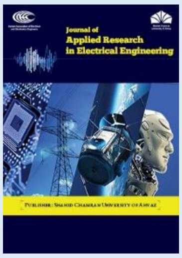
J. Appl. Res. Electr. Eng., Vol. 3, No. 1, pp. 19-32, 2024 DOI: https://doi.org/10.22055/jaree.2024.45869.1102

Shahid Chamran University of Ahvaz

Iranian Association of Electrical and Electronics Engineers

Journal of Applied Research in Electrical Engineering

E-ISSN: 2783-2864
P-ISSN: 2717-414X
Homepage: https://jaree.scu.ac.ir/



Research Article

Solving Combined Economic Emission Dispatch Problem Using the Rain Optimization Algorithm

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Abstract: An obstacle in managing economic dispatch is the integration of diverse factors such as pollution and heat. By introducing the price penalty coefficient, this class of two-objective problems is transformable to a single-objective form. The formulation considers various practical constraints of the system, including non-smooth cost functions, the balance of production, demand, and losses, and the limitation of power generation by active generators. One of the fundamental difficulties in tackling these types of complex problems lies in the algorithms and solvers employed to identify optimal solutions for a range of operation problems. The rain optimization algorithm (ROA) has been utilized in this paper. ROA is derived from the inherent tendency of raindrops to seek out the lowest areas on the earth's surface. This algorithm possesses exceptional efficacy in resolving problems characterized by stringent constraints and is adept at circumventing local optima. To validate the proposed method for cost and emission reduction, the scheme under consideration has been developed using software on standard systems. The implementation of the scenarios has revealed that the limits of the power system have led to a decrease in the overall generation cost of fossil fuel generation units. In this article, the ROA algorithm managed to plan the production with an optimal cost of 38481.54 dollars in case 1, which obtained a more optimal value than all the compared algorithms. This reduction in cost is considered one of the triumphs of the optimization problems. The results showcased and juxtaposed in the software simulation verify the effective performance of the suggested approach in comparison to prior research.

Keywords: EED, smooth cost function, penalty coefficient, rain optimization algorithm.

Article history
Received 17 January 2024; Revised 23 April 2024; Accepted 14 May 2024; Published online 26 June 2024.

How to cite this article
Narges Yousefi, Mahmood Joorabian, and Mahyar Abasi, " Solving combined economic emission dispatch problem using the rain optimization algorithm," *J. Appl. Res. Electr. Eng.*, Vol. 3, No. 1, pp. 19-32, 2024.
DOI: https://doi.org/10.22055/jaree.2024.45869.1102

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Nomenclature

Variables	Description
Fi	i-th power plant fuel cost
$Fcost$	Total power plant fuel cost
a_i, b_i, c_i, d_i	Cost coefficients of i-th power plant
P_d	System consuming power
P_L	Transmission line loss
$P_{i.min}$	Minimum admissible power generation in i-th power plant
$P_{i.max}$	Maximum admissible power generation in i-th power plant
α	drop percentage volume that can be absorbed, depending on the soil property

Variables	Description
n	Number of power plants
e_i, f_i	Return coefficients of knee points of i-th power plant cost
B_{ij} , B_{oi} , B_{oo}	Transmission line loss function coefficients
h_i	Utilization factor
φ_T	The value of the balance coefficient
w_1 , w_2	Wight coefficient
E_{cost}	Total power plants pollution amount
$\beta_i . \gamma_i . c_i . \lambda_i$	power plants pollution coefficient

Variables	Description	Variables	Description
$\boldsymbol{M}$	Daily hours	P_G	Power plants total power generation based on pollution power flow
$\boldsymbol{m}$	An hour of the day and night	r_1 *and* r_2	Drop radius
$\mathbf{UR_i}$	Maximum ramp rate	R	Total radius
$\boldsymbol{E_{cost}}$	Total power plant emission cost	$\mathrm{DR_i}$	Minimum ramp rate
B	Inequality constraints	A	Constraints of equality
PS	Pattern Search	V	Valve-point loading effects
L	Transmission line losses	N	Voltage limits
R	Ramp rate	P	Prohibited Operating Zones
LR	Lagrange relaxation	T	Start time limit
LI	Lambda Iteration	BBO	Biogeography-based optimizer
MHBA	Hybridizing bat algorithm with artificial bee colony	GA–WOA	Genetic algorithm-whale optimization algorithm
QP	Quadratic Programming	DE-CQPSO	Differential evolution-crossover quantum PSO
NR	Newton-Raphson	IABC	Incremental artificial bee colony
ANN	Artificial Neural Networks	CBBO	Improved biogeography-based optimization
AHNN	Adaptive Hopfield neural network	GA	Genetic algorithm
DHS	Differential harmony search method	PSO	Particle swam optimization
HPSO-GSA	Hybrid Particle swam optimization and Gravitational search algorithm	DE	Differential evolution
JAYA–TLBO	JAYA and Teaching learning-based optimization	DE-BBO	Differential evolution-Biogeography-based optimizer

1. Introduction

1.1. Research motivation

Industrialized nations have endeavored to substitute renewable energies for fossil fuels since the 19th century, driven by concerns over air pollution, climate change, and escalating fuel expenses. The studies on power system operation indicate that the concern of economic-emission dispatch (EED) is focused on efficiently supplying the anticipated generation for loads while maintaining a balance between generation and demand. The utilization of contractive methods typically yields favorable outcomes. However, when the research space becomes non-linear and non-continuous, the problem-solving process gets highly intricate and the convergence of this strategy to find the ideal solution occurs at a notably slow pace. One of the issues that is important for the power grid today is the cost of production, but with international commitments, the issue of reducing pollutant emissions has also become one of the concerns of producers. Therefore, manufacturers should think of a method for cheap production and at the same time without producing pollution. One of the solutions that can help to solve this problem is the optimal planning of the production of power plant units. Various methods have been proposed to solve these problems. In general, these methods are divided into three categories: classical, meta-heuristic and artificial intelligence. Among them, artificial intelligence and meta-heuristic methods are more popular than classical methods due to their speed and accuracy. In this article, ROA meta-heuristic method is used to solve the EED problem.

1.2. Research background and literature review

The EED problem has been solved by various optimization methods based on numerical and metaheuristic methods, which have been briefly examined in this section. In general, these methods can be classified into three categories, which include classic or traditional, modern, and combined methods. The objective of optimization is to identify the optimal solution that meets the constraints and requirements of the problem. Multiple options may exist, and the ideal solution is chosen after conducting a thorough comparison. Traditional methods are generally based on iteration techniques, which face issues such as high number of iterations and huge calculations, and finally, even in different states of the system, there is a possibility of divergence. The other category is the new methods which are defined based on the search space and have subsets of stochastic, heuristic, metaheuristic, etc., where all possible solutions are examined and finally the best solution is selected. Yet, in multi-objective problems where the objective function is transformed into a single function with defined variables, and considering the need to correct the problems of the previous two methods, the combined method helps significantly in the optimization problem and ultimately leads to more accurate solutions. However, not all these methods can solve all the optimization problems with non-smooth, non-continuous functions in the nonlinear solution space with acceptable efficiency, considering that research space is evolving and innovating. In the following, articles related to the described methods are reviewed. Power plants use the process of energy conversion to produce electricity, and the main costs of electricity production have roots in fuel costs. On the one hand, the ability to produce electricity with a high capacity is important, which can be achieved by using coal-fueled steam power plants. Moreover, reducing the negative effects on the environment is an issue that can be investigated. It is necessary to manage the system by optimizing the economic problem and reducing greenhouse gas emissions. In recent years, economic power distribution in systems has been the focus of researchers, but the problem of pollution caused by fossil fuels has not been paid special attention in these studies. In the proposed model, the problem will be transformed into an economic-emission multi-objective function, and in the same way, a new model of the said problem will be presented, where the optimization algorithm will be investigated to solve the economic power distribution problem by considering the pollution function in multi-area power systems, the general concept of which can be defined in different structures. Algorithms used are classified according to their results into traditional, modern, and combined methods, each of which has been investigated to solve the issues of the previous methods. To validate the efficacy and application of the suggested approaches, different test systems have been used under different practical conditions. Table 1 summarizes the widely used systems in power planning problems.

Table 1: Introducing the test systems adopted for solving the economic/emission dispatch problem.

TEST SYSTEM	NUMBER OF THERMAL GENERATION UNITS
Test system 1	3- IEEE3 ELD
Test system 2	4- GENERATION
Test system 3	5- IEEE14 BUS
Test system 4	6- IEEE30 BUS
Test system 5	6- IEEE26 BUS
Test system 6	7- IEEE57 BUS
Test system 7	8- IEEE25 BUS
Test system 8	10- IEEE39 BUS
Test system 9	10- IEEE24 BUS
Test system 10	13- IEEE13 ELD
Test system 11	14 -GENERATION
Test system 12	15- GENERATION
Test system 13	19- IEEE118 BUS
Test system 14	20 GENERATION
Test system 15	26 GENERATION
Test system 16	30 GENERATION
Test system 17	38 GENERATION
Test system 18	40- IEEE13 ELD
Test system 19	54 GENERATION
Test system 20	57 GENERATION
Test system 21	69- IEEE300 BUS
Test system 22	110 GENERATION
Test system 23	120 GENERATION
Test system 24	140 GENERATION

- **Review of conventional EED methods**

Conventional (traditional) techniques are among the common methods when it comes to solving the economic power/pollution problem. Among them are quadratic programming method, Newton-Raphson method, Lambda iteration, and Lagrangian relaxation [1-5]. The quadratic programming method was first developed [1-2] to deal with the economic dispatch problem by taking the line current limitations into account. The formulation of the problem with this method enables adopting a linear network model and operational constraints besides the explicit presentation of the costs exposed by transmission loss. After that, the Newton-Raphson technique was adopted [3] to address the economic dispatch problem by observing the same line current constraints. This method was formulated based on a Jacobian replacement matrix with transmission losses in terms of sensitivity factors, line current, and line resistance. The convergence of the mentioned method was achieved linearly with a very low speed. Next, the Lambda iteration technique was discussed [4] and implemented on 3, 6, 13, and 26-unit test systems. The method presented directly calculates the optimal value of Lambda for a certain power demand and is considered an efficient method for online information transmission.

In that method, generator limitations and transmission line losses were considered as problem constraints to prove its efficiency. Among other traditional methods, one can mention the technique based on Lagrangian relaxation for the EED problem [5]. In this reference, limitation on the generator, line current, and transmission line losses were considered. To perform this dispatch, the operation point of the system and network losses are also considered in the optimization process.

Issues such as the limitation of generators, line current, voltage profile, line losses, etc. are considered in these methods for the EED problem and finding the best optimal solution [6]. By carefully examining the mentioned methods, it can be seen that all of them have a high dependence on the initial solutions and also have a weak convergence or finally converge with some local optima, even in some solutions, the solution diverges. Regrettably, this technique is also accompanied by two fundamental limitations. Firstly, this approach is unsuitable for resolving non-convex or non-linear problems. Secondly, due to the high calculation time and sometimes exponential calculation time, it was unable to effectively handle a significant amount of inequality constraints, and it controlled and improved only one solution in one run, failing to solve two-variable problems.

- **Review of recent EED methods**

The methods that are included in this category are based on education-oriented, innovative, or meta-heuristic methods. Among the famous techniques of this category that were used for the EED problem are the methods of artificial neural networks, improved artificial bee colony optimization algorithm, improved biogeography optimization algorithm based on the Cauchy operator, the differential evolutionary optimization algorithm, the elitist multi-objective evolutionary optimization algorithm, and the particle swarm optimization algorithm [7-14]. Solving the economic dispatch problem by considering the piecewise quadratic cost function, based on the adaptive Hopfield artificial neural networks method, was proposed [7]. The method was tested on 3, 4, 40 and 120-unit test systems and its successful results confirmed the performance of the suggested scheme. An improved incremental artificial bee colony method was used to deal with the EED problem by observing the constraints of generators and transmission line losses [8]. Based on the local search with better convergence efficiency, modifications to the classical artificial bee colony algorithm further improved the performance and provided near-optimal solutions. In [9-10], the biogeography-based optimizer algorithm and improved biogeography-based optimization methods were presented to address the EED problem. In [9], the problem of the convex nonlinear cost function minimization was considered, where the voltage and current constraints of the transmission line were added to the problem constraints. In [10], based on the Cauchy operator with improved capabilities of local and global exploration and convergence rate, the biogeography optimization algorithm applied to the EED problem achieved more suitable results. In another study, the EED problem was addressed using a differential evolutionary optimization algorithm in the form of a multifaceted nonlinear problem [11]. The results of this technique showed that the solution converged on the local optimum and performed poorly for more complex calculations. The EED problem was presented [12-13] using the basic method of genetic optimization algorithm as well as its improved method in the form of an elitist multi-objective evolutionary algorithm. This technique provided possible solutions and, as a result, a more suitable Pareto optimal front than the multi-objective problem, which presented a better view of the solution space. Another stochastic optimization approach called particle swarm optimization was employed by [13]. This approach offers numerous benefits that are well-suited for non-convex optimization problems characterized by stringent constraints. The effectiveness of the suggested technique was assessed in a system consisting of 10 units, taking into account limitations on the generator, valve-point loading effects, and transmission losses. In another study, the economic-environmental dynamic dispatching problem including wind energy, solar photovoltaic, thermal and water power plants, taking into account the limits of slope rate limits and the influence of valve-point loading, was solved by adopting the multi-objective particle swarm optimization [14].

- **Review of combined EED methods**

In the combined methods, several algorithms are used to benefit their advantages and reduce their weaknesses in solving more complicated problems. So, they are impactful in finding global optimal solutions of economic power/pollution problems with different constraints. In [15], the combination of differential evolutionary and biogeographic algorithms was presented to solve the problem of EED of thermal power plants in power systems. The combination of both methods increased the accuracy and speed of the implementation results on the EED problem. In [16], the challenge of non-convex economic dispatching was solved by combining differential evolutionary mechanisms and harmony search algorithm. In that study, the proposed method was tested on 6, 10, 13, 15, 24, and 40 generation units with constraints such as the effects of valve-point loading, multi-fuel, slope rate limits, and prohibited operating zones. In [17], a new combination of Java methods and teaching-learning-based optimization was utilized to solve the challenge of economic distribution in non-convex and non-smooth conditions. The method was tested and evaluated on 5, 10 and 40-unit systems. The accuracy and speed of the results compared to other methods were also examined. Reference [18] presented a combination of the non-dominant elitist sorting algorithm and a modified distance-crowding sorting method to obtain a Pareto optimal front with a uniform distribution for EED problem. In that reference, the slope rate limits and the prohibited operating ones were modeled on three standard IEEE 6, 19, and 57-unit systems to evaluate the proposed method. In [19], a method based on the combination of bat-inspired algorithm and artificial bee colony with search strategy to solve large-scale, highly nonlinear, non-convex, non-smooth, non-differential, and non-continuous problems related to EED problem was introduced. In [20], a method composed of genetic algorithm and whale optimization was presented to obtain global optimal results for EED problems. The efficacy of this proposed methodology was examined on four distinct test systems and its performance was contrasted with other heuristic approaches. In [21], to solve the challenge of EED, a method relying on the combination of particle swarm optimization and time-varying acceleration coefficient was proposed.

The distribution of greenhouse gas emissions considered in this reference consisted of multi-objective optimization problems of combined economic-environmental dispatching of heat and power and dynamic economic-environmental dispatching taking into account various operational limitations. The main theoretical solutions and innovations presented in that study proposed a new test case by observing the maximum practical limitations such as the limits of the slope rate, the prohibited operating zones, and the creation of a novel methodology to choose the most optimal compromise options and guarantee a diverse range of Parto solutions that are more suitable for economic-environmental dynamic dispatch problems. And finally, a hybrid method called Differential Evolutionary Crossover Quantum Particle Swarm Optimization Algorithm was introduced [22] to deal with the EED problem. In that research, the authors took advantage of the rapid convergence of the differential evolutionary approach and the diversity of particles of genetic algorithm crossover operators. Table 2 summarizes the methods presented in the reviewed references.

1.3. Contributions and novelty

The contribution and innovation of this article is to solve EED problem based on rain optimization algorithm (ROA). In general, this article has two main contributions and objectives. The first objective is to formulate and solve the problem of economic dispatch combined with the pollution emission caused by the emission of greenhouse gases in fossil fuel power plants using the ROA method. The second objective is to consider the practical limitations in the EED problem. Since the cost function of a fossil fuel power plant is not smooth in practice and has knee-shaped points on the third curve, EED will be investigated considering this limitation. In summary, the innovations of this article are as follows:

- Solving the ED problem with two objective functions to reduce cost and pollutant
- Using the new ROA algorithm to optimize the ED problem
- Checking and verifying the results obtained with other methods

1.4. Paper organization

The subsequent sections of the paper are structured as follows. Section 2 presents the modeling of the EED problem, and then using the ROA for deal with the problem is fully introduced. In Section 3, implementation of the scheme in standard networks in MATLAB software are presented. Also, in this section, the test results of the suggested algorithm and those presented in the background research are reviewed in detail, and eventually, Section 5 provides the conclusion of the paper.

2. Proposed method

This section presents solving the emission dispatch problem based on the ROA method. In order to explain the problem, the equations and formulation of economic dispatch are first given, then the emission dispatch problem and the combination of these two dispatches are provided in the form of EED in the next subsections. In the rest of this section, the general theory of the ROA and finally the complete flowchart of the implementation of the EED problem are provided.

2.1. Economic dispatch

The economic dispatch problem minimizes the fuel cost function for the generation of a certain amount of power while satisfying the restrictions governing the generation. In this paper, the fuel cost function is modelled using a smooth quadratic and a cubic function. However, in fact, the cost function is not smooth and has local maxima and minima. To show this feature of the quadratic cost function and the second part of the function, the absolute value cost is a sinusoidal function, which are called non-smooth functions [14]. For this purpose, the cost of fuel used to produce P_i in the ith power plant is determined by F_i.

2.1.1. Smooth quadratic function of fuel cost

In this model, the smooth quadratic function of fuel cost is given in terms of the power generation of the power plant. Equations (1) and (2) show the model considered in this paper.

$$minimize\ Fcost = \sum_{i=1}^{n} (a_i + b_i P_i + c_i P_i^2) \tag{1}$$

$$Fcost = F_1 + F_2 + \cdots \ldots \ldots . . + F_n \tag{2}$$

2.1.2. Non-smooth function of fuel cost

The non-smooth function of fuel cost is provided in Equation (3) for minimization purposes.

$$minimize\ Fcost = \sum_{i=1}^{n} a_i + b_i P_i + \left| e_i \times \sin(fi\ (P_{imin)} - P_i) \right| \tag{3}$$

Table 2: Summary and summation of previously presented algorithms based on references

	Ref.	Optimization method	Test system	Abbreviated constraints											
				A	B	C	M	N	P	L	R	T	V	S	LF
Traditional methods	[1]	LR	1–4–8												
	[2]	LI	1 and 1–5												
	[3]	PS	3–1–10–18–3–8												
	[4]	QP	3–11–13–16–20												
	[5]	NR	3–4–7												
Novel methods	[7]	ANN	1–2–18–23												
	[8]	AHNN	1–4												
	[9]	BBO	1–4–5–10–14–18–22												
	[10]	IABC	1–3–4–18												
	[11]	CBBO	4–5–18												
	[12]	GA	1–4												
	[13]	PSO	1–3–4–13												
	[14]	DE	5												
Combined methods	[15]	DE-BBO	1–4												
	[16]	DHS	10–18												
	[17]	HPSO-GSA	1-10-18												
	[18]	JAYA–TLBO	5–9–10												
	[19]	MHBA	2–10												
	[20]	CSA-BA-ABC	8												
	[21]	GA–WOA	1–3–8–18–20												
	[22]	DE-CQPSO	4-9												

problem, the equations and formulation of economic dispatch are first given, then the emission dispatch problem and the combination of these two dispatches are provided in the form of EED in the next subsections. In the rest of this section, the general theory of the ROA and finally the complete flowchart of the implementation of the EED problem are provided.

2.1.3.Constraints

The problem constraints, including the generation and consumption equality condition, taking into account losses, generation limits of generators, and applying the slope rate of power plants, are given in Equation (4)-(8).

$$\sum_{i=1}^{n} P_i = P_d + P_L \tag{4}$$

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i . B_{ij} . P_j + \sum_{i=1}^{n} B_{oi} . P_i + B_{oo} \tag{5}$$

$$P_{i.min} \leq P_i \leq P_{i.max} \tag{6}$$

$$P_{im} - P_{i(m-1)} \leq UR_i \qquad i \in n . m \in M \tag{7}$$

$$P_{i(m-1)} - P_{im} \leq DR_i \qquad i \in n . m \in M \tag{8}$$

Fig. 1 shows the fuel cost function model of power plants with smooth functions considering the slope rate of power plants.

2.2. Emission dispatch

The main goal of solving emission dispatch problems is to reduce the output emission of power plants. By examining the amount of pollutant, i.e., NO_X and SO_X output from power plants, it is seen that many factors impact the emission rate of power plants, the most important of which is the active power output. The relationship between these two variables is nonlinear.

The simplest emission model according to the ISO standard for emission dispatch is a quadratic function. However, the research shows that the emission cost function of a power plant is assumed to be the sum of a quadratic function and an exponential function in terms of active power generation so that a more accurate solution can be achieved [15].

2.2.1. Smooth quadratic function of fuel cost

Equations (9) and (10) express the minimization and smooth functions of fuel cost:

$$minimize\ Ecost = \sum_{i=1}^{n} (\alpha_i + \beta_i P_i + \gamma_i P_i^2) \tag{9}$$

$$E_{cost} = E_1 + E_2 + \cdots E_n \tag{10}$$

2.2.2. Non-smooth function of fuel cost

Equation (11) presents the non-smooth function model of fuel cost.

$$minimize\ Ecost = \sum_{i=1}^{n} (\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \delta_i e^{\lambda_i P_i}) \tag{11}$$

Fig. 2 illustrates the emission cost functions of plants using non-smooth functions.

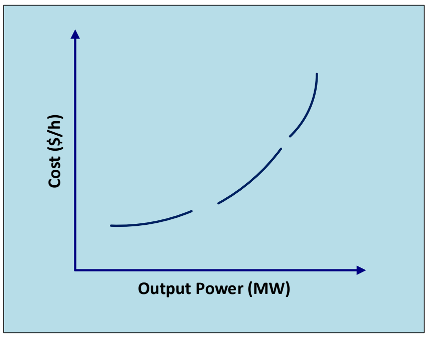

Fig. 1: Fuel cost functions of power plants with smooth functions by applying the slope rate of power plants.

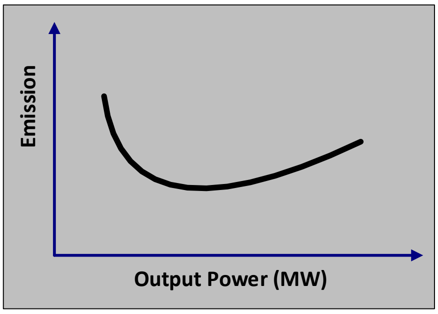

Fig. 2. Model of emission cost functions of power plants with non-smooth functions.

2.3. EED problem

Economic dispatch and emission dispatch problems are used together in this part of the paper to optimize fuel cost and reduce the amount of emission of power plants. The formulation of the EED problem is provided by considerations made on the objective functions of economic dispatch and emission dispatch.

The multi-objective EED problem becomes a single-objective problem by defining the price penalty coefficient. The price penalty coefficient method is proposed based on the PSO algorithm to obtain the optimal Pareto curve, which is one of the best possible solutions to solve the EED problem. The optimal Pareto curve shows the relationship between the results of economic and emission dispatches, and the optimal point of this curve is obtained by determining the penalty coefficient of power plants.

The EED can find the optimal point from the Pareto curve considering the objectives of the problem, i.e., the cost and emission reduction. To convert the multi-objective EED into a single-objective problem, the penalty coefficients of power plants must be obtained.

The necessary equations to implement the proposed method are given in Equations (12)-(17).

$$P_{G_i} = \frac{(\lambda - \beta_i)}{2\gamma_i} MW \tag{12}$$

$$\begin{cases} \min \Phi_T = \sum_{i=1}^{n} [F_i(PG_i).E_i(PG_i)] \\ \min \Phi_T = \sum_{i=1}^{n} [F_i(PG_i)] + h_i \sum_{i=1}^{n} [E_i(PG_i)] \end{cases} \quad (13)$$

$$h_i = \frac{F_i(P_{i.max})}{E_i(P_{i.max})} \quad (14)$$

Thus, the cost and emission functions in equation (13) are transformed into the objective function.

$$\begin{cases} F_1 = \sum_{i=1}^{n} [F_i(PG_i)]\,;\; F_2 = \sum_{i=1}^{n} [E_i(PG_i)] \\ F_{total} = \sum_{i=1}^{n} (a_i + h_i\alpha_i) + (b_i + h_i\beta_i)P_i \\ \qquad +(c_i + h_i\gamma_i)P_i^2 \\ \qquad F_{total} = F_1 + h_i F_2 \end{cases} \quad (15)$$

By defining the mass coefficient w_1 and w_2, the relationship between the total cost of EED can be calculated based on the cost obtained from economic dispatch, F_1, and emission dispatch, F_2:

$$F_{total} = W_1F_1 + hW_1F_2 \quad (16)$$

$$if \begin{cases} W_1 + W_2 = 1 \\ W_1 = W \end{cases} \rightarrow W_2 = 1 - W$$

$$F_{total} = W_1F_1 + (1 - W)hF_2 \quad (17)$$

$$if \begin{cases} W = 1 \\ W = 0 \end{cases} \rightarrow \begin{matrix} F_{tot} = F_1 \\ F_{tot} = F_2 \end{matrix}$$

For w=1 and w=0, the economic/emission dispatch equation is transformed into the economic and emission dispatch equations, respectively.

Overall, the aim of performing EED is to obtain the mass coefficient in the range of $0 \le W \le 1$ so that an optimal point is found on the Pareto curve [23].

2.4. Rain optimization algorithm

Metaheuristic optimization methods are employed to address intricate global challenges across several domains. These algorithms aim to replicate natural processes by employing iterative sequences to discover a rapid and efficient resolution to complex issues. This section aims to thoroughly investigate the behavior of rain.

A raindrop can serve as a model for any solution. In certain issue scenarios, certain points inside the solution space are chosen at random, analogous to the random distribution of raindrops on the ground. The primary characteristic of every raindrop is its radius. Over time, the radius of each raindrop undergoes a process of diminishing and subsequent enlargement when the raindrop merges with other drops. After the initial population of solutions is created, the radius of each drop can be randomly decided within an appropriate range.

During each iteration, every droplet examines its immediate environment based on its size. Isolated droplets without any connections just consider the largest area they cover. When a problem is resolved in n-dimensional space, every individual element comprises n variables. Hence, the initial stage involves scrutinizing the lower and upper bounds of the variable, as these bounds are dictated by the drop's radius.

Subsequently, the two endpoints of the second variable are subjected to testing, and this process is repeated until the final variable is reached.

Currently, the cost of the first descent is being revised as it descends. These declines are not yet in their ultimate stage, and although the cost function is lowering, it is moving downward in a consistent path.

This process is carried out for every individual instance, after which the expense and location of each instance are ascertained. Based on Equations (18) and (19), the radius of each drop undergoes modifications in two distinct states:

1. If two drops with radii r_1 and r_2 are close to each other and have a common area with each other; they can join together to form a larger drop of radius R:

$$R = (r_1^n + r_2^n)^{1/n} \quad (18)$$

where, n is the number of variables in each drop.

2. If a drop of radius r_1 does not move, a percentage of its volume can be absorbed, depending on the soil property, denoted by α.

$$R = (\alpha\, r_1^n)^{1/n} \quad (19)$$

where, α is the proportion of drop volume that can be absorbed in each iteration, ranging from 0 to 100%. The minimum drop radius is denoted as $r_{\min}$, and any drops with radii smaller than this value are excluded. It is evident that the population size reduces over a few iterations, and more significant declines occur with bigger amplitudes. Expanding the research range for each drop leads to a proportional improvement in the local search capability of the drops, corresponding to the size of the drops.

Consequently, as the number of iterations grows, the weak drops with low amplitude will either vanish or merge with stronger drops that have a wider radius. This will lead to a significant reduction in the original population, thereby expediting the discovery of accurate solutions.

The subsequent discussion outlines the fundamental distinctions between ROA and search-based algorithms. In the context of the ROA, the starting population number undergoes changes in each iteration as a result of neighboring drops attaching or being absorbed by the soil, despite the implementation of various search algorithms.

This challenge improves the algorithm's search capability and significantly reduces the cost of optimization. Following each repetition, the dimensions of each droplet undergo modifications as a result of neighboring droplets adhering to them or being absorbed by the soil. This action enhances the search capability of each item and classifies the items based on their significance. In numerous other search algorithms, every population (drop) in each iteration is composed of randomly chosen neighboring points, and the drop is randomly enhanced by one step. Conversely, in ROA, every drop identifies the optimal route to reach the minimal point. Once the path is discovered, it descends gradually, with the cost function decreasing in a single iteration.

This results in the rapid departure of the original population from the incompatible sites. Essentially, the technique requires the user to input specified parameters such as the beginning number of raindrops (population size) and the initial radius of each raindrop (search space) in the first stage. Subsequently, a numerical value is allocated to every droplet based on the cost function.

Subsequently, every droplet commences its descent. Hence, the cost function scrutinizes the endpoints of each drop. Once a droplet is set in motion, it will persist in its trajectory until it reaches a point of minimal elevation along its course. This scenario is replicated for every individual drop.

Along the path, nearby drops can join each other and significantly increase the speed of the algorithm. When a drop reaches the minimum point, its radius gradually decreases, thus significantly enhancing the response accuracy. This strategy enables the algorithm to identify all the largest (end) points of the objective function.

When it rains, raindrops fall on the surface of the earth. After some time, it is observed that some of these drops connect to each other and form more significant drops that can move under the influence of their force on the surface to places with a lower level of the earth's surface. Along the path, other amazing things happen to these drops. Some drops may move to other drops and join them, or some of each drop may vaporize or be absorbed depending on different soil properties such as the nature of the soil surface, including permeability, leakiness, and soil moisture. In addition, a portion of the soil undergoes dissolution in the water.

During this process, the drops that land on the level surface can be fully absorbed by the soil and vanish, whereas the ones that fall on the inclined area descend and merge with other drops, resulting in the formation of a water stream. Certain streams have the potential to interconnect and create a river.

Obstacles in the passage of streams or rivers can lead to the formation of lakes, highlighting the significance of water volume in such cases. Following the cessation of rainfall, the water currents and rivers converge into nearby lakes, and over time, smaller lakes may dissipate as a result of water evaporation or absorption by the soil. Therefore, depending on the surface topology and soil characteristics, only a few significant lakes remain.

These lakes represent a local minimum and deeper lakes represent a global minimum. As the type of rain changes, the previous scenario may change slightly. For example, if heavy rain is accompanied by large drops, all the drops will connect very quickly and, without absorption and evaporation, will lead to flooding. Only the global minimum can be discerned in this scenario, as all the local minima are interconnected as a result of intense rainfall.

In contrast, in the presence of light rain characterized by little droplets, the soil has the capacity to absorb all the drops, so preventing any runoff. Hence, it is evident that establishing the parameters when utilizing the ROA holds great significance. The particle movement in the suggested technique bears resemblance to slope-based optimization methods and conventional single-point algorithms, such as hill climbing, slope optimization algorithm, and rainfall optimization. These strategies iteratively tweak a single parameter to determine if modifying it enhances the cost performance. Nevertheless, the ROA employs a collection of answers that all converge towards the optimal outcome concurrently.

During each iteration of this movement, certain traits undergo changes. For instance, their dimensions may undergo alterations or they may vanish. Furthermore, the ROA has the capability to identify all points of maximum rather than solely minimum or maximum points. Fig. 3 shows the flowchart of the ROA.

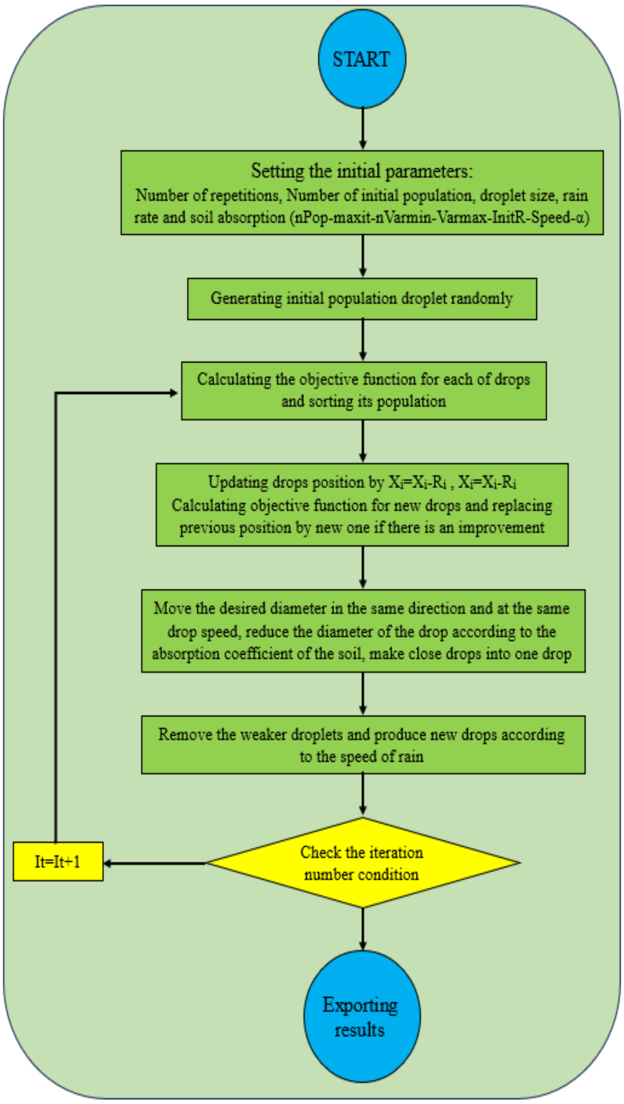

Fig. 3: Flowchart of the ROA [24].

2.5. The ultimate flowchart of the proposed algorithm

In this subsection, the final flowchart for solving the EED problem based on the ROA is given in a general format. The flowchart is designed in two blocks according to Fig. 4.

3. Simulation and results

This section applies the ROA to deal with the EED problem. For evaluation and comparison purposes, the results obtained from the implementation of the suggested design together with similar optimization algorithms are used. The successful results of the implementation of the proposed design in comparison with the rest of algorithms confirm the acceptable performance of the suggested. Five different cases have been used for this evaluation. Table 1 lists the definitions of each of the cases. The information included for each case includes test system, number of units, power demand, heat demand, and system losses. In Table 3, the information required for each case is given. The power generation units provide function inputs in each case depending on the design of the problem so that it is possible to compare the emission rate and the fuel cost rate of each scenario according to the power consumption of the load. For each test system, the convergence behavior of the objective function can also be observed using the ROA method. All simulations were conducted on a computer using MATLAB software.

3.1. Evaluation of Case I

According to the information provided in Table 3, Case I includes three generator units. According to the results presented in Table 4, it can be seen in this test system that the technique proposed in this paper has outperformed the techniques presented in other references. According to the result obtained with the value of 11.658, the ROA optimized the consumption of generator units to create a better fuel cost and emission rate and reduce losses. Next, Fig. 5 presents the convergence behaviour of the objective function by ROA. emission rate obtained using the ROA are presented in Table 5. By comparing the techniques mentioned in Table 5, it is observed that the ROA provides the lowest emission rate while the SFLA gives the best fuel cost.

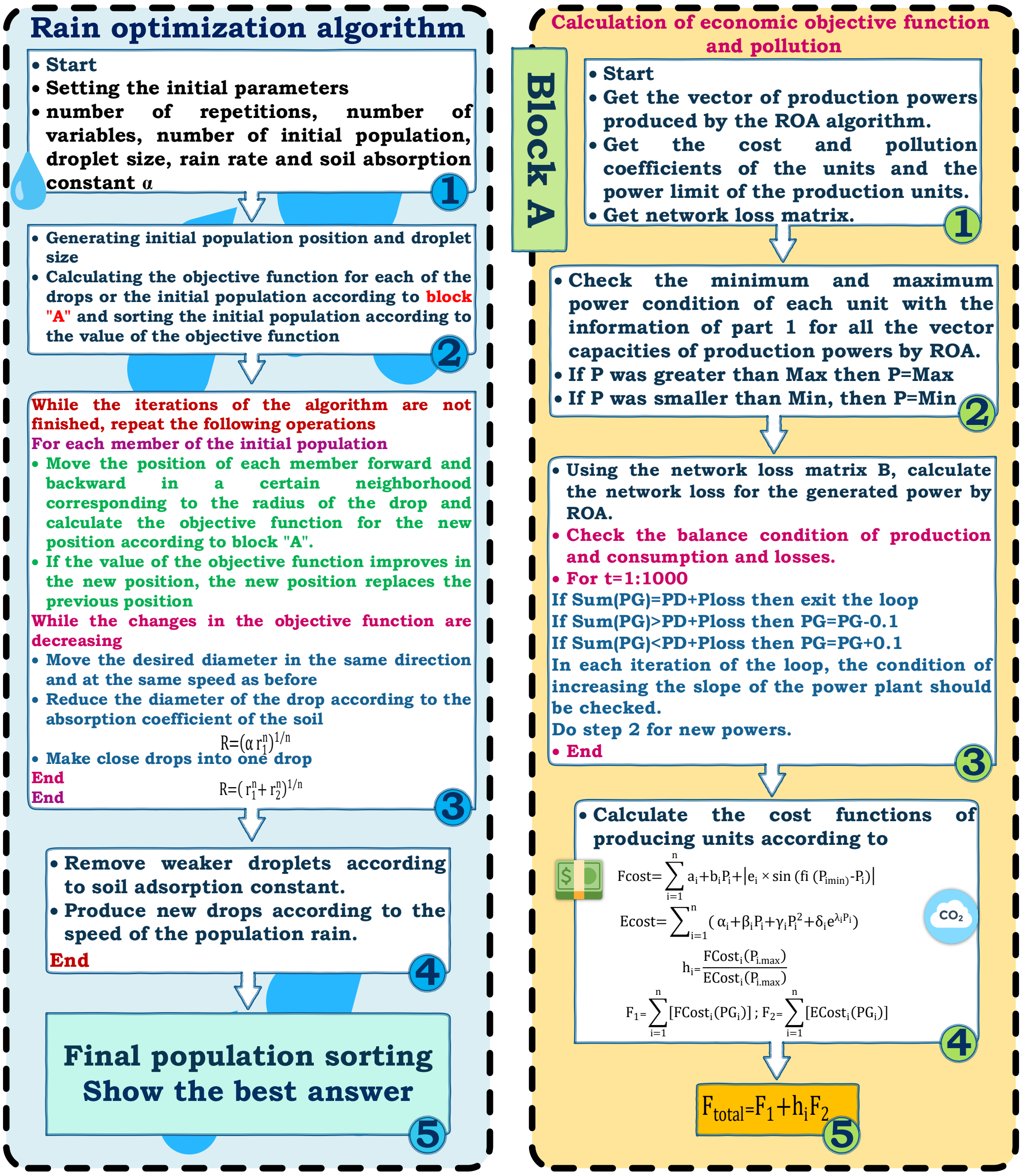

Fig. 4: Flowchart of solving the EED problem by ROA.

3.2. Evaluation of Case II

In this scenario, simulations have been performed on the 10-bus test system. The optimal fuel cost and the target convergence behavior of the ROA for this scenario is shown in Fig. 6.

3.3. Evaluation of Case III test system

Case III was simulated on the IEEE 30-bus system. Table 6 shows the optimal power allocation that provides the best fuel cost in this case. The convergence curve of the objective function concerning the best optimization report is provided in Fig. 7.

3.4. Evaluation of Case IV test system

Table 7 presents the outcomes of Case IV for various optimization strategies. The ROA yields the most favourable outcome for this system, while the CSOA ranks third in terms of performance. Fig. 8 illustrates the convergence of the objective function in this scenario.

3.5. Evaluation of Case V

For the experimental system of Case V, the power allocation achieved for fourteen generators is displayed in Table 8. Based on the comparison study and the data presented in the table, it can be concluded that the suggested algorithm has achieved the smallest fuel cost and emission rate. Furthermore, the Fig. 9 illustrates the convergence pattern of the objective function.

Table 3: Different cases considered for problem testing and evaluation

Problem	Case	No. of units	Power demand (MW)	Loss
CEED	Case I	3	500	✣
	Case II	10	2000	✣
	Case III	6	283.4	✣
	Case IV	40	10500	-
	Case V	19	950	✣

Table 4: Obtained results for Case I.

Case 1	G1	G2	G3	C	Fc	FE	LP
FA	128.884	192.585	190.282	39209.93	-	311.15	11.693
BA	128.828	192.579	190.285	39209.94	-	311.15	11.693
HYB	128.834	192.567	190.291	39209.96	-	311.15	11.693
GA	128.997	192.683	190.110	39220	-	311.27	11.696
PSO	128.984	192.645	190.063	39210.20	-	311.15	11.691
FPA	128.807	192.590	190.295	39210.15	-	311.155	11.693
MSFLA	128.338	191.946	191.389	32209.81	-	311.163	11.692
KKO	129.011	192.303	190.274	39199.7	25490.5	311.013	11.687
ROA	129.394	192.270	190.875	38481.54	25459.2	311.06	11.658

Table 5: Obtained results for Case II.

Case 2	NSGA-2	PDE	SPEA-2	GSA	PSO	EMOC	FPA	LFA	KKO	ROA
G1	51.9515	54.9853	5.97612	5.99924	55	55	53.188	5.99204	5.99234	57.654
G2	67.2584	79.3803	72.813	7.95869	80	80	79.975	7.86798	7.89148	79.548
G3	73.6879	83.9842	7.11288	7.43419	81.14	8.55943	78.105	7.71688	7.79468	83.538
G4	91.3554	86.5942	8.60883	85	84.213	8.60314	97.119	7.10558	8.74798	87.866
G5	134.0522	144.4386	1.24323	1.10634	1.33773	1.56324	152.74	1.62724	15.8149	145.79
G6	174.9504	165.7756	1.91887	1.56706	1.50866	1.24816	163.08	1.09365	16.5550	17.6510
G7	289.4350	283.2122	2.20238	2.87499	2.83389	300	258.61	2.99549	26.1742	288.77
G8	314.0556	312.7709	3.40232	3.23871	3.58241	3.34941	302.22	3.22190	30.8578	316.91
G9	455.6978	440.1135	4.88144	4.17754	4.33632	4.91831	433.21	4.32434	43.3070	430.88
G10	431.8054	432.6783	4.90252	4.63062	4.15984	4.31333	466.70	4.69473	46.0391	455.65
F_C	1.13539	1.1351	1.1352	1.1349	1.1342	1.13445	1.1337	1.13246	1.13481	1.1338
F_E	4130.2	4111.1	4109.1	4111.4	4120.1	4119.83	3997.7	4138.9	3988.52	3886.7

4. CONCLUSION AND FUTURE TRENDS

In this paper, the optimization of the EED problem was carried out using the ROA. To realize this, various limitations, such as cost functions with non-smooth points, reducing the amount of pollution, limitations of power generation, and considering losses as well as thermal power plants of the system are taken into account. In this research, the proposed algorithm was applied to reduce cost and emission in the EED model on 3, 10, 6, 40, and 15-unit systems. The findings of simulation confirmed the effectiveness of the ROA method in achieving the best solution for the problem. In this article, the ROA algorithm managed to plan the production with an optimal cost of 38481.54 dollars in case 1, which obtained a more optimal value than all the compared algorithms.

Also, in the case 2, the ROA algorithm was able to increase the value of the F_E function to 3886.7, which is much lower than other algorithms, and this shows the power of this algorithm in solving EED problems. In case 2, the ROA algorithm was able to reduce the value of the FC economic objective function to 1.1338, which is much lower compared to the PSO, GSA, KKO, etc. algorithms. In case 3, it can be seen that the FC and FE target function values for rain optimization algorithm are 603.65 and 0.2013, respectively. As the results of all three case studies showed, the ROA algorithm has been able to reduce the cost and environmental pollution in the best way in all cases, which indicates the strength and accuracy of this algorithm in finding the global optimum. A summary of the contributions of the paper include:

- Reduction of system losses compared to economic dispatch,
- Reduction of emission compared to economic dispatch, and
- Reduction of total cost compared to economic dispatch and emission dispatch

And, below are the suggestions for future studies:

- Implementing EED for systems with multi-piece fuel cost curve with non-smooth functions considering wind energy uncertainty, and
- Implementing EED by considering the dynamic model for the slope constraints of power plants and using virtual power plants for problem solving and investigating their effects.

Table 6: Obtained results for Case III.

Case 3	MHBA	FSBF	NSBF	KKO	ROA
G1	10.94	19.43	17.80	12.9546	13.6
G2	29.85	37.26	33.66	32.2445	38.7
G3	58.29	68.57	72.92	54.51935	70.5
G4	99.48	59.19	59.08	96.9029	87.6
G5	51.81	60.85	57.66	52.9564	58.9
G6	36.20	40.61	44.74	36.548	43.6
F_C	607.39	619.3679	619.6086	605.68	603.65
F_E	0.2208	0.2015	0.2027	0.217897	0.2013
L_P	3.204	2.51	2.46	2.396	2.42

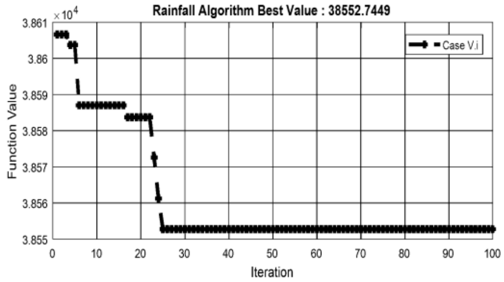

Fig. 5: Convergence behaviour of ROA objective function in Case I.

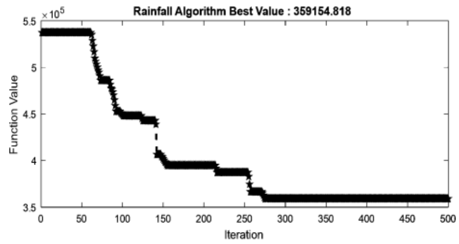

Fig. 6: Convergence behaviour of ROA objective function in Case II.

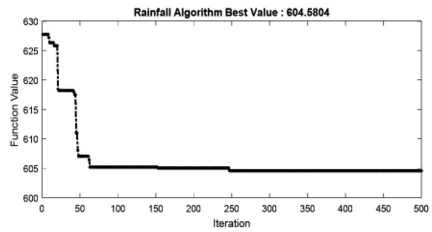

Fig. 7: Convergence behaviour of ROA objective function in Case III.

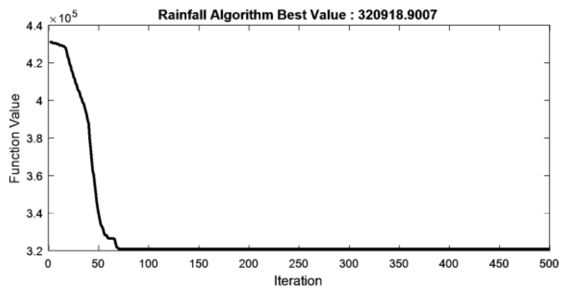

Fig. 8: Convergence behaviour of ROA objective function in Case IV.

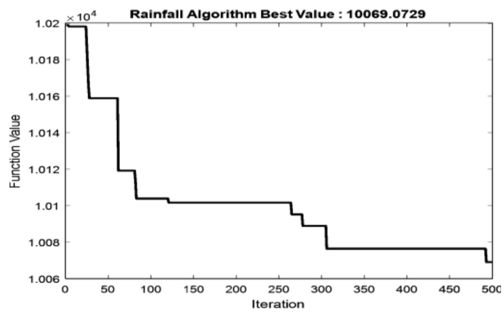

Fig. 9: Convergence behaviour of ROA objective function in Case V.

Table 7: Obtained results for Case IV.

Case 4	NSGA-II	SPEA-2	GSA	MABC	MABC	FPA	ISA	KKO	ROA
G1	113.8685	113.9694	113.9989	110.7998	110.8998	43.405	43.567	114	113.65
G2	113.6381	114	113.9896	110.7998	110.7998	113.95	113.56	113.045	113.47
G3	120	119.8719	199.9995	97.3999	97.3999	105.86	105.76	119.744	111.52
G4	179.94	179.9284	179.7857	174.5504	174.5486	169.65	169.43	181.102	180.6
G5	180.7887	97	97	87.7999	97	96.659	96.62	96.5081	96.66
G6	140	139.2721	139.0128	105.3999	105.3999	139.02	139.23	139.796	139.55
G7	300	300	299.9885	259.5996	259.9556	273.28	273.36	299.686	295.8
G8	299.0084	298.2706	300	284.5996	284.5996	285.15	285.15	298.619	288.76
G9	298.8890	290.5228	296.2025	284.5996	284.5996	241.96	241.54	289.447	290.5
G10	131.6132	131.4832	130.3850	130	130	131.26	131.26	131.386	132.5
G11	246.5138	244.6704	245.7475	318.1921	318.2129	312.13	312.12	241.114	250.6
G12	318.8748	317.2003	318.2101	243.5996	243.5996	362.58	362.45	318.381	350.3
G13	395.7224	394.7358	394.6257	394.2793	394.2793	346.24	346.34	395.689	395.8
G14	394.1369	394.6223	395.2016	394.2793	394.2793	306.06	306.06	393.82	395.1
G15	305.5781	304.7271	306.0014	394.2793	394.2793	358.78	358.54	305.891	355.4
G16	394.6968	394.7289	394.1005	394.2793	394.2793	260.68	260.23	394.283	394.8
G17	489.4234	487.9857	489.2569	399.5195	399.5195	415.19	415.26	489.706	489.43
G18	488.2701	488.5321	488.7598	399.5195	399.5195	423.94	423.56	487.897	488.3
G19	500.8	501.1683	499.2320	506.1985	506.1716	549.12	549.03	500.104	537.5
G20	455.2006	456.4324	455.2821	506.1985	506.2206	496.7	496.74	455.719	500.4
G21	434.6639	434.7877	434.45202	514.1472	514.105	539.17	538.76	434.334	520.4
G22	434.15	434.3937	433.8125	514.1455	514.1472	546.46	546.46	434.86	544.5
G23	445.8385	445.0772	445.5136	514.5237	514.5664	540.06	540.56	446.6	533.3
G24	450.7509	451.8970	452.0547	514.5386	514.4868	514.5	514.55	451	500.4
G25	491.2745	492.3946	492.8864	433.5196	433.5195	453.46	453.67	451.259	490.5
G26	436.3418	436.9926	433.3695	433.5195	433.5196	517.31	516.891	435.7721	500.6
G27	11.2457	10.7784	110.0026	10	10	14.881	14.345	11.079	12.45
G28	10	10.2955	10.0246	10	10	18.79	18.64	10.3466	15.4
G29	12.0714	13.7018	10.0125	10	10	26.611	26.578	12.2337	11.65
G30	97	96.2431	96.9125	97	87.8042	59.581	59.565	96.6001	96.1
G31	189.4926	190.0000	189.9689	159.733	159.733	183.48	183.36	189.436	188.76
G32	174.7971	174.2196	175	159.733	159.7331	183.39	182.87	175.188	176.5
G33	189.2845	190	189.0181	159.733	159.733	189.02	189.22	189.992	189.4
G34	200	200	200	200	200	198.73	198.65	198.679	199.8
G35	199.9138	200	200	200	200	198.77	198.76	199.89	198.6
G36	199.5066	200	199.9978	200	200	182.23	182.45	199.905	198.52
G37	108.3061	110	109.9969	89.1141	89.1141	39.673	39.635	108.554	109.89
G38	110	102.6912	109.0126	89.1141	89.1141	81.596	81.625	109.71	109.6
G39	107.7899	108.5560	109.4560	89.1141	89.1141	42.96	42.91	108.639	109.4
G40	421.5609	421.8521	421.9987	56.1879	506.1951	537.17	537.15	421.912	588.8
F_c	1.5283	1.2581	12.2587	1.24490903	1.2449116	1.23170	1.23034	1.25852	1.21
F_E	2.1095	2.1110	2.1093	2.56560267	2.5656026	2.0846	2.0643	2.10837	2.55

Table 8: Obtained results for Case V.

Case 5	CSAISA	ISA	HSA	DE	PSO	GA	KKO	ROA
G1	102.6468	100.3485	100.3839	100.5473	100.7363	100.8578	65.43	68.65
G2	59.1816	58.8270	58.6583	58.5372	58.2314	58.3547	75.2154	76.55
G3	50.0599	50.8309	50.8302	50.8474	50.5242	50.9973	69.7721	69.5
G4	70.3498	73.3932	73.5292	73.0932	73.3238	73.4352	76.7522	75.34
G5	63.1042	59.1153	59.1846	59.9323	59.7272	59.4636	78.5975	77.44
G6	51.0080	50.1468	50.9231	50.7397	50.2726	50.6254	74.8284	73.23
G7	50.0000	507470	50.2832	50.5360	50.8362	50.5363	64.9154	65.4
G8	51.0166	53.2494	53.0220	53.2324	53.5242	53.1321	64.005	65.5
G9	83.9497	85.1551	85.8231	85.4235	85.4355	85.3546	73.8251	70.43
G10	87.1409	92.1870	92.6484	92.5426	92.0388	92.7522	66.2354	60.33
G11	58.6019	61.3470	91.9233	61.5243	61.6493	61.4368	68.8125	70.4
G12	119.1476	121.8597	121.4353	121.6357	121.7468	121.2463	65.6357	66.53
G13	50.0000	50.0000	50.4352	50.5367	50.6484	50.7468	64.8102	66.42
G14	50.0000	50.0000	50.5327	50.6382	50.8202	50.4373	50.0000	50.33
G15	7.2070	7.2069	7.3536	7.6388	7.8447	7.4357	8.854	8.88
F_c	4352.39	4353.57	4366.27	4387.44	4427.26	4453.85	4304.62	4277.6
F_E	135.23	136.46	144.85	153.42	176.75	184.38	108.85	104.7

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Narges Yousefi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Roles/Writing - original draft. **Mahmood Joorabian**: Conceptualization, Funding acquisition, Validation, Visualization, Writing - original draft, Writing. **Mahyar Abasi**: Methodology, Project administration, Supervision, Resources, Roles/Writing - original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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