Vokasi Unesa Bulletin of Engineering, Technology and Applied Science (VUBETA)
https://journal.unesa.ac.id/index.php/vubeta
Vol. 2, No. 1, 2025, pp. 1~11 DOI: 10.26740/vubeta.v2i1.37066
ISSN: 3064-0768

Modified FATA Morgana Algorithm Based on Lévy Flight

Aditya Prapanca[1*], Nasreddine Belhaouas[2], Imed Mahmoud[3]
[1]Department of Informatics Engineering, Faculty of Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia
[2]Centre de Développement des Energies Renouvelables, CDER,B.P. 62, Route de l'observatoire, Bouzaréah, 16340, Alger, Algérie
[3]Department of Electronic Engineering, University of Tunis, Bizerte, Tunisia

Article Info

Article history:

Received December 18, 2024
Revised January 20, 2025
Accepted February 15, 2025

Keywords:

Fata Morgana Algorithm
Metaheuristic
Lévy Flight
Novel Algorithm
Artificial Algorithm

ABSTRACT

Metaheuristics, as an algorithmic approach is used to solve complex optimization problems that are difficult to solve using conventional methods. The wide application of metaheuristics demonstrates the flexibility and effectiveness of this method in solving multiple optimization problems across multiple fields. With the continuous development of technology and the need for more efficient solutions, the use of metaheuristics is expected to increase in the future. A novel group intelligence technique, called the modified mirage algorithm (FATA), is introduced to tackle continuous multitype optimization problems. FATA formulates the mirage light filtering (MLF) principle and light propagation strategy (LPS) by replicating the mechanism of mirage formation. The MLF approach, together with the final integration concept, enhances the algorithmic population's exploration capacity within FATA. This study presents the application of the lévy flight method to the Fata Morgana Algorithm. The proposed method is validated against the original Fata Morgana Algorithm. Simulation results demonstrate that the proposed method achieves better performance on both unimodal and multimodal functions.

1. INTRODUCTION

Artificial Intelligence, as a discipline within computer science, focuses on developing systems or machines capable of performing activities that typically require human intelligence [1]-[3]. These tasks encompass logical reasoning, decision-making, problem-solving, pattern detection, natural language comprehension, and experiential learning [4][5]. Metaheuristics is versatile optimization techniques employed to identify near-optimal solutions for complex problems that standard methods struggle to resolve. Metaheuristics do not ensure an ideal result; rather, its strive to identify a satisfactory solution within an acceptable timeframe [6]-[8].

Metaheuristics have undergone significant development since their introduction as a method for solving complex optimization problems that are difficult to solve using conventional techniques [9]-[11]. Challenges and future directions for the application of metaheuristics include developing efficient algorithms for large-scale and high-complexity problems, combining metaheuristics with machine learning techniques to enhance algorithm adaptability and performance, and advancing the scientific and computational infrastructure to support the development, analysis, and comparison of new metaheuristic approaches[12][13].

The application of metaheuristics is very diverse and broad. Here are some examples of the application of metaheuristics, namely the application of metaheuristics in engineering is used to optimize power generation systems, such as in scheduling and load management [14]-[17], the application of metaheuristics in informatics is used in recommendation systems, such as in marketplace application recommendation systems [18][19] and the application of metaheuristics in other fields is used in route optimization, such as in optimizing goods delivery routes [20]-[23].

The wide application of metaheuristics demonstrates the flexibility and effectiveness of these methods in solving multitype optimization problems across multiple fields [24]-[27]. With the continuous development of

*Corresponding Author
Email: adityaprapanca@unesa.ac.id

technology and the growing demand for more efficient solutions, the use of metaheuristics is expected to increase in the future [28]-[31]. The application of hybrid metaheuristics is increasingly popular. The benefits of hybrid metaheuristics include improving the efficiency of searching for optimal solutions by combining the advantages of multiple algorithms, as well as enhancing the accuracy of the search process by reducing the risk of getting trapped in local optima [32]-[39]. Additionally, hybrid metaheuristics can reduce computational time by leveraging the search speed of multiple algorithms and can flexibly handle multitype optimization problems. This research has a contribution, namely Presenting a combination of the Fata Morgana Algorithm (FATA) method with Lévy Flight and validation is applied by comparing the FATA method and the proposed method using the benchmark function.

This article is structured as follows: Section 2 discusses the Fata Morgana Algorithm and Lévy Flight. Section 3 delineates the proposed control scheme. Section 4 contains discussions and simulations. The conclusion is articulated in the final section.

2. METHOD

Metaheuristics, as a general approach or framework, is used to solve complex optimization problems, especially when using conventional methods, such as exact algorithms, are inefficient or impractical due to the problem's size, complexity, or non-linear nature of the solution [40]-[44]. Metaheuristics do not guarantee a globally optimal solution, but aim to find a "good enough" solution in a reasonable time.

2.1. Fata Morgana Algorithm

Fata morgana, or known as mirage, is a physical phenomenon that often occurs in nature. The mirage phenomenon is formed when light from an object is reflected into an atmosphere that has uneven density, namely from a medium that is optically denser to a thinner medium. FATA population search strategy (named mirage light filtering principle) is inspired by the light reflected by the boat into the medium. The light propagation principle inspires FATA individual search strategy (named light propagation strategy) in the medium with inhomogeneous density. These two strategies are the core of FATA (mirage algorithm). FATA balances the mirage light filtering principle and the light propagation strategy responsible for the global exploration and local exploitation of the algorithm. Therefore, the mirage formation process is fully consistent with it, which creates conditions for the proposed Fata Morgana Algorithm [45].

2.1.1. The mirage light filtering principle

This section demonstrates the population search strategy of the Fata Morgana Algorithm, which is based on the definite integral concept. Two different kinds of light rays are released by the hull during the physical process of mirage creation. The first kind of light rays, which do not spread and create a mirage, makes up the bulk of light rays. The other kind, known as the mirage light (x), is created when light beams undergo physical changes that cause a mirage to develop. The algorithm's ability to identify $xbest$ in FATA depends on its ability to differentiate between the two kinds of light populations. In order to evaluate the various kinds of light populations, FATA uses a light population quality evaluation approach founded on the definite integral principle. By determining each person's fitness and then adding up all of the fitness values for the population, swarm intelligence algorithms assess the quality of the population. A cumulative curve is created when the fitness of individuals within a light population is ranked. FATA uses definite integration to assess the curve and uses the integral value as a fitness metric to effectively calculate the fitness of various light populations (other light, the mirage light). The filtered mirage light population is another name for the mirage light (x) that is chosen using the definite integral concept.

To undertake various search methods, the strategy first determines the population as other light or the mirage light depending on the population quality (Eq. (1)). The general quality of the population is referred to as population quality. The population quality is represented in the strategy by the integrated area (S) of the population fitness function ($f(x)$).

$$x_i^{next} = \begin{cases} L_b + (U_b - L_b) \cdot rand & ,rand > P \\ x_{best} + x_i \cdot Para_1 & ,rand \le P \ \ and \ \ rand < q \\ x_{rand} + [0.5 \cdot (\alpha + 1)(U_b - L_b) - \alpha x_i] \cdot Para_2 & ,rand \le P \ \ and \ \ rand \ge q \end{cases} \quad (1)\,(2)\,(3)$$

$$P = \frac{S - S_{worst}}{S_{best} - S_{worst}} \quad (4)$$

$$q = \frac{fit_i - fit_{worst}}{fit_{best} - fit_{worst}} \quad (5)$$

$$y = f(x) = \sum_{j=0}^{n} c_j \varphi_j x \quad (6)$$

$$S = \int_a^b f(x)dx \approx \frac{b-a}{n} \cdot (\frac{y_0 + y_1}{2} + \frac{y_1 + y_2}{2} + \cdots + \frac{y_{n-1} + y_n}{2}) \quad (7)$$

where (x) is the light individual. (x_i^{next}) is the new individual. Method 1 demonstrates how the fata morgana method uses mirage light filtering. Equations (2-3) represent the first half refraction strategy, the second half refraction strategy, and the total internal reflection approach, respectively. In equation (4), (P) represents the quality factor of the light population. A lower value of (S) indicates a higher population quality. (S_{worst}) indicates the worst population quality. (S_{best}) indicates the best population quality. A bright mirage population has a high population quality. In equation (5), (q) represents the individual quality factor. (fit_i) represents the fitness of the current individual (x). (fit_{worst}) represents the fitness of the worst individual. (fit_{best}) represents the fitness of the best individual. Equation (6-7) demonstrates a method to find the area of the population fitness curve $f(x)$) using the idea of definite integration. The theory of definite integrals uses the concept of limits to calculate the area (S) of the integration $f(x)$) Equation (6) represents the population fitness function $f(x)$).

2.1.2 Principle of light propagation

The individual search strategy is created by the Fata Morgana Algorithm using trigonometric functions and the light propagation principle. Based on the individual quality factor (in Eq. (5)), the algorithm decides which of the three strategies—the refraction strategy, the reflection strategy (the second half phase), and the reflection strategy (the first half phase) to implement.

First half phase: light refraction. Figure 1(a) demonstrates how the light x changes size and direction as it passes through an optically denser medium and into an inhomogeneous density medium in the first half of refraction. The angle of refraction (i_1) is greater than the angle of incidence (i_2). The light individual's refraction mechanism is examined in Figure 1(a). The refractive surface is $level$, and the light individual is x. Eq. (8) demonstrates that following the first half of the reflection method, $xnext$ is a new person. The formulas for the approach are found in Equations (8–10).

$$x^{next} = x_{best} + x_z \quad (8)$$

$$x_z = x \cdot Para_1 \quad (9)$$

$$Para_1 = \frac{sin\ (i_1)}{C \cdot cos\ (i_2)} = tan\ (\theta) \quad (10)$$

Figure 1. (a) First refraction process of light (b) Second refraction process of light

Light refraction (the second half phase). At random spots, the light conducts the second half refraction phase after completing the first half refraction phase. Figure 1(b) examines the light's second half refraction process. Inflection angle i_3 is smaller than refraction angle i_6. Since the material in which light travels have an uneven density, the refractive index $(Para_2)$. Based on random individuals $(xrand)$ in the search space, the light individual (x_f) will create a new individual (x^{next}) in the second half refraction method. The FATA strategy formulas are found in Equations (11–13).

$$x^{next} = x_{rand} + x_s \tag{11}$$

$$x_s = x_f \cdot Para_2 \tag{12}$$

$$Para_2 = \frac{cos(i_5)}{C \cdot sin\,(i_6)} = \frac{1}{tan\,(\theta)} \tag{13}$$

The second half refraction strategy's refraction step is called x_s. A random member of the population is x_{rand}. The second refraction ratio is $Para_2$. As the number of repetitions increases, the value of $Para_1$ in Figure 2(a) progressively approaches zero after fluctuating arbitrarily between -2 and 2. The value of $Para_2$ fluctuates randomly between [-150,150] in Figure 2(b) and progressively rises as the number of repetitions increases. Figure 9 demonstrates that both parameters have comparatively high values and standardized to make $Para_1$ and $Para_2$ more uniform. The two parameters are scaled to the interval,0,1- by the technique. The capacity to escape the local optimum is enhanced by the significant oscillation of $Para_2$ at the last stage of the Fata Morgana Algorithm.

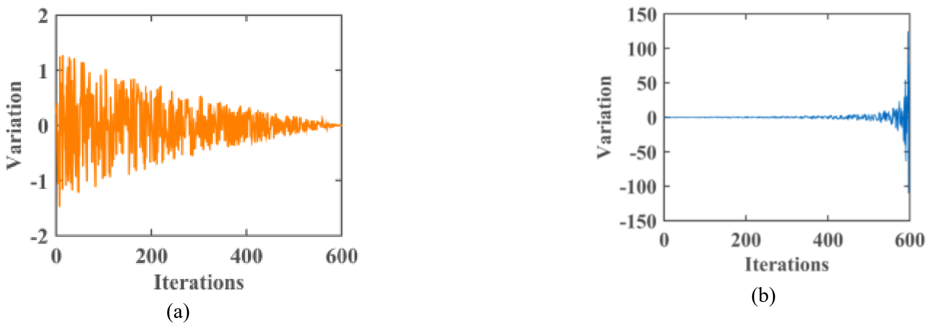


Figure 2. (a)Trends of $Para1$ (b) Trends of $Para2$

Total internal reflection of light. The last stage of light transmission that contributes to the production of the mirage phenomena is the total internal reflection phase. This is since light experiences complete internal reflection in the material with an uneven density as the refraction angle rises. The FATA populace explores in the opposite direction as a result of the whole internal reflection technique. The process of light reflection is examined in Figure 3. The angle of reflection, i_6, is equal to the angle of incidence, i_5. The centre point of the interval ($[U_b, L_b]$) in the figure is represented by $O(x_0, 0)$. The incident and refracted light distances to the horizontal plane are denoted by E and F, respectively. To find the goal in the other direction, the method changes the bright individual (x) into the individual (x^{next}). The formulas for the Fata Morgana Algorithm's strategy are found in equations (14–17).

$$x^{next} = x_f = 0.5 \cdot (\alpha + 1)(U_b + L_b) - \alpha x \tag{14}$$

$$\alpha = \frac{F}{E} \tag{15}$$

$$x_0 - x_f = \frac{F \cdot (x - x_0)}{E} \tag{16}$$

$$x_0 = \frac{U_b - L_b}{2} + L_b = \frac{U_b + L_b}{2} \tag{17}$$

The whole internal reflection method reflects the individual, x_f. is the strategy for reflection's reflectivity. regulates the light individual's change pattern. $\alpha \in [0,1]$, crosses the barrier when is bigger than 1. The particular position's upper limit is denoted by U_b. L_b refers to the specific position's lower limit.

2.2. Lévy flight optimization

Lévy flight is a specific category of general random walks characterised by stride lengths determined by a heavy-tailed probability distribution and be able to characterise all scale-invariant stochastic processes. Lévy flight is a random walk pattern that has a step size characteristic that follows the Lévy flight distribution. This distribution is a probability distribution with a long tail (heavy-tailed distribution). This characteristic makes Lévy flight have a combination of short steps for local exploration and long steps for global exploration. Its function is to enhance the algorithm's ability to find optimal solutions. Lévy flight helps the algorithm escape the local optima trap and find a global solution. Lévy flight is an important concept in optimization and natural behaviour modelling because of its ability to balance local and global exploration through a probability distribution that has a long tail.

$$L(X_j) \approx |X_j|^{1-\alpha} \tag{18}$$

Where X_j is the flight length, and $1 < \alpha \leq 2$ is the exponential power. The integral form of the probability density for the Lévy flight stable process is specified as Eq. (19).

$$f_L(x;\alpha,\gamma) = \frac{1}{\pi}\int_0^\infty exp(-\gamma q^\alpha)\cos\ (qx)\ dq \tag{19}$$

Where α is the distribution index and controls the scale properties of the process while γ selects the scale units. Integrals in Eq. (19) have an analytical solution only in some cases. When α equals 2, it represents a Gaussian distribution and when α equals 1, it represents a Cauchy distribution. The solution to the integral in Eq. (19) generally requires the use of the series expansion method only when x has very large values as Eq. (20):

$$f_L(x;\alpha,\gamma) = \frac{\gamma\Gamma(1+\alpha)\sin(\frac{\alpha\pi}{2})}{\pi X^{(1+\alpha)}}\ , x\ \rightarrow \infty \tag{20}$$

Where Γ is Gamma function. Mantegna proposed an accurate and fast algorithm to generate stable Lévy flight processes for absolute values of the index distribution (α) ranging between 0.3 and 1.99. Mantegna's method for random number generation is based on the Lévy flight distribution in Eq.21

$$Levy(\alpha) = 0.05 \times \frac{x}{|y|^{1/\alpha}} \tag{21}$$

$$x = Normal\ (0, \sigma_x^2) \tag{22}$$

$$y = Normal\ (0, \sigma_x^2) \tag{23}$$

$$\sigma_x\ = \left[\frac{\Gamma(1+\alpha)\sin(\frac{\alpha\pi}{2})}{\Gamma(\frac{(1+\alpha)}{2})\alpha\, 2^{\frac{(\alpha-1)}{2}}}\right]^{1/\alpha} and\ \sigma_x\ = 1 \text{ dan } \alpha = 1.5 \tag{24}$$

Where x and y are two normally distributed variables with standard deviations σ_x and σ_y. The Lévy flight algorithm is employed as a search tool for optimisation purposes.

3. Proposed Method

Modified FATA (MFATA) algorithm is proposed to enhance exploration, prevent local optima, enhance exploitation, and facilitate convergence of FATA. The proposed approach integrates FATA with Lévy flight optimization. Lévy flight optimization enhances the diversification of search agents, allowing the algorithm to explore the search space efficiently and minimize local avoidance. Lévy flight trajectories facilitate a more effective transition from exploration to exploitation in FATA. Consequently, Lévy flight trajectories are used to revise positions after position updates. The proposed method is to modify Eq. 4 by adding Eq. 21 to Eq. 25.

$$P = \frac{(S - S_{worst}) * Levy(\alpha)}{S_{best} - S_{worst}} \tag{25}$$

Algorithm 1: Pseudocode of Modified Fata Morgana Algorithm

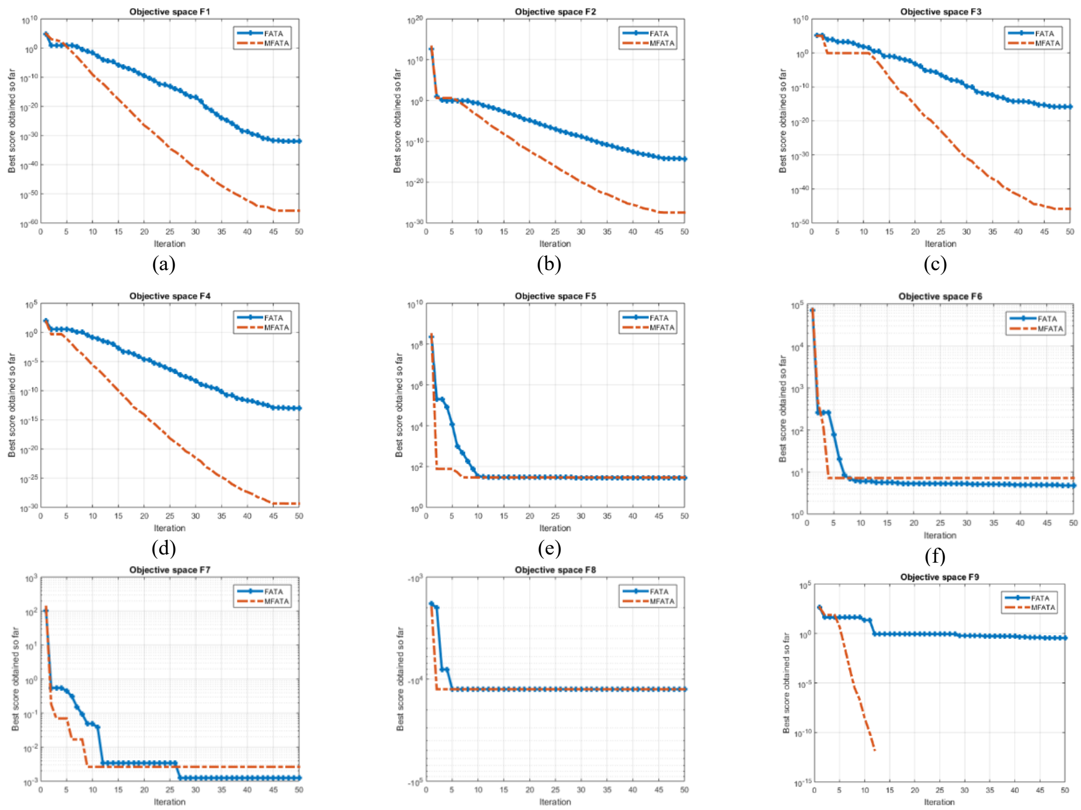
Input: parameters n, d, $MaxFEs$;
Output: best Individual;
Initialization parameters $Para_1$, $Para_2$, α;
Initialize a population x of size n;
Calculate the fitness of each individual;
While ($FEs \leq MaxFEs$)
  update $best\ fitness$, x_{best};
  Calculate weights P by Eq. (25);
  Calculate $Para_1$ and $Para_2$ by Eq. (10) and Eq. (17);
  For $i = 1 : n$
    Execute Algorithm 1 to realize the mirage light filtering principle;

If $and > P$
the light population performs Eq. (1) to initialize the population randomly;
Else
If $rand < q$
Update the individual x_i by Eq. (8) according to the first half light refraction strategy;
Else
Update the individual x_i by Eq. (11) according to the second half light refraction strategy;
Update the individual x_i by Eq. (14) according to the light total internal reflection strategy.
End If
End If
End For
$t = t + 1$;
End While
Return the best individual x_{best};

4. RESULTS AND DISCUSSION

The outcomes of the suggested MFATA methodology are juxtaposed with the results of FATA approaches. This study assesses the efficacy of MFATA through benchmark functions. Initially, it is essential to evaluate 23 CEC2017 benchmark functions. Functions F1 through F7 are defined as unimodal. Functions F8 to F13 exhibit multimodality. F14–F23 denote fixed-dimensional multimodal functions expressed by mathematical equations. The simulations are executed using the MATLAB/Simulink software. Figure 3 illustrates the comparison of benchmark function outcomes utilising the FATA technique.

Statistical analysis is presented on the performance of the MFATA algorithm and competitors to determine whether MFATA has a significant statistical advantage or not. By knowing the rank of each function, the average rank value for each algorithm is obtained. Table 1 demonstrates the statistical analysis of each function. Rank is a number that indicates the best average value. Table 2 is a comparison of the unimodal function ranks of the algorithms. MFATA on multimodal has a rank of 1. The comparison of the multimodal function ranks of all algorithms used able to be seen in Table 3. The MFATA rank value is 1. In Table 4, the comparison of the fixed multimodal rank of MFATA is 2. The comparison and distribution characteristics of the solutions of each algorithm when solving 23 CEC2017 benchmark functions are shown in Figure 3 and Figure 4.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure 3. The convergence curve of benchmark function: (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, (f) F6,(g) F7, (h) F8, (i) F9

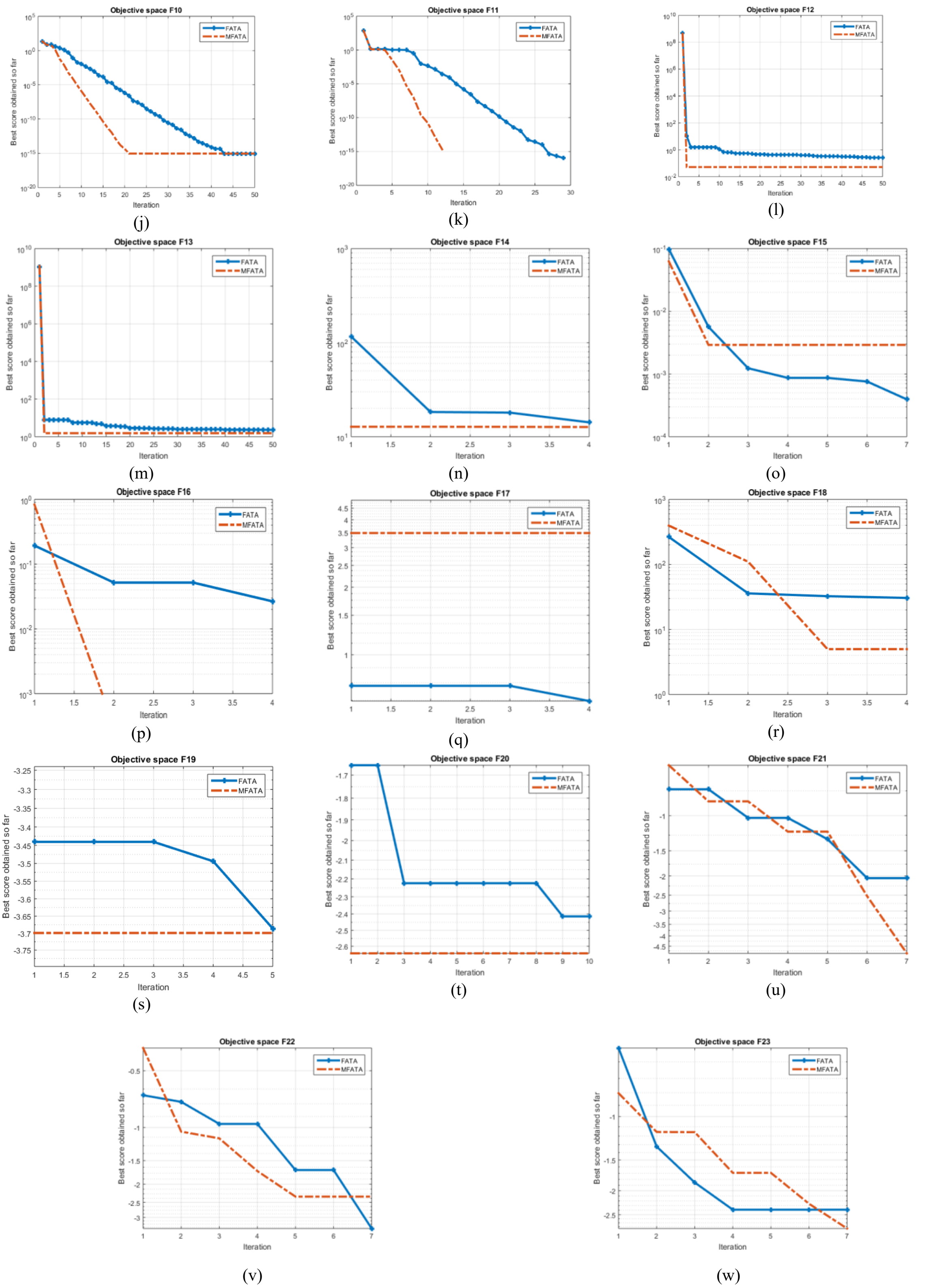


Figure 4. The convergence curve of benchmark function: (j) F10, (k) F11, (l) F12, (m) F13, (n) F14, (o) F15, (p) F16, (q) F17, (r) F18, (s) F19, (t) F20, (u)F21, (v) F22, (w) F23.

Table. 1 Comparison of MFATA and other algorithms

Function		FATA	MFATA
F1	Best	9.63E-35	1.94E-59
	Mean	2.50E-31	1.62E-52
	Worst	3.80E-30	4.49E-51
	Std	7.20E-31	8.07E-52
	Rank	2	1
F2	Best	1.53E-15	4.58E-29
	Mean	1.04E-13	2.35E-22
	Worst	1.86E-12	8.06E-21
	Std	3.28E-13	1.21E-21
	Rank	2	1
F3	Best	5.47E-21	3.51E-51
	Mean	5.53E-10	1.66E-21
	Worst	2.45E-08	8.23E-20
	Std	3.47E-09	1.16E-20
	Rank	2	1
F4	Best	3.72E-15	2.32E-30
	Mean	1.15E-13	7.85E-30
	Worst	6.11E-13	2.36E-29
	Std	1.24E-13	4.73E-30
	Rank	2	1
F5	Best	0.012052	0.14252
	Mean	25.2336	25.6936
	Worst	53.0044	28.985
	Std	11.157	8.337
	Rank	1	2
F6	Best	0.025312	0.001028
	Mean	3.9432	5.4544
	Worst	5.8778	7.2745
	Std	1.6542	2.3763
	Rank	1	2
F7	Best	2.16E-05	2.64E-07
	Mean	0.001115	0.000817
	Worst	0.003381	0.003129
	Std	0.000919	0.000829
	Rank	2	1
F8	Best	-1.26E+04	-1.26E+04
	Mean	-1.26E+04	-1.26E+04
	Worst	-1.25E+04	-1.25E+04
	Std	1.03E+01	8.96E+00
	Rank	2	1
F9	Best	0.00E+00	0.00E+00
	Mean	2.52E-02	0.00E+00
	Worst	5.00E-01	0.00E+00
	Std	8.86E-02	0.00E+00
	Rank	2	1
F10	Best	8.88E-16	8.88E-16
	Mean	3.02E-15	8.88E-16
	Worst	7.99E-15	8.88E-16
	Std	2.03E-15	0.00E+00
	Rank	2	1
F11	Best	0.00E+00	0.00E+00
	Mean	0.00E+00	0.00E+00
	Worst	0.00E+00	0.00E+00
	Std	0.00E+00	0.00E+00
	Rank	1	1
F12	Best	1.48E-05	0.012409
	Mean	0.25134	0.72872
	Worst	0.62961	1.4039
	Std	0.2301	0.49484
	Rank	1	2

Table 1. Comparison of MFATA and other algorithms *(continued)*

Function		FATA	MFATA
F13	Best	0.009608	0.016478
	Mean	1.6352	2.054
	Worst	2.9927	2.9988
	Std	1.0351	1.1895
	Rank	1	2
F14	Best	9.98E-01	9.98E-01
	Mean	5.61E+00	5.74E+00
	Worst	1.58E+01	1.40E+01
	Std	4.84E+00	4.72E+00
	Rank	1	2
F15	Best	3.12E-04	1.08E-03
	Mean	1.93E-03	9.49E-03
	Worst	2.43E-02	3.85E-02
	Std	4.14E-03	9.32E-03
	Rank	1	2
F16	Best	-1.03E+00	-1.03E+00
	Mean	-6.70E-01	-7.56E-01
	Worst	2.66E-02	4.78E-02
	Std	4.05E-01	3.28E-01
	Rank	1	2
F17	Best	4.08E-01	4.03E-01
	Mean	2.03E+00	1.91E+00
	Worst	7.52E+00	8.70E+00
	Std	1.74E+00	1.84E+00
	Rank	2	1
F18	Best	3.28E+00	3.3036
	Mean	19.2897	19.4225
	Worst	98.2178	48.5131
	Std	19.4655	12.6027
	Rank	1	2
F19	Best	-3.8593	-3.8542
	Mean	-3.7011	-3.4574
	Worst	-2.9833	-2.9009
	Std	0.15766	0.24922
	Rank	1	2
F20	Best	-3.1379	-2.6501
	Mean	-2.7215	-1.9501
	Worst	-1.9873	-1.2252
	Std	0.30935	0.39139
	Rank	2	1
F21	Best	-10.1521	-10.1224
	Mean	-4.8859	-5.5112
	Worst	-1.3141	-1.4864
	Std	2.5397	2.5828
	Rank	1	2
F22	Best	-10.3551	-10.3698
	Mean	-5.0738	-5.133
	Worst	-1.2709	-2.04
	Std	2.6696	2.2495
	Rank	2	1
F23	Best	-10.3424	-10.5251
	Mean	-4.8966	-5.9417
	Worst	-1.7757	-1.5863
	Std	2.3916	2.6635
	Rank	1	2

Table 2. Rank comparison of unimodal functions between algorithms (F1-F7)

Function	FATA	MFATA
Sum rank	12	9
Mean rank	1.714285714	1.285714286
Total rank	2	1

Table 3. Rank comparison of multimodal functions between algorithms (F8-F13)

Function	FATA	MFATA
Sum rank	9	8
Mean rank	1.5	1.333333333
Total rank	2	1

.

Table 4. Rank comparison of fixed-multimodal functions between algorithms (F14-F23)

Function	FATA	MFATA
Sum rank	13	17
Mean rank	1.3	1.7
Total rank	1	2

5. CONCLUSION AND LIMITATION

A novel group intelligence method, termed the modified mirage algorithm (FATA), is presented to address continuous multi-type optimization challenges. FATA develops the mirage light filtering principle (MLF) and light propagation strategy (LPS) by emulating the process of mirage creation. The MLF technique, in conjunction with the definitive integration principle, enhances the algorithmic population's exploration capability within FATA. The LPS method, in conjunction with the trigonometric principle, enhances the algorithmic individual's convergence speed and exploitation capability. These two search algorithms can optimize the utilization of the FATA population and enhance individual search capabilities. This research introduces a modified FATA optimization Levy Flight, termed MFATA. MFATA is evaluated against other competitive optimizers using 23 benchmark functions and the IEEE CEC 2017 to assess its optimization capability. This study is specifically crafted for qualitative analysis, competency analysis of exploration and exploitation, avoidance analysis of local best solutions, and thorough comparative experiments. The experimental findings demonstrate the comprehensiveness and competitiveness of MFATA in addressing functions.

REFERENCES

[1] L. Messeri and M. J. Crockett, "Artificial intelligence and illusions of understanding in scientific research," *Nature*, vol. 627, no. 8002, pp. 49–58, 2024. https://doi.org/10.1038/s41586-024-07146-0.

[2] V. Bolón-Canedo, L. Morán-Fernández, B. Cancela, and A. Alonso-Betanzos, "A review of green artificial intelligence: Towards a more sustainable future," *Neurocomputing*, p. 128096, 2024. https://doi.org/10.1016/j.neucom.2024.128096.

[3] Y. I. Alzoubi and A. Mishra, "Green artificial intelligence initiatives: Potentials and challenges," *Journal of Cleaner Production*, p. 143090, 2024. https://doi.org/10.1016/j.jclepro.2024.143090.

[4] O. A. Bello and K. Olufemi, "Artificial intelligence in fraud prevention: Exploring techniques and applications challenges and opportunities," *Computer Science and IT Research Journal*, vol. 5, no. 6, pp. 1505–1520, 2024. http://doi.org/10.51594/csitrj.v5i6.1252.

[5] M. A. Fadhel et al., "Navigating the metaverse: unraveling the impact of artificial intelligence—a comprehensive review and gap analysis," *Artificial Intelligent Review*, vol. 57, no. 10, p. 264, 2024. https://doi.org/10.1007/s10462-024-10881-5.

[6] P. Sharma and S. Raju, "Metaheuristic optimization algorithms: A comprehensive overview and classification of benchmark test functions," *Soft Computing*, vol. 28, no. 4, pp. 3123–3186, 2024. https://doi.org/10.1007/s00500-023-09276-5.

[7] G. H. Valencia-Rivera et al., "A systematic review of metaheuristic algorithms in electric power systems optimization," *Applied Soft Computing*, vol. 150, p. 111047, 2024. https://doi.org/10.1016/j.asoc.2023.111047.

[8] G. Li, T. Zhang, C.-Y. Tsai, L. Yao, Y. Lu, and J. Tang, "Review of the metaheuristic algorithms in applications: Visual analysis based on bibliometrics (1994–2023)," *Expert Systems and Applications*, p. 124857, 2024. https://doi.org/10.1016/j.eswa.2024.124857.

[9] R. Narayanan and N. Ganesh, "A Comprehensive Review of Metaheuristics for Hyperparameter Optimization in Machine Learning," *Metaheuristics Machine Learning Algorithms Applications*, pp. 37–72, 2024. https://doi.org/10.1002/9781394233953.ch2.

[10] V. Tomar, M. Bansal, and P. Singh, "Metaheuristic Algorithms for Optimization: A Brief Review," *Engineering Proceedings*, vol. 59, no. 1, p. 238, 2024. https://doi.org/10.3390/engproc2023059238.

[11] K. Rajwar and K. Deep, "Structural bias in metaheuristic algorithms: Insights, open problems, and future prospects," *Swarm Evolution Computing*, vol. 92, p. 101812, 2025. https://doi.org/10.1016/j.swevo.2024.101812.

[12] A. Lameesa, M. Hoque, M. S. Bin Alam, S. F. Ahmed, and A. H. Gandomi, "Role of metaheuristic algorithms in healthcare: a comprehensive investigation across clinical diagnosis, medical imaging, operations management, and public health," *Journal of Computational Design and Engineering*, vol. 11, no. 3, pp. 223–247, 2024. https://doi.org/10.1093/jcde/qwae046.

[13] S. S. Aljehani and Y. A. Alotaibi, "Preserving Privacy in Association Rule Mining Using Metaheuristic-Based Algorithms: A Systematic Literature Review," *IEEE Access*, 2024. https://doi.org/10.1109/ACCESS.2024.3362907.

[14] P. Megantoro, S. Abd Halim, N. A. M. Kamari, L. J. Awalin, M. S. Ali, and H. M. Rosli, "Optimizing reactive power dispatch with metaheuristic algorithms: A review of renewable distributed generation integration with intermittency considerations," *Energy Reports*, vol. 13, pp. 397–423, 2025. https://doi.org/10.1016/j.egyr.2024.12.020.

[15] A. Yernar and C. Turan, "Recent developments in vehicle routing problem under time uncertainty: a comprehensive review," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 2, pp. 1263–1275, 2025. https://doi.org/10.11591/eei.v14i2.8636.

[16] A. Saini and O. P. Rahi, "Optimal power flow approaches for a hybrid system using metaheuristic techniques: a comprehensive review," *International Journal of Ambient Energy*, vol. 45, no. 1, p. 2345839, 2024. https://doi.org/10.1080/01430750.2024.2345839.

[17] S. Mohapatra, H. Lala, and P. Mohapatra, "Modified random-oppositional chaotic artificial rabbit optimization algorithm for solving structural problems and optimal sizing of hybrid renewable energy system," *Evolutionary Intelligence*, vol. 18, no. 1, p. 21, 2025. https://doi.org/10.1007/s12065-024-01004-8.

[18] E. Crespo-Martínez, L. Tonon-Ordóñez, M. Orellana, and J. F. Lima, "Applied Metaheuristics in International Trading: A Systematic Review," *Conference on Information and Communication Technologies of Ecuador*, pp. 95–112, 2023. https://doi.org/10.1007/978-3-031-45438-77.

[19] D. Fatima, A.B Manar, N. Qassir, and S. Tracy, "Artificial intelligence techniques in financial trading: A systematic literature review," *Journal of King Saud University - Computer and Information Sciences*, vol. 36, no. 3, 2024. https://doi.org/10.1016/j.jksuci.2024.102015.

[20] W. F. Mahmudy, A. W. Widodo, and A. H. Haikal, "Challenges and Opportunities for Applying Meta-Heuristic Methods in Vehicle Routing Problems: A Review," *Engineering Proceedings*, vol. 63, no. 1, p. 12, 2024. https://doi.org/10.3390/engproc2024063012.

[21] L. Dong-liang, L. Bei, and W. Hai-hua, "The importance of nature-inspired metaheuristic algorithms in the data routing and path finding problem in the internet of things," *International Journal of Communication Systems*, vol. 36, no. 10, p. e5450, 2023. https://doi.org/10.1002/dac.5450.

[22] S. Faramarzi-Oghani, P. Dolati Neghabadi, E.-G. Talbi, and R. Tavakkoli-Moghaddam, "Meta-heuristics for sustainable supply chain management: A review," *International Journal of Production Research*, vol. 61, no. 6, pp. 1979–2009, 2023. https://doi.org/10.1080/00207543.2022.2045377.

[23] K. Joni, "Parameter Estimation of Photovoltaic based on Chaotic Elite Mountain Gazelle Optimizer," *Vokasi Unesa Bulletin of Engineering Technology and Applied Science*, pp. 30–37, 2024. https://doi.org/10.26740/vubeta.v1i1.34073

[24] S. Jomah, "Meta-Heuristic Scheduling: A Review on Swarm Intelligence and Hybrid Meta-Heuristics Algorithms for Cloud Computing," *Operations Research Forum*, vol. 5, no. 4, p. 94, 2024. https://doi.org/10.1007/s43069-024-00382-0.

[25] A. Seyyedabbasi, W. Z. Tareq Tareq, and N. Bacanin, "An Effective Hybrid Metaheuristic Algorithm for Solving Global Optimization Algorithms," *Multimedia Tools and Applications*, pp. 1–36, 2024. https://doi.org/10.1007/s11042-024-19437-9.

[26] H. Alqahtani and G. Kumar, "Efficient Routing Strategies for Electric and Flying Vehicles: A Comprehensive Hybrid Metaheuristic Review," *IEEE Transactions on Intelligent Vehicles*, 2024. https://doi.org/10.1109/TIV.2024.3358872.

[27] S. Mahmoudinazlou, A. Alizadeh, J. Noble, and S. Eslamdoust, "An improved hybrid ICA-SA metaheuristic for order acceptance and scheduling with time windows and sequence-dependent setup times," *Neural Computing and. Applications*, vol. 36, no. 2, pp. 599–617, 2024. https://doi.org/10.1007/s00521-023-09030-w.

[28] R. Martí, M. Sevaux, and K. Sörensen, "Fifty years of metaheuristics," *European Journal of Operational Research*, vol. 321, no. 2, pp. 345–362, 2025. https://doi.org/10.1016/J.EJOR.2024.04.004.

[29] M. A. L. Silva, J. F. da Silva, S. R. de Souza, and M. J. F. Souza, "A scalability analysis of a Multi-agent framework for solving combinatorial optimization via Metaheuristics," *Engineering Applications of Artificial Intelligence*, vol. 142, p. 109738, 2025. https://doi.org/10.1016/j.engappai.2024.109738.

[30] A. Dvivedi and P. Kumar, "Optimizing the quality characteristics of glass composite vias for RF-MEMS using central composite design, metaheuristics, and bayesian regularization-based machine learning," *Measurement*, vol. 243, p. 116323, 2025. https://doi.org/10.1016/j.measurement.2024.116323.

[31] Y. Ahmed et al., "Advanced ciprofloxacin quantification: A machine learning and metaheuristic approach using ultrasensitive chitosan-gold nanoparticle based electrochemical sensor," *Journal of Environmental and Chemical Engineering*, vol. 13, no. 1, p. 115094, 2025. https://doi.org/10.1016/j.jece.2024.115094.

[32] M. Sadrani, A. Tirachini, and C. Antoniou, "Bus scheduling with heterogeneous fleets: Formulation and hybrid metaheuristic algorithms," *Expert Systems Applications*, vol. 263, p. 125720, 2025. https://doi.org/10.1016/j.eswa.2024.125720.

[33] N. Van Thieu, E. H. Houssein, D. Oliva, and N. D. Hung, "IntelELM: A python framework for intelligent metaheuristic-based extreme learning machine," *Neurocomputing*, vol. 618, p. 129062, 2025. https://doi.org/10.1016/j.neucom.2024.129062.

[34] T. Wu, C. Miao, Y. Zhang, and C. Chen, "A RankNet-Inspired Surrogate-Assisted Hybrid Metaheuristic for Expensive Coverage Optimization," *arXiv Prepraration arXiv2501.07375*, 2025. https://doi.org/10.48550/arXiv.2501.07375.

[35] T. U. Badrudeen, F. K. Ariyo, and N. Nwulu, "Optimal Sizing of FACTS Controller through Hybrid Metaheuristic Algorithm for Static Security Enhancement in Transmission Power Systems," *Scientific African*, p. e02543, 2025. https://doi.org/10.1016/j.sciaf.2025.e02543.

[36] P. Samui, "Hybrid Metaheuristic Optimization of Artificial Neural Networks for Liquefaction Probability Prediction Using Various Historical CPT Data," *Transportation Infrastructure Geotechnology*, vol. 12, no. 1, pp. 1–33, 2025. https://doi.org/10.1007/s40515-024-00504-5.

[37] J. Zhao, Y. Long, B. Xie, G. Xu, Y. Liu, "Optimizing quay crane scheduling using deep reinforcement learning with hybrid metaheuristic algorithm," *Engineering Applications of Artificial Intelligence*, vol. 143, 2025. https://doi.org/10.1016/j.engappai.2025.110021.

.

[38] L. Zhao, Z. Peng, P. Pirozmand, "A Hybrid Metaheuristic Method To Optimize The Total Weighted Tardiness And Delivery Cost For An Integrated Production And Distribution Scheduling Model In Supply Chain Management," *Journal of Industrial and Management Optimization*, vol. 21, no.3, pp. 2396-2415, 2025. https://doi.org/10.3934/jimo.2024176.
[39] N.Van Thieu, S.H. Houssein, D. Oliva, N.D. Hung," IntelELM: A python framework for intelligent metaheuristic-based extreme learning machine," *Neurocomputing*, vol. 618, 2025. https://doi.org/10.1016/j.neucom.2024.129062.
[40] A. P. Piotrowski, J. J. Napiorkowski, and A. E. Piotrowska, "Metaheuristics should be Tested on Large Benchmark Set with Various Numbers of Function Evaluations," *Swarm and Evolutionary Computation*, vol. 92, p. 101807, 2025. https://doi.org/10.1016/j.swevo.2024.101807.
[41] B. G. Thengvall, S. N. Hall, and M. P. Deskevich, "Measuring the Effectiveness and Efficiency of Simulation Optimization Metaheuristic Algorithms," *Journal of Heuristics*, vol. 31, no. 1, pp. 1–21, 2025. https://doi.org/10.1016/j.swevo.2024.101807.
[42] C. Zheng, Z. Li, M. Janardhanan, Z. Zhang, and L. Zhang, "Improved Swarm-Based Metaheuristics for Optimizing Human–Robot Collaborative Assembly Lines with Multi-Type Collaborative Robots," *Flexible Services and Manufacturing Journal*, pp. 1–63, 2025. https://doi.org/10.1007/s10696-024-09582-6
[43] B. S. Domingues, M. A. C. Rodrigues, and É. C. Alves, "Optimum Design Of Truss Structures Considering Nonlinear Analysis And Dynamic Loading Using Metaheuristic Algorithms," *REM-International Engineering Journal*, vol. 78, no. 1, p. e240008, 2025. https://doi.org/10.1590/0370-44672024780008
[44] S. Dhibar and M. Jain, "Metaheuristics and Strategic Behavior of Markovian Retrial Queue Under Breakdown, Vacation and Bernoulli Feedback," *Applied Intelligence*, vol. 55, no. 4, p. 273, 2025. https://doi.org/10.1007/s10489-024-05978-x.
[45] A. Qi, D. Zhao, A. A. Heidari, L. Liu, Y. Chen, and H. Chen, "FATA: an efficient optimization method based on geophysics," *Neurocomputing*, vol. 607, p. 128289, 2024. https://doi.org/10.1016/j.neucom.2024.128289

BIOGRAPHIES OF AUTHORS

Aditya Prapanca received his Bachelor of Engineering from Sepuluh Nopember Institute of Technology (ITS), Surabaya, Indonesia, in 2000, and his Master of Computer from Sepuluh Nopember Institute of Technology (ITS), Indonesia, in 2007. He is currently a lecturer at the Department of Computer Engineering, Universitas Negeri Surabaya, Indonesia. His research interests include artificial intelligence. He can be contacted at email: adityaprapanca@unesa.ac.id

Nasreddine Belhaouas received his engineering degree in electronic engineering from the National Polytechnic School, Algiers, Algeria, in 2007. He obtained a Magister degree (equivalent to MSc) in electronics/photovoltaic energy in 2010 and a Doctorate of Science (equivalent to PhD) in electronics in 2017. He is currently a senior researcher, team leader, and project manager at the Renewable Energy Center (CDER), Algiers, Algeria. His main research interests include photovoltaic (PV) energy, PV system performance, PV module degradation, IEC 61215, partial shading effects, MPPT techniques, and PV array reconfiguration.

Imed Mahmoud was born in Mahdia, Tunisia in 1982. He received M.Sc. degree of Electrical Engineering option Electrical engineering and Power Electronics from High School of Sciences and Technology of Tunis, University of Tunis (ESSTT), Tunisia, in 2006, Master degree, and Ph.D from ESSTT, Tunisia in 2008 and 2015 respectively. From 2008 to 2015, he had been an assistant in the Electronic Engineering Department of ISSAT, Mateur, Bizerte, Tunisia. He has been promoted to the assistant professor grade in the same department since June 2016. From September 2016, he has been an assistant professor in the Electrical Engineering Department of ISSAT, Mahdia, Tunisia. His main research interests cover several aspects related to control of the Static Converters, the Electric Machines Drives in biomedical and Renewable energy applications. I published in this field several indexed papers.