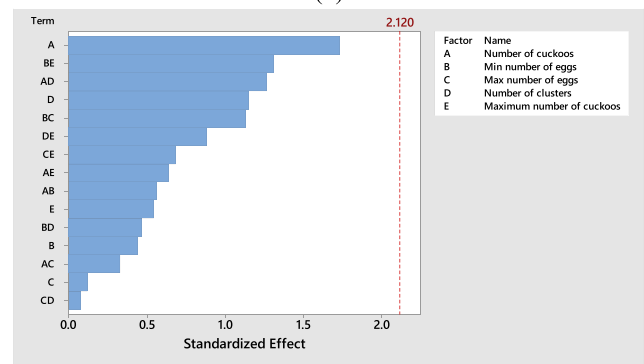
(m)



(n)



(o)



(p)

Fig. 4 (continued)

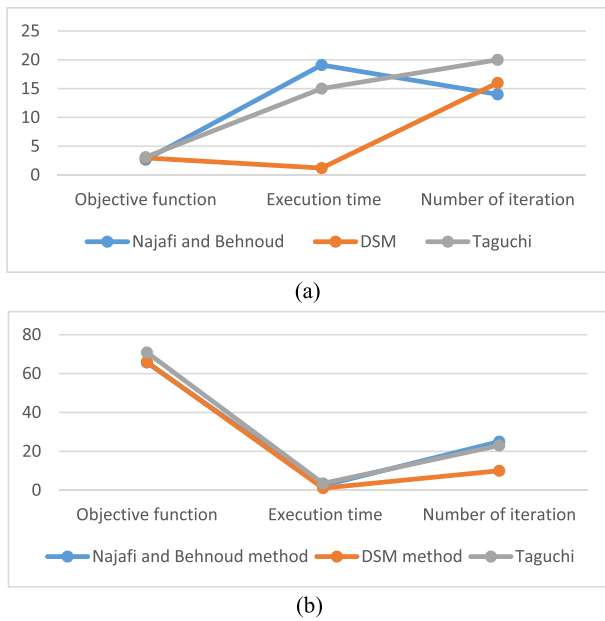


Fig. 5 Comparison of response values in DSM and Najafi and Behnoud method. **a** Ackley. **b** Rastrigin

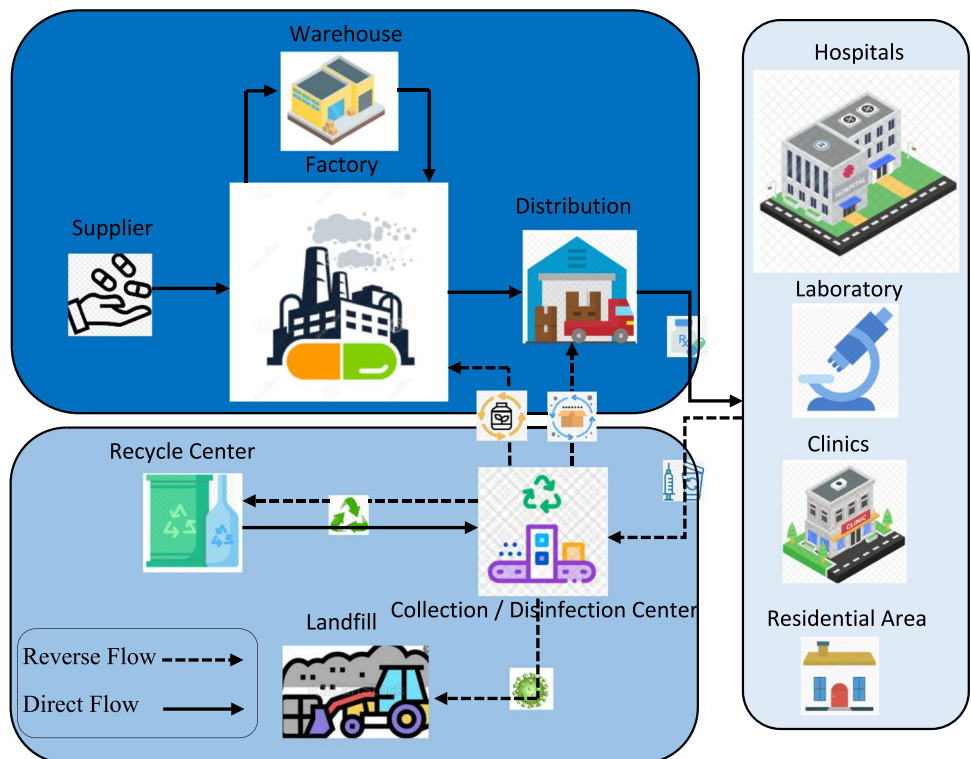
Problem description

The proposed model is a direct and reverse single-cycle and single-purpose logistics network that includes three parts: production, consumption, and recycling. These three

sections are shown in Fig. 6. The production part includes suppliers, factories, warehouses, and distribution centers. These departments are responsible for the production and production of coronavirus (vaccine) drugs. The raw materials are sent to the factory, and from the factory, coronavirus (vaccine) drugs are transported to distribution centers, while the rest are stored. Coronavirus drugs (vaccines) are delivered from distribution centers to the consumption department. Consumption includes hospitals, clinics, laboratories, and residential areas that use corona (vaccine) drugs. The recycling part includes a collection/disinfection center, a recycling center, and a landfill. In the reverse flow, the wastes of coronavirus drugs (vaccine) are transferred from the consumption section to the collection/disinfection center. In this center, medical wastes are collected and disinfected, and from there, depending on the type of waste, it is transferred to distribution centers, factories, landfills, or recycling sites. It is assumed that corona vaccine wastes after disinfection are divided into two categories: recyclable and non-recyclable. Recyclable wastes are also divided into three categories.

A batch must be completely recycled and reused as a raw material. This group is recyclable and not dangerous and is sent to the recycling center for reuse in the factory. The second group is sent directly to the factory for further use in the production of corona medicine, and the third group is sent to the distribution center for use in the process of transporting drugs and vaccines. Non-recyclable

Fig. 6 Schematic of the proposed reverse logistics network for corona drug wastes (vaccine) Shadkam (2021a, 2021b, 2021c)



wastes are sent directly to the landfill for safe disposal and disposal. In this way, the proposed network will be a closed-loop logistics network.

Index

I	Index of potential supplier centers $i \in I$
J	Index of fixed factory centers $j \in J$
K	Index of potential distribution centers $k \in K$
L	Index of fixed consumer centers (including hospital, clinic, laboratory, residential area) $l \in L$
M	Index of potential collection/disinfection centers $m \in M$
P	Index of potential recycle centers $p \in P$
N	Index of potential landfill centers $n \in N$

Parameters

d_l	Consumer demand (drug coronavirus and vaccine) from consumption center l
r_l	Consumer returns (wastes of drug coronavirus and vaccine) from consumption center l
B_m	The return rate of the wastes of drug corona from the consumption center l to the collection/disinfection center m
$B_o, o \in \{j, p, n, k\}$	Return rate from the collection/disinfection center m to: the factory center j , the recycle center p , the landfill center n , the distribution center k
$f_o, o \in \{k, m, p, n\}$	The fixed cost of building a distribution center at the site k , collection/disinfection center at the site m , recycle center at the site p , landfill center at the site n
$c_{ij}, c_{jk}, c_{kl}, c_{lm}$	Total transportation costs of each unit from the supplier's center i to the factory's center j , the factory's center j to distribution center k , the distribution center k to the consumption's center l , consumption center l to collection/disinfection center m

d_l	Consumer demand (drug coronavirus and vaccine) from consumption center l
cq_{ij}	Total transportation costs of each unit from the factory's center j to the its warehouse center
cq_{jk}	Total transportation costs of each unit from the warehouse j to the distribution center k
$c_{mo}, o \in \{p, n, j, k\}$	Total transportation costs of the returned unit from the collection/disinfection center m to the recycle center p , the landfill center n , the factory's center j , the distribution center k
$Ca_o, o \in \{i, j, k, m, p, n\}$	The capacity of the supplier at site i , factory at site j , distribution center at the site k , collection/disinfection center at site m , recycle center at site p , landfill center at site n
Ca_{jj}	The warehouse capacity at the place j
$Cr_o, o \in \{j, k\}$	The factory's capacity j , the distribution capacity k to wastes recycling
h_j	The cost of maintaining each unit in warehouse j

Variables

$Y_o = \begin{cases} 1 & o \in \{m, k, p, n\} \\ 0 & \text{otherwise} \end{cases}$	If the collection/disinfection center m is constructed 1 otherwise 0, if the distribution center k is constructed 1 otherwise 0, if the recycle center p is constructed 1 otherwise 0, if the landfill center n is constructed 1 otherwise 0
$X_{ij}, X_{jk}, X_{kl}, X_{lm}$	The amount of medical products flow from the supplier's center i to the factory's center j , the factory's center j to the distribution center k , the distribution center k to the consumption center l , the consumption center l to the collection/disinfection center m
Q_{jj}	The amount of medical products flow from the factory's center j to its warehouse
Q_{jk}	The amount of medical products flow from the warehouse j to the distribution center k
$X_{mo}, o \in \{p, n, j, k\}$	The amount of return flow of medical products from the collection/disinfection center m to the recycle center p , landfill centers n , factory's center j , distribution center k

$Y_o = \begin{cases} 1, & o \in \{m, k, p, n\} \\ 0, & \text{otherwise} \end{cases}$	If the collection/disinfection center m is constructed 1 otherwise 0, if the distribution center k is constructed 1 otherwise 0, if the recycle center p is constructed 1 otherwise 0, if the landfill center n is constructed 1 otherwise 0
U_j	The amount of medical products in warehouse j as inventory

Mathematical model

The mixed integer model for integrated reverse logistics network with the aim of reducing costs is presented as follows:

$$MinTC = f_1 + f_2 + f_3 + f_4 + f_5 \tag{19}$$

S.t.

$$\sum_{k \in K} X_{kl} = d_l \quad \forall l \in L \tag{20}$$

$$\sum_{m \in M} X_{lm} = r_l \quad \forall l \in L \tag{21}$$

$$\sum_{p \in P, n \in N, j \in J, k \in K} X_{mo} = B_o \sum_{l \in L} X_{lm} \quad \forall o \in \{p, n, j, k\}, \forall m \in M \tag{22}$$

$$\sum_{j \in J} (X_{jk} + Q_{jk}) = \sum_{l \in L} X_{kl} - \sum_{m \in M} X_{mk} \quad \forall k \in K \tag{23}$$

$$\sum_{k \in K} (X_{jk} + Q_{jj}) = \sum_{l \in L} X_{ij} + \sum_{m \in M} X_{mj} \quad \forall j \in J \tag{24}$$

$$U_j = Q_{jj} - \sum_{k \in K} Q_{jk} \quad \forall j \in J \tag{25}$$

$$\sum_{k \in K} Q_{jk} \leq Q_{jj} \quad \forall j \in J \tag{26}$$

$$\sum_{j \in J} X_{ij} \leq Ca_i \quad \forall i \in I \tag{27}$$

$$\sum_{k \in K} X_{jk} + \sum_{s \in S} Q_{jj} \leq Ca_i \quad \forall j \in J \tag{28}$$

$$\sum_{l \in L} X_{kl} \leq Ca_k Y_k \quad \forall k \in K \tag{29}$$

$$\sum_{o \in \{p, n, j, k\}} \sum_{p \in P, n \in N, j \in J, k \in K} X_{mo} B_o \leq Ca_m Y_m \quad \forall m \in M \tag{30}$$

$$\sum_{m \in M} X_{mo} \leq Cr_o Y_o \quad \forall o \in \{k, j\}, \forall k \in K, \forall j \in J \tag{31}$$

$$\sum_{m \in M} X_{mo} \leq Ca_o Y_o \quad \forall o \in \{n, p\}, \forall n \in N, \forall p \in P \tag{32}$$

$$U \leq Ca_{jj} \quad \forall j \in J \tag{33}$$

$$\sum_{m \in M, k \in K, p \in P, n \in N} Y_o \geq 1 \quad \forall o \in \{m, k, p, n\} \tag{34}$$

$$\sum_{o \in \{j, p, n, k\}} B_o = 1 \tag{35}$$

$$Y_o \in \{0, 1\} \quad \forall o \in \{m, k, p, n\}, \forall m \in M, \forall k \in K, \forall p \in P, n \in N \tag{36}$$

$$X_{ij}, X_{jk}, Q_{jj}, U_j, X_{kl}, Q_{jk}, X_{lm}, X_{mo} \geq 0, \quad \forall o \in \{p, n, j, k\}, \forall i \in I, \forall j \in J, \forall k \in K, \forall l \in L, \forall m \in M, \forall n \in N, \forall p \in P \tag{37}$$

$$f_1 = \sum_{o \in \{m, k, p, n\}} \sum_{m \in M, k \in K, p \in P, n \in N} f_o Y_o \tag{38}$$

$$f_2 = \sum_{i \in I} \sum_{j \in J} c_{ij} X_{ij} + \sum_{j \in J} \sum_{k \in K} c_{jk} X_{jk} + \sum_{k \in K} \sum_{l \in L} c_{kl} X_{kl} + \sum_{l \in L} \sum_{m \in M} c_{lm} X_{lm} \tag{39}$$

$$f_3 = \sum_{j \in J} c q_{jj} Q_{jj} + \sum_{j \in J} \sum_{k \in K} c q_{jk} Q_{jk} \tag{40}$$

$$f_4 = \sum_{o \in \{p, n, j, k\}} \sum_{m \in M} \sum_{p \in P, n \in N, j \in J, k \in K} c_{mo} X_{mo} \tag{41}$$

$$f_5 = \sum_{j \in J} h_j U_j \tag{42}$$

In Eq. 19, the objective functions f_1 to f_5 represent fixed cost, direct transportation costs, warehouse transportation costs, reverse transportation costs, and inventory costs. These objective functions indicate the minimization of the cost of building facilities, the cost of transporting medical products directly and inversely, and inventory in accordance with Eqs. 38, 39, 40, 41, and 42. Constraints (20) and (21) ensure that all medical needs are met in direct flow and that all returned waste is collected from consumers in reverse flow. Constraints (22) to (25) are related to the flow level in the centers. Constraint (26) ensures that the output flow of the warehouse is less than the total revenue stream of the warehouse. Constraints (27) to (33) ensure that the flow is only between the centers where the facility is constructed and that the total flow in each center does not exceed its capacity. Constraint (34) ensures that at least one potential center is active. Constraints (35) ensure that the sum of the return waste coefficients is 1. Constraints (36) and (37) determine the types of model decision variables.

Solving the COVID-19 waste management model using the DSM method

In this section, the parameters of the cuckoo optimization algorithm for use in the mentioned logistics network are

Table 6 Optimal values of the cuckoo meta-heuristic algorithm parameters and optimal criteria for the proposed logistics problem from experimental method

	Experimental method	DSM method
Parameter		
Number of clusters	4	3
Initial number of cuckoos	4	6
Max number of cuckoos	20	17
Min number of eggs	3	4
Max number of eggs	5	6
Criteria		
Objective function	1,942,717.3191	1,911,509.8228
Number of iteration	201	201
Execution time (s)	5483	4765

examined. These parameters are examined and compared using two approaches, including the experimental approach and the DSM method. The optimal parameters of the cuckoo algorithm using the experimental approach are shown in Table 6. Also, after implementing the DSM method in a similar way in the previous sections, the results are as shown in Table 6. In order to compare the performance of both methods, the criteria of the value of the objective function, execution time, and number of iterations are calculated using the configuration of both methods (Table 6). Also, the convergence diagram of the value of the objective function and the number of iterations for both approaches is shown in Fig. 7. As can be seen, using the parameters created from the proposed method of the paper, a better objective function can be achieved in the same iterations with less execution time than the experimental approach, which shows the optimal performance of the proposed method.

Also, in order to compare the efficiency of both methods, the values of Table 6 are considered as inputs, and the values of Table 6 are considered as outputs, and after implementing the CCR model of data envelopment analysis, the efficiency values are calculated. To better differentiate between the two methods, the CCR model is allowed to obtain performance values greater than one. The results show an efficiency value of 1.23456 for the proposed method and efficiency value of 0.98753 for the experimental method. Therefore, it can be seen that the efficiency of the proposed method is better than the experimental method.

Conclusion

In this paper, the hybrid DSM method was presented by combining two methods of RSM and DEA. One of the advantages of the DSM method is the reduction in the number of response surfaces to one efficiency surface, and

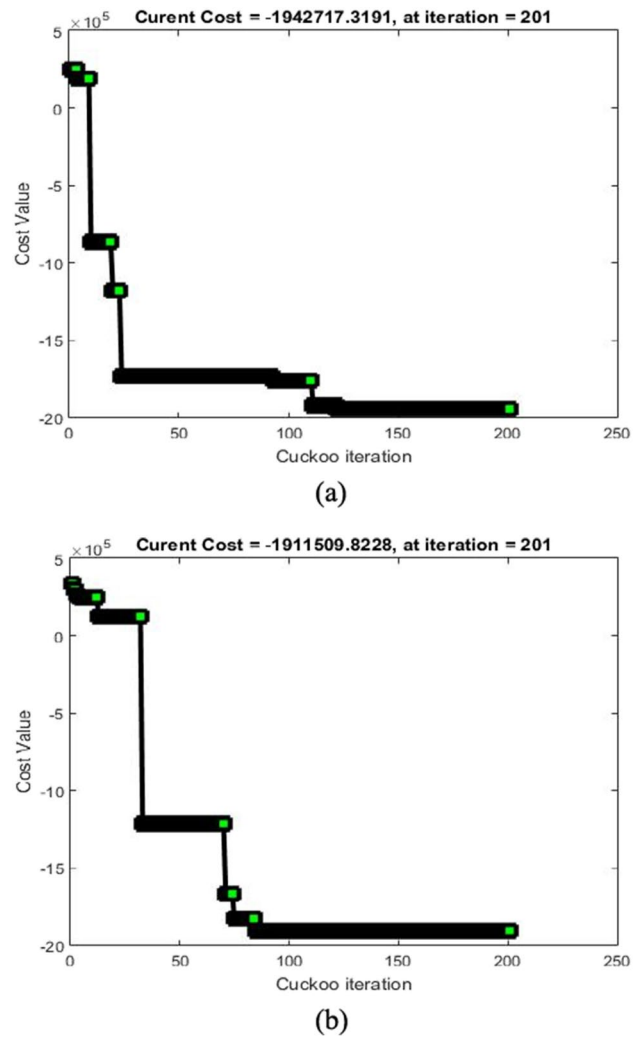


Fig. 7 The implementation of the cuckoo algorithm on the proposed inverse logistics network based on the **a** experimental method and **b** DSM method

instead of optimizing multiple response surfaces for the problem outputs, only efficiency surface optimization is considered. With this proposed method, in addition to optimizing the objective function of the problem, it is possible to maximize its efficiency simultaneously. In this paper, the hybrid DSM method was used to set the optimal parameters of the COA. In order to evaluate the performance of the DSM method, two types of problems were investigated, which included standard functions and COVID-19 waste management problem. Standard functions include Ackley and Rastrigin functions. In order to validate the proposed method, the Taguchi and the Najafi and Behnoud methods were implemented and the results of the proposed method were compared with these methods. The numerical results indicate the higher efficiency of the proposed DSM hybrid algorithm. Then, the cuckoo algorithm parameter was adjusted using the proposed method for the inverse logistics

problem of COVID-19 waste, and the results were compared with the experimental approach which shows the superiority of the proposed method over the experimental method according to the objective function, execution time and efficiency value.

Finally, it can be said that by setting the parameters of meta-heuristic algorithms scientifically, errors related to trial and error can be avoided. As future research, the DSM method can be used to parameterize other meta-heuristic algorithms, and by assigning appropriate values to the effective parameters in the algorithms, a suitable and acceptable solution can be achieved in the shortest time and with the least error and high reliability. Also, the process in this paper can also be applied similarly to other real-world problems.

Author contribution The whole process of the preparing the paper, including coding, modeling, and writing, etc., has been done by Elham Shadkam.

Code availability All paper codes are written by the author with the Lingo and Minitab software and can be presented if needed.

Declarations

Consent for publication The author agrees to participate and publish.

Competing interests The author declares no competing interests.

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