Mayfly optimization algorithm: a review

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Abstract. This paper gives a review on the bio-inspired optimization methodology known as mayfly (MA) algorithm in order to resolve issues in optimization techniques. It is a newly formed meta-heuristic optimization algorithm that focuses on the movements of masculine and feminine mayflies. It is encouraged from flying behaviour also the methods of mating in mayflies. With the help of a realistic-world separate flow planning issue along with the coupling behaviour in numerous objective optimizations, the performance of the mayfly algorithm (MA) is well evaluated. Some of the implementations of this algorithm are discussed in this paper: Bearing fault diagnosis based on the mayfly algorithm, optimizing the performance of PEMFC, Covid diagnosis, wind speed optimization, improving the scheduling of solar wind speed using mayfly optimization, detecting fault in the wind turbine gearboxes, patterning in the array antennas with the help of optimization and so on .One of the main advantages of the MA is that it combines the other optimization algorithms namely swarm optimization (PSO) with the evolutionary optimizations (GA). The motion of the mayflies that resemble nuptial dance model along with the arbitrary flight helps in the improvement of the stability within the exploration and exploitation methods. In addition, allows escape from the community peak. All the above work reviewed shows promising results from the algorithm. More work can be carried out using this algorithm in future.

Keywords: mayfly algorithm, nature-inspired algorithm, optimization.

1. Introduction

Metaheuristic optimization is a method used to resolve the issues in optimization. Optimization basically involved in almost every application such as the design engineering, economical sector, internet of things applications as well [1]. In order to resolve the issues in optimization various algorithms are been used [2].

Artificial intelligence and machine learning offer solutions to a variety of real-world problems, ranging from discrete to continuous, and constrained to unconstrained challenges. However, it's been shown that conventional techniques may struggle with large-scale multimodal situations that lack continuity or differentiability. In response, metaheuristic algorithms have emerged as effective alternatives due to their simplicity and ease of implementation. These strategies operate independently of gradient specifics or mathematical properties of the landscape, making them competitive options for a diverse array of problems [3, 4].

In a study, some algorithms from 2018 to 2020 were evaluated for the optimization [3]. They included the Atom Search Optimization (ASO) [5], Beetle Antennae Search (BAS) [5], Sunflower Optimization (SFO) [7], Mayfly Algorithm (MA) [8], Parasitism Predation Algorithm (PPA) [9], Slime Mould Algorithm (SMA) [10] and Tunicate Swarm Algorithm (TSA) [11]. In cuckoo algorithm [12] study is performed on egg laying pattern of cuckoo bird, in particle swarm optimization [13] research on swarm behaviour is observed, also behavioural pattern of firefly [14], grasshopper [15-18], salp swarm [19, 20] and bat [21] is studied.

On the basis of bio related inspirations, numerous types of developments in the bio-inspired algorithms [22]. These types of algorithms are basically categorized into the four categories. Namely are the evolutionary based [23], swarm intelligence [11], ecology based [24] and the multi objective algorithms [25].

The evolutionary based algorithms consist of the artificial neural networks, genetic algorithms, evolution strategies, differential evolution, paddy field algorithms. Further the second category which is the swarm intelligence consist of the ant colony optimization, artificial bee colony, fish swarm, firefly algorithms, group search optimizers and so on. The ecology-based algorithms include the invasive weed optimization, biogeography-based optimization, etc. The last category which is the multi-objective optimization basically consist of the non-dominated sorting genetic algorithm, population-based ant colony algorithm, etc.

The mayfly is a small, weak, and gentle bug that numbers way extra than out of 3,100 types in the globe. Nevertheless, this bug takes nearly a yearly to be born; passes away after a maximal of one period day of life. The major goal of their childbirth is coupling [26]. A number of them are not even bothered to eat [3]. Mayflies intended for coupling normally consist a number of males of a small number of tons of separate ones, that are roughly around meters of 1 to 4 more than bottom for roughly about 1.5 to 2 hourly periods early in forenoon. Forming pattern and taking adult female, male perform a nuptial dance to a characteristically upward along with downward motion orientation. This mayfly algorithm uses this concept for optimization.

In 2020, Zervoudakis and Tsafarakis developed the mayfly (MA) algorithm inspired by the mating behaviour of mayflies. Upon hatching, mayflies become adults and, although the lifespan may be short, are the healthiest mayflies that can survive. The solutions to an optimization problem are given by the position of the mayfly in a search space [8].

2. Mayfly algorithm (MA)

To serve men and women, the algorithm initially generates two sets of instants. It is assumed that all adult mayflies, including the best-adapted ones, survive after hatching from eggs, regardless of how long they live. The condition of each mayfly in the search room represents a potential fix for this problem. Here's how the algorithm operates: First, a random set-in number of twos of the mayflies are generated, designating the male and female populations separately. It indicates that each mayfly is positioned at a random room in form of contender solution defined as vector of dimension d, $x = (x_1, \dots, x_d)$ and its performances are examined on the default functional objective $f(x)$ [8]. The change in its place and direction of flight of each one mayfly is a robust communication of the individual and communal flight experience which defines the speed of a mayfly. Specifically, each one mayfly adapts its flight path to theirs best one's own position ($pbest$) until now, in addition the best distinction achieved by any mayfly flock until now ($gbest$) [27].

3. Algorithm modelling

The implementation of the mayfly optimization algorithm could well be summarized with the following steps [28]:

(1) Initialization: The population of corresponding masculine and feminine are firstly denoted by $x = [x_1, \dots, x_d]$ and $y = [y_1, \dots, y_d]$ respectively. Also, the velocity is $v = [v_1, \dots, v_d]$ [28].

(2) Male movements: The male mayflies are not able to move at a higher speed when they dance over a certain height of water. The functional objective $f(x)$, which marks the $f(gbest)$ decides the best overall position for the current iteration.

Assume that the x_i^t is the present position of the male mayfly denoted by i in the search room at step time period t, then its positional value is modified with the addition of v_i^{t+1} which denotes the velocity to the ongoing present position. It is represented by:

$$x_i^{t+1} = x_i^t + v_i^{t+1}. \tag{1}$$

Therefore, the velocity of the male mayfly i is calculated as follows [28]:

$$v_{ij}^{t+1} = v_{ij}^{t} + a_1 e{-}\beta r^2 p\left(pbest_{ij} - x_{ij}^{t}\right) + a_2\, e - \beta g^2 g\left(gbest_j - x_{ij}^{t}\right), \tag{2}$$

where x_{ij}^{t} denotes mayfly i in dimension j at the current iteration of the space time step t. a_1 and a_2 are the positive constants that represent the attraction. $pbest$ is the best position the mayfly i has visited. The best position for the mayfly can be found out at step time $t+1$ as following:

$$pbest_i = \begin{cases} x_i\,(t+1), & f\left(x_i(t+1)\right) < f(pbest_i), \\ \text{is kept the same,} & \end{cases} \tag{3}$$

where $f: Rn \rightarrow R$ is function to minimize $gbest_j$ is the best global reach during the iteration t. In the Eq. (2) r_p is the distance of x_i from $pbest_i$ and r_g is the distance of x_i from $gbest_j$. r_p and r_g are calculated by the following:

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n} (x_{ij} - X_{ij})^2}, \tag{4}$$

where x_{ij} is the jth element of mayfly i, while X_i is corresponding to $pbest_i$ and $gbest_j$.

The velocity of best mayfly is given by $v^{t+1} = v^t + d * r$, where d is the nuptial dance and r is the random variable in [1, –1] [28].

(3) Female movements: Compared to male mayflies, female mayflies do not gather in swarm. Instead, they fly towards male in order to breed. Let us consider y_i^t is the current position of the female mayfly i in space time step t. The location change can be given as:

$$y_i^{t+1} = y_i^t + v_i^{t+1}. \tag{5}$$

The female mayflies' velocities can be given as y:

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + a_3\, e^{-\beta r2mh}\left(x_{ij}^{t} - y_{ij}^{t}\right), & f(y_i) > f(x_i), \\ v_{ij}^{t} + f_l * r, \quad f(y_i) \leq f(x_i), & \end{cases} \tag{6}$$

where y is the female mayfly, a_3 is learning coefficient, β is distance coefficient which is constant, r_{mf} is the interspace between the masculine and feminine mayflies, f_l denotes the arbitrary walk value when the feminine is not being allured by the masculine, r is random value in [1, –1].

(4) Mating of mayflies: The mate process within the two mayflies is represented with the help of a cross operator as following: selection of one parent is from the masculine population along with the other from the feminine population is done. The selection of the parents is done on the same basis of how the feminine is attracted to the masculine. Specifically, the selection can be based on either of the randomly nature or on their fitness function. In second of the two, the finest feminine mates with the finest masculine, the second-finest feminine with the second-finest male, and so forth. Two offspring are generated as the result of the cross operator as follows:

$$\begin{aligned} offspring_1 &= L * male + (L+1) * female, \\ offspring_2 &= L * female + (1-L) * male, \end{aligned} \tag{7}$$

where L is random number, initial velocity of two offsprings set 0 [28].

(5) Updating: The solution which is not suitable is replaced by the best suitable solution and the above procedure is repeated till the stopping criteria is satisfied. The upcoming next position

could be acquired with the addition of v_i^{t+1} which denotes the velocity. It could be represented by:

$$p_i^{t+1} = p_i^t + v_i^{t+1}, \tag{8}$$
$$q_i^{t+1} = q_i^t + v_i^{t+1}. \tag{9}$$

(6) Calculating fitness and updating $pbest$ and $gbest$.

(7) If the stopping criterion is encountered, do the exit and output the result. Else do repeat the steps (5)-(7).

The Mayfly Optimization Algorithm flowchart is depicted in Fig. 1.

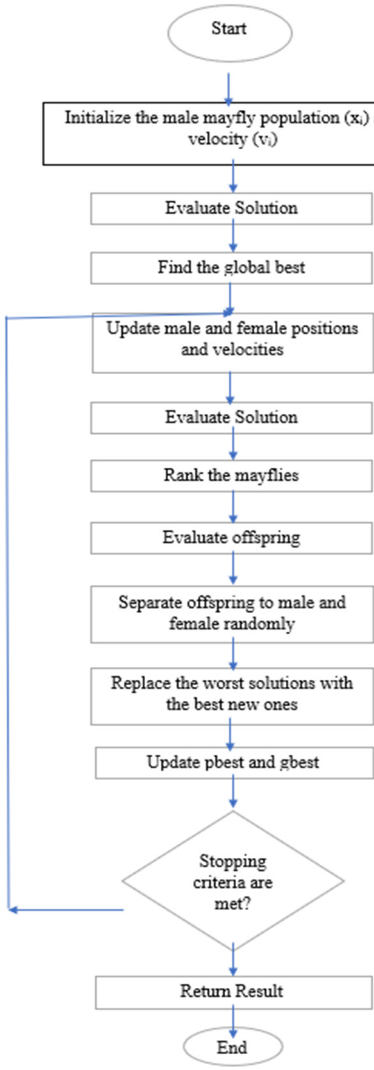

Fig. 1. Flowchart of algorithm [27]

4. Pseudo code of algorithm

The following pseudo code summarises the fundamental phases of the Mayfly Algorithm (MA) which is shown in Fig. 2.

```
#Mayfly Algorithm [25]
Objective function f(x), x =(x_1, ..., x_d)^T
Initialize the male mayfly position x_i (i = 1, 2, ..., N) and velocities v_mi
Initialize the female mayfly position y_i (i = 1, 2, ..., M) and velocities v_fi
Evaluate the solutions
Find global best gbest
while t ≤ T
find pbest by (3), the best solution of male mayfly
for i = 1: M
            for j = 1: d
                        Adjust the female velocity by (6)
                        Adjust the female position by (9)
end for
   end for
for i = 1: M
            for j = 1: d
                        Adjust the male velocity by (2)
                        Adjust the female position by (8)
end for
Update pbest
end for
Do while stopping criteria not met
                        Update velocities and solutions of males and
females
Evaluate the solutions
                        Rank the mayflies
                        Mate the mayflies
                        Evaluate offspring
                        Separate offspring to male and female randomly
                        Replace the worst solutions with best new ones
                        Update pbest and gbest
end while
Postprocess the results and visualization
```

Fig. 2. Pseudo code of Mayfly algorithm

5. Different variants of Mayfly

5.1. Modified individual experience Mayfly algorithm

The mean of the locations the mayfly has visited in the search space is used to represent the mayfly's experience in this modification. This offers a more accurate depiction of the experience and a clearer image of how the mayflies are getting closer to the global optimum, which yields the best value in the search space. Moreover, a chaotic random decreasing gravity coefficient technique is used to improve the MA's capacity for both exploration and exploitation [29].

5.2. Modified Mayfly algorithm

When applied to low-dimensional scenarios, the standard MA outperforms alternative swarm algorithms in terms of convergence speed. However, because of the impact of velocity fluctuation, the MA's stability is low, which produces subpar outcomes. Furthermore, the MA performs badly on the multimodal functions since it cannot simply rely on its mechanism to escape the local optimal zone while dealing with high-dimensional nonlinear difficult scenarios. In order to enhance the MA, Xing Wang et al. suggests using a modified mayfly algorithm called modMA, which incorporates three techniques. Three strategies have been proposed to improve MA: the exponent decreasing inertia weight approach, the adaptive Cauchy mutation technique, and the increased crossover operator strategy [30].

5.3. Bioinspired bare bones Mayfly algorithm

The issue with the basic MA is that it includes a lot of beginning factors, which greatly affect the outcome. Furthermore, because of a lack of exploitation capacity, the precision of MA is insufficient. By canceling the velocity, the bare bones mayfly algorithm prevents the influence of parameters. Individual position is determined directly using random sampling that adheres to a Gaussian distribution, just like the bare bones PSO. BBMA does the random flight of the superb female and the nuptial dance of the optimal male using Lévy flight to improve the exploitation ability and aid the algorithm in escaping from the local optimal solution [31].

5.4. Dynamic elite strategy Mayfly algorithm

Male and female mayfly populations are distinguished by MA based on the social structure of the mayfly community. The male mayfly bases its movement on the worldwide optimal position, while the female mayfly follows his movements when the individual population moves. The initial stage mayfly spots are randomly dispersed in the search space. A new global optimal solution will be found after comparing the population's optimal male mayfly individual with the global optimal individual in each iteration. The majority of the ideal male mayfly individuals will, however, be concentrated close to the global optimal solution in the later stages of the algorithm, falling into the local optimal solution. To solve this, Qianhang Du and Honghao Zhu [32], presented an enhanced Mayfly Algorithm Based on Dynamic Elite Strategy (DESMA), which begins with the global optimal solution and executes a more precise elite selection strategy in proximity to the global optimal solution, to address the aforementioned issues. The algorithm can, on the one hand, break out of the local optimum, increase population diversity, broaden the search space, and potentially discover a new global optimal solution that outperforms the optimal global solution from the previous generation; on the other hand, when maintaining population integrity, it not only increases convergence accuracy but also speeds up convergence and finds the optimal global solution more steadily.

6. Application areas

Effectiveness of the applications of Mayfly Optimization Algorithm have promisingly been shown in the optimization problems in engineering sector. In the literature, improved solutions than the current existing solutions have been achieved by the MA. Some of the MA applications are:

Yuhu Liu et al. [33] provided the Initial Center Frequency Guided Filter (ICFGF) which is a novel method of selecting the resonant demodulation frequency band to detect the bearing failure [23]. Through the initial step, a statistical index for variance is applied to estimate the distribution of the spectrum of energy, which can compatibly decide the central frequency of the faulty pulse and effectively quash the intervention of the arbitrary pulse. Based on the central frequency to find out the excellent resonant frequency from the initial step, a modified mayfly algorithm (MMA) is applied as it has a speedy convergence rate.

Mohamed A.M Shaheen et al. [27] presented a new optimization method “Chaotic MayFly Optimization Algorithm” (CMOA) to obtain the parameters of proton exchange membrane fuel cells (PEMFC) [34]. A nonlinear problem has been worked out as the optimization problem into this case. As the metaheuristic optimization approaches are eminently affected by the initialization problem, a newer hybridization within disorderly mapping also the mayfly optimization algorithm is used for solving the problems in estimating variables of the project called PEMFC and also achieve improved outcomes. In order of finding the better solution for the functional objective in satisfying the prefixed situations, a CMOA is put in application. Also, the application from the CMOA results in a precise development of the PEMFC model.

Aihua Hu et al. [35] used the mayfly optimization algorithm in finding the optimal station of the semi-passive positioning system of the multiple base station in flight of the unmanned aerial vehicle (UAV) [36]. Comparing to the similar terminal layout methods alike the genetic algorithm (GA), artificial bee colony (ABC), particle swarm optimization (PSO), a simulation and optimization analysis of different numbers of base terminals is offered [3]. Along the simulation, the implementation of the four base terminals and five base terminals in numerous circumstances, the MA could accomplish superior distribution effects.

Ahmed Fathy et al. [37] used the mayfly optimization algorithm along with other optimization algorithms as the strategy for energy management based on the recent metaheuristic optimizing of the hybrid origin parasitism-predation algorithm employed includes photovoltaics, fuel cells, batteries, supercapacitors to refuel aerodyne into urgent situation state throughout the time of landing [38, 39]. One of the most important objectives is the minimization of consumption in hydrogen, so makes it possible to improve the duration of the power supply of the aerodyne in the instances for the reduction of the important source of power. Achieved outcomes certified the prevalence for planned technique accomplishing 95.34 % efficiency along with the minimal utilization of 15.7559 gm of H where MA came second in order of efficiency 91.83 % and H utilization of 16.0579 gm.

Lian Cheng et al. [40] used an improved metaheuristic optimization called as balanced mayfly algorithm (BMA) to optimize the EVCS configuration taking into accounting of the Real Power Loss Reduction Index (PLRI), the Reactive Power Loss Reduction Index (QLRI), the Voltage Profile Improvement Index (VPII) and the cost of preparatory evolution in order to obtain the minimal value for installing cost also providing a better high-quality of boundaries in the electrical network. BMA used two changes, including pairs of elites and chaos mechanism to solve these problems as this is possible [9].

Ali Farki et al. [41] developed a classic setup in correcting detections of COVID19 established on (FCOM) Opti mized Fuzzy Wired Media also an enhanced sort like the (ECN) Enhanced Capsule Network [42]. ECN has been bettered based on the mayfly optimization algorithm (MOA). This method then was carried out on COVID19 x-ray images of chest from generally ready datasets [43]. The outcomes were evaluated by using the comparison methods that included the MID, FOMPA, and 4SDT, also the outcomes displayed highest efficiency for Mayfly optimization approach.

Mohamed Abd Elaziz et al. [44] used the mayfly-based (MO) optimization algorithm to implement with the (RVFL) Random Vector Functional Link Network to amplify the precision of prediction. The suggested AI model which is hybrid has been instructed and tried out by utilizing the experimental statistics. For the suggested PVTCEHP system, outside experiments were performed which works along the two distinct coolants named as the water and air into the weather conditions of India, their outcomes were then collated with the assumed outcomes of RVFLMO also the prevailing RVFL [45, 46].

Mahmoud Elsisi et al. [37] used the optimization method of mayfly algorithm (MA) for finding excellent boundaries of (PID) the proportional integral derivative controller in order to search the excellent data set in the instructing of controller and trying out of the Wind Energy Conversion Systems (WECS) based on the adaptive neuro-fuzzy interface system (ANFIS) [48]. In order to give a demonstration of the benefits of the suggested method, this was collated with three distinct algorithms. The suggested method assures the highly minimized of stabilization period of time and the maximized exceed of 0.4497 and 0.7989 %, individually, collated to the alike three methods. The suggested ANFIS based on MA could balance WECS also manage the variations in speed of the wind, variations in demand of loading, lagging issues of time, also uncertainty in boundaries for the structure.

Zhenkun Liu et al. [49] proposed a whole thing prediction system for the integration of data break down applied science, selection for the sub model, a new version of the multi aim of the mayfly algorithm and several assumptions to best perform the speculations and variation into the data from speed of wind [50]. Established from the three trials and four evaluations, the whole suggested structure is confirmed to be effectual in order to achieve timely and periodic accurate and firm forecast performance, thus helping to plan and distribute the power grid.

Ratna Patil et al. [51] used a vector machine which is modified with the help of mayfly support for the implementation of accuracy in the stage of prediabetes. To evaluate the efficacy from the suggested model, benchmarking research had been taken on and collated to assumption replicas which is T2DM formed by similar analysts during over the past five years. The proposed model has been validated on the data collected by the communal health centres also (PIMA) reference data set accessible on the depository of (UCI). The researches discover this the revised MayflySVM have a significant advantage onto the metaheuristic algorithms in the communal as well as worldwide search abilities also achieved a maximal correctness of the test to be 94.5 % when compared to the (PIMA).

Eunice Oluwabunmi Owoola et al. [52] proposed a mayfly algorithm to resolve the pattern array synthesis in antennas [53]. In this task, he put in an application to the linear antenna arrays [54] to obtain better outcomes. He performed it as follows: he took two cases for the optimization of the antenna. The two cases were to preserve unfluctuating positioning and other was unfluctuating excitation. After comparing the results with the other alike algorithms, he performed a simulation of electromagnetism onto the Ansys software to analyse the behaviour of the MA for the optimization of beam pattern. The outcomes showcased that the suggested algorithm had the ability for optimizing the antenna arrays with excellent outcomes. He also suggested to improve the MA for the reduction of computing time period along with the boundary counts.

Syed Kumayl Raza Moosavi et al. [55] suggested a mayfly algorithm to classify the artificial neural network [56] structure. This method was used for finding a global minimal costing for the lesser number of repetitions along with greater accurate outcomes. He used two inputs of database available from the University of California Irvine which were the Banknote Authentication and other one as the Cryotherapy. He then collated the MA along with the two algorithms named as grey wolf optimization neural network and the particle swarm optimization neural network [56]. The suggested MA showcased the outcomes as efficacy of around 1 %-2 % while the training database and an efficacy of around 2 % while the tested database [57].

Juan Zhao et al. [58] used the Chebyshev mapping technique for the further improvement of the mayfly algorithm. For the experimentation purpose he used a disordered MA along the Chebyshev map for the improvement of the algorithm. A simulation method called Monte Carlo was also taken into account for the outcomes. The outcomes of the suggested technique showcased the algorithm improved with the help of the Chebyshev map.

Manickam Amudha et al. [59] formed a mayfly algorithm that associates the benefits of alike algorithms such as PSO, GA and so on. On collating the suggested algorithm along with other such seven approaches, it was found out that the MA was the dominant one [60]. They used the algorithm for the prediction of sea level rise resulting climatic change over the Atlantic as well as the Pacific in northern hemisphere. The outcomes showed that the suggested algorithm produced superior outcomes than the combination of (PSO) and the (DE).

Muhammad Hamza Zafar et al. [61] introduces a technique named as the (MPPT) which is formed by combining the (MPA) and the (MA) to overcome the flaws occurring in the photovoltaic structures such as the partial shading situations, [62]. They created a mathematical representation of the PV structure for obtaining the outcomes. He connected the PV structure with a double diode and a loading and put into application the suggested technique [63]. They then collated the suggested algorithm with the alike algorithms namely (PSO), (GWO), (CS) [54], [55]. They found out that the suggested technique showcased efficacy of up to 99.99 %, speedy tracking of nearly 20 %-50 % and a reduction in the oscillation of 97 %.

Kingsuk Majumdar et al. [65] introduces the mayfly algorithm for obtaining superior outcomes for the scheduling in hydro thermal solar wind application. They combined the suggested algorithm with a number of schedulers say IEEE 9, IEEE 39, IEEE 118 buses for improving the efficacy. Later on, performing the experimental work it was found out that the suggested method showed superior outcomes by 19 % and an enhancement of about 56 % in (ATC) [16].

Mohamed A. M. Shaheen et al. [46] tried to improve modeling and simulation results by accurately extracting PEMFC models' design factors. Under varied settings, the CMOA is used to minimize the sum of square errors between the measured and terminal voltages of fuel cells. The approach highlights the nonlinearity of the PEMFC model by predicting unknown design factors well and exhibiting great sensitivity to certain parameters. The simulation results demonstrate the convergence of the optimization methodologies and the comparison between estimated and empirically measured voltages for several PEMFC types, including the Ballard Mark V fuel cell.

7. Conclusions

The presented paper gives a description on optimization algorithm known as the Mayfly (MA) algorithm. The paper describes its operating principle and its various fields of application. The described method which is based on population unites the main benefits of current algorithms also provoked on behavioural by mayflies which are adult, incorporating the methods of crossing, evolution, flock aggregation, method of proposed walking in arbitrary form and dancing of nuptial, which improve exploration. Throughout this study, has been established that with the help of two distinct equations into every population (masculine and feminine), survey is enhanced.

Even though the described process does not look to be speedy when compared with the rest of the processes from whose outcomes are obtained, has a greater likeliness for detecting an overall excellence. The behaviour of combination from suggested algorithm looks likewise remarkable, because it most identically reaches excellent global solutions through first iteration carried out. The mayfly algorithm outcomes look sufficient good for problems that are discrete and for optimization with numerous objectives.

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contributions

Mohit N Bogar: study conception, data collection, analysis and interpretation of results, validation. Ishwar D Shirodkar: data collection, analysis and interpretation of results, draft manuscript preparation. Omkar Kulkarni: study conception, validation. Samidha Jawade: supervision. Ganesh Kakandikar: supervision.

Conflict of interest

The authors declare that they have no conflict of interest.

References

[1] Z. Lukač, "Metaheuristic optimization," in *11th International Symposium on Operational Research*, 2011.

[2] C. Blum and A. Roli, "Metaheuristics in combinatorial optimization," *ACM Computing Surveys*, Vol. 35, No. 3, pp. 268–308, Sep. 2003, https://doi.org/10.1145/937503.937505

[3] S. Sukpancharoen, "Global performance test of metaheuristics optimization and engineering applications," *Progress in Applied Science and Technology*, Vol. 11, No. 1, pp. 10–24, Jan. 2021, https://doi.org/10.14456/past.2021.7

[4] A. Khare, G. M. Kakandikar, and O. K. Kulkarni, "An insight review on Jellyfish optimization algorithm and its application in engineering," *Review of Computer Engineering Studies*, Vol. 9, No. 1, pp. 31–40, Mar. 2022, https://doi.org/10.18280/rces.090103

[5] Y. Fu, Z. Li, C. Qu, and H. Chen, "Modified atom search optimization based on immunologic mechanism and reinforcement learning," *Mathematical Problems in Engineering*, Vol. 2020, pp. 1–22, Jan. 2020, https://doi.org/10.1155/2020/4568906

[6] J. Wang and H. Chen, "BSAS: beetle swarm antennae search algorithm for optimization problems," *arXiv:1807.10470*, Jan. 2018, https://doi.org/10.48550/arxiv.1807.10470

[7] G. F. Gomes, S. S. Da Cunha, and A. C. Ancelotti, "A sunflower optimization (SFO) algorithm applied to damage identification on laminated composite plates," *Engineering with Computers*, Vol. 35, No. 2, pp. 619–626, May 2018, https://doi.org/10.1007/s00366-018-0620-8

[8] K. Zervoudakis and S. Tsafarakis, "A mayfly optimization algorithm," *Computers and Industrial Engineering*, Vol. 145, p. 106559, Jul. 2020, https://doi.org/10.1016/j.cie.2020.106559

[9] A.-A. A. Mohamed, S. A. Hassan, A. M. Hemeida, S. Alkhalaf, M. M. M. Mahmoud, and A. M. Baha Eldin, "Parasitism – predation algorithm (PPA): A novel approach for feature selection," *Ain Shams Engineering Journal*, Vol. 11, No. 2, pp. 293–308, Jun. 2020, https://doi.org/10.1016/j.asej.2019.10.004

[10] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime Mould algorithm: A new method for stochastic optimization," *Future Generation Computer Systems*, Vol. 111, pp. 300–323, Oct. 2020, https://doi.org/10.1016/j.future.2020.03.055

[11] S. Kaur, L. K. Awasthi, A. L. Sangal, and G. Dhiman, "Tunicate swarm algorithm: a new bio-inspired based metaheuristic paradigm for global optimization," *Engineering Applications of Artificial Intelligence*, Vol. 90, p. 103541, Apr. 2020, https://doi.org/10.1016/j.engappai.2020.103541

[12] A. S. Joshi, O. Kulkarni, G. M. Kakandikar, and V. M. Nandedkar, "Cuckoo search optimization – a review," *Materials Today: Proceedings*, Vol. 4, No. 8, pp. 7262–7269, Jan. 2017, https://doi.org/10.1016/j.matpr.2017.07.055

[13] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft Computing*, Vol. 22, No. 2, pp. 387–408, Jan. 2017, https://doi.org/10.1007/s00500-016-2474-6

[14] G. M. Kakandikar, O. Kulkarni, S. Patekar, and T. Bhoskar, "Optimising fracture in automotive tail cap by firefly algorithm," *International Journal of Swarm Intelligence*, Vol. 5, No. 1, p. 136, Jan. 2020, https://doi.org/10.1504/ijsi.2020.106396

[15] S. Jawade, O. K. Kulkarni, and G. M. Kakandikar, "Parameter optimization of AISI 316 austenitic stainless steel for surface roughness by Grasshopper optimization algorithm," *Journal of Mechanical Engineering, Automation and Control Systems*, Vol. 2, No. 2, pp. 87–97, Dec. 2021, https://doi.org/10.21595/jmeacs.2021.22149

[16] M. T. Bhoskar, M. O. K. Kulkarni, M. N. K. Kulkarni, M. S. L. Patekar, G. M. Kakandikar, and V. M. Nandedkar, "Genetic Algorithm and its Applications to Mechanical Engineering: A Review," *Materials Today: Proceedings*, Vol. 2, No. 4-5, pp. 2624–2630, Jan. 2015, https://doi.org/10.1016/j.matpr.2015.07.219

[17] A. G. Neve, G. M. Kakandikar, and O. Kulkarni, "Application of Grasshopper optimization algorithm for constrained and unconstrained test functions," *International Journal of Swarm Intelligence and Evolutionary Computation*, Vol. 6, No. 3, pp. 4402–4412, Jan. 2017, https://doi.org/10.4172/2090-4908.1000165

[18] A. G. Neve, G. M. Kakandikar, O. Kulkarni, and V. M. Nandedkar, "Optimization of railway bogie snubber spring with Grasshopper algorithm," *Advances in Intelligent Systems and Computing*, Vol. 1079, pp. 941–952, Jan. 2020, https://doi.org/10.1007/978-981-15-1097-7_80

[19] Q. Duan, L. Wang, H. Kang, Y. Shen, X. Sun, and Q. Chen, "Improved Salp swarm algorithm with simulated annealing for solving engineering optimization problems," *Symmetry*, Vol. 13, No. 6, p. 1092, Jun. 2021, https://doi.org/10.3390/sym13061092

[20] S. P. Mhatugade, G. M. Kakandikar, O. K. Kulkarni, and V. M. Nandedkar, "Development of a multi-objective Salp swarm algorithm for benchmark functions and real-world problems," *Optimization for Engineering Problems*, pp. 101–130, Jul. 2019, https://doi.org/10.1002/9781119644552.ch5

[21] C. G. Burande, O. K. Kulkarni, S. Jawade, and G. M. Kakandikar, "Process parameters optimization by bat inspired algorithm of CNC turning on EN8 steel for prediction of surface roughness," *Journal of Mechatronics and Artificial Intelligence in Engineering*, Vol. 2, No. 2, pp. 73–85, Dec. 2021, https://doi.org/10.21595/jmai.2021.22148

[22] X. Fan, W. Sayers, S. Zhang, Z. Han, L. Ren, and H. Chizari, "Review and classification of bio-inspired algorithms and their applications," *Journal of Bionic Engineering*, Vol. 17, No. 3, pp. 611–631, May 2020, https://doi.org/10.1007/s42235-020-0049-9

[23] T. Bäck and H.-P. Schwefel, "An overview of evolutionary algorithms for parameter optimization," *Evolutionary Computation*, Vol. 1, No. 1, pp. 1–23, Mar. 1993, https://doi.org/10.1162/evco.1993.1.1.1

[24] S. Goings, H. Goldsby, B. H. C. Cheng, and C. Ofria, "An ecology-based evolutionary algorithm to evolve solutions to complex problems," in *International Conference on the Simulation and Synthesis of Living Systems*, Jul. 2012, https://doi.org/10.7551/978-0-262-31050-5-ch024

[25] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, Vol. 6, No. 2, pp. 182–197, Apr. 2002, https://doi.org/10.1109/4235.996017

[26] S. Patel, G. M. Kakandikar, and O. Kulkarni, "Applicability and efficiency of socio-cultural inspired algorithms in optimizing mechanical systems – a critical review," *Review of Computer Engineering Studies*, Vol. 7, No. 2, pp. 31–41, Jun. 2020, https://doi.org/10.18280/rces.070203

[27] M. A. M. Shaheen, H. M. Hasanien, M. S. El Moursi, and A. A. El-Fergany, "Precise modeling of PEM fuel cell using improved chaotic MayFly optimization algorithm," *International Journal of Energy Research*, Vol. 45, No. 13, pp. 18754–18769, Oct. 2021, https://doi.org/10.1002/er.6987

[28] Y. Liu, Y. Chai, B. Liu, and Y. Wang, "Bearing fault diagnosis based on energy spectrum statistics and modified mayfly optimization algorithm," *Sensors*, Vol. 21, No. 6, p. 2245, Mar. 2021, https://doi.org/10.3390/s21062245

[29] N. K. Prah Ii, E. A. Frimpong, and E. Twumasi, "Modified individual experience mayfly algorithm," *Carpathian Journal of Electrical Engineering*, Vol. 16, No. 1, pp. 62–74, 2022.

[30] X. Wang, J.-S. Pan, Q. Yang, L. Kong, V. Snášel, and S.-C. Chu, "Modified mayfly algorithm for UAV path planning," *Drones*, Vol. 6, No. 5, p. 134, May 2022, https://doi.org/10.3390/drones6050134

[31] T. Zhang, Y. Zhou, G. Zhou, W. Deng, and Q. Luo, "Bioinspired bare bones mayfly algorithm for large-scale spherical minimum spanning tree," *Frontiers in Bioengineering and Biotechnology*, Vol. 10, p. 830037, Mar. 2022, https://doi.org/10.3389/fbioe.2022.830037

[32] Q. Du and H. Zhu, "Dynamic elite strategy mayfly algorithm," *Plos One*, Vol. 17, No. 8, p. e0273155, Aug. 2022, https://doi.org/10.1371/journal.pone.0273155

[33] R. Nishat Toma, C.-H. Kim, and J.-M. Kim, "Bearing fault classification using ensemble empirical mode decomposition and convolutional neural network," *Electronics*, Vol. 10, No. 11, p. 1248, May 2021, https://doi.org/10.3390/electronics10111248

[34] R. Zeng, X. Zhang, Y. Deng, H. Li, and G. Zhang, "An off-design model to optimize CCHP-GSHP system considering carbon tax," *Energy Conversion and Management*, Vol. 189, pp. 105–117, Jun. 2019, https://doi.org/10.1016/j.enconman.2019.03.062

[35] A. Hu, Z. Deng, H. Yang, Y. Zhang, Y. Gao, and D. Zhao, "An optimal geometry configuration algorithm of hybrid semi-passive location system based on mayfly optimization algorithm," *Sensors*, Vol. 21, No. 22, p. 7484, Nov. 2021, https://doi.org/10.3390/s21227484

[36] G. Wu, "UAV-based interference source localization: a multimodal Q-learning approach," *IEEE Access*, Vol. 7, pp. 137982–137991, Jan. 2019, https://doi.org/10.1109/access.2019.2942330

[37] A. Fathy, D. Yousri, T. Alanazi, and H. Rezk, "Minimum hydrogen consumption based control strategy of fuel cell/PV/battery/supercapacitor hybrid system using recent approach based parasitism-predation algorithm," *Energy*, Vol. 225, p. 120316, Jun. 2021, https://doi.org/10.1016/j.energy.2021.120316

[38] A. Fathy, M. A. Elaziz, E. T. Sayed, A. G. Olabi, and H. Rezk, "Optimal parameter identification of triple-junction photovoltaic panel based on enhanced moth search algorithm," *Energy*, Vol. 188, p. 116025, Dec. 2019, https://doi.org/10.1016/j.energy.2019.116025

[39] P. Amirchoupani, R. Nodeh Farahani, and G. Abdollahzadeh, "The constant damage inelastic displacement ratio for performance design of self-centering systems under far-field earthquake ground motions," *Structures*, Vol. 57, p. 105254, Nov. 2023, https://doi.org/10.1016/j.istruc.2023.105254

[40] L. Chen, C. Xu, H. Song, and K. Jermsittiparsert, "Optimal sizing and sitting of EVCS in the distribution system using metaheuristics: A case study," Elsevier BV, Energy Reports, Nov. 2021.

[41] A. Farki, Z. Salekshahrezaee, A. M. Tofigh, R. Ghanavati, B. Arandian, and A. Chapnevis, "COVID-19 diagnosis using capsule network and fuzzy C – means and mayfly optimization algorithm," *BioMed Research International*, Vol. 2021, pp. 1–11, Oct. 2021, https://doi.org/10.1155/2021/2295920

[42] R. Ranjbarzadeh et al., "Lung infection segmentation for COVID-19 pneumonia based on a cascade convolutional network from CT images," *BioMed Research International*, Vol. 2021, pp. 1–16, Apr. 2021, https://doi.org/10.1155/2021/5544742

[43] K. T. Islam, S. Wijewickrema, and S. O. 'Leary, "A deep learning framework for segmenting brain tumors using MRI and synthetically generated CT images," *Sensors*, Vol. 22, No. 2, p. 523, Jan. 2022, https://doi.org/10.3390/s22020523

[44] M. Abd Elaziz, S. Senthilraja, M. E. Zayed, A. H. Elsheikh, R. R. Mostafa, and S. Lu, "A new random vector functional link integrated with mayfly optimization algorithm for performance prediction of solar photovoltaic thermal collector combined with electrolytic hydrogen production system," *Applied Thermal Engineering*, Vol. 193, p. 117055, Jul. 2021, https://doi.org/10.1016/j.applthermaleng.2021.117055

[45] W. Fan, G. Kokogiannakis, and Z. Ma, "Optimisation of life cycle performance of a double-pass photovoltaic thermal-solar air heater with heat pipes," *Renewable Energy*, Vol. 138, pp. 90–105, Aug. 2019, https://doi.org/10.1016/j.renene.2019.01.078

[46] M. N. K. Kulkarni, M. S. Patekar, M. T. Bhoskar, M. O. Kulkarni, G. M. Kakandikar, and V. M. Nandedkar, "Particle swarm optimization applications to mechanical engineering – a review," *Materials Today: Proceedings*, Vol. 2, No. 4-5, pp. 2631–2639, Jan. 2015, https://doi.org/10.1016/j.matpr.2015.07.223

[47] M. Elsisi, M.-Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Robust design of ANFIS-based blade pitch controller for wind energy conversion systems against wind speed fluctuations," *IEEE Access*, Vol. 9, pp. 37894–37904, Jan. 2021, https://doi.org/10.1109/access.2021.3063053

[48] F. Cheng, L. Qu, and W. Qiao, "Fault prognosis and remaining useful life prediction of wind turbine gearboxes using current signal analysis," *IEEE Transactions on Sustainable Energy*, Vol. 9, No. 1, pp. 157–167, Jan. 2018, https://doi.org/10.1109/tste.2017.2719626

[49] Z. Liu, P. Jiang, J. Wang, and L. Zhang, "Ensemble forecasting system for short-term wind speed forecasting based on optimal sub-model selection and multi-objective version of mayfly optimization algorithm," *Expert Systems with Applications*, Vol. 177, p. 114974, Sep. 2021, https://doi.org/10.1016/j.eswa.2021.114974

[50] Aasim, S. N. Singh, and A. Mohapatra, "Repeated wavelet transform based ARIMA model for very short-term wind speed forecasting," *Renewable Energy*, Vol. 136, pp. 758–768, Jun. 2019, https://doi.org/10.1016/j.renene.2019.01.031

[51] R. Patil, S. Tamane, S. A. Rawandale, and K. Patil, "A modified mayfly-SVM approach for early detection of type 2 diabetes mellitus," *International Journal of Electrical and Computer Engineering (IJECE)*, Vol. 12, No. 1, p. 524, Feb. 2022, https://doi.org/10.11591/ijece.v12i1.pp524-533

[52] E. O. Owoola, K. Xia, T. Wang, A. Umar, and R. G. Akindele, "Pattern synthesis of uniform and sparse linear antenna array using Mayfly algorithm," *IEEE Access*, Vol. 9, pp. 77954–77975, Jan. 2021, https://doi.org/10.1109/access.2021.3083487

[53] Y. Wang, S. Kang, J. D. Doerksen, A. K. Glaser, and J. T. C. Liu, "Surgical guidance via multiplexed molecular imaging of fresh tissues labeled with SERS-coded nanoparticles," *IEEE Journal of Selected Topics in Quantum Electronics*, Vol. 22, No. 4, pp. 154–164, Jul. 2016, https://doi.org/10.1109/jstqe.2015.2507358

[54] S. U. Rahman, Q. Cao, M. M. Ahmed, and H. Khalil, "Analysis of linear antenna array for minimum side lobe level, half power beamwidth, and nulls control using PSO," *Journal of Microwaves, Optoelectronics and Electromagnetic Applications*, Vol. 16, No. 2, pp. 577–591, Apr. 2017, https://doi.org/10.1590/2179-10742017v16i2913

[55] S. K. R. Moosavi, M. H. Zafar, M. N. Akhter, S. F. Hadi, N. M. Khan, and F. Sanfilippo, "A novel artificial neural network (ANN) using the mayfly algorithm for classification," in *2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, May 2021, https://doi.org/10.1109/icodt252288.2021.9441473

[56] L.-X. Guo and D.-N. Dao, "A new control method based on fuzzy controller, time delay estimation, deep learning, and non-dominated sorting genetic algorithm-III for powertrain mount system," *Journal of Vibration and Control*, Vol. 26, No. 13-14, pp. 1187–1198, Dec. 2019, https://doi.org/10.1177/1077546319890188

[57] R. Nodeh Farahani, G. Abdollahzadeh, and A. Mirza Goltabar Roshan, "The modified energy-based method for seismic evaluation of structural systems with different hardening ratios and deterioration hysteresis models," *Periodica Polytechnica Civil Engineering*, Vol. 68, No. 1, pp. 37–56, Aug. 2023, https://doi.org/10.3311/ppci.21359

[58] J. Zhao and Z.-M. Gao, "The improved mayfly optimization algorithm with Chebyshev map," in *Journal of Physics: Conference Series*, Vol. 1684, No. 1, p. 012075, Nov. 2020, https://doi.org/10.1088/1742-6596/1684/1/012075

[59] M. Amudha, M. Ramachandran, Chinnasami Sivaji, and R. Gayathri, "A study on climate change with mayfly algorithm optimization," *Recent trends in Management and Commerce*, Vol. 2, No. 3, pp. 23–28, Dec. 2021, https://doi.org/10.46632/rmc/2/3/5

[60] O. Kulkarni, N. Kulkarni, A. J. Kulkarni, and G. Kakandikar, "Constrained cohort intelligence using static and dynamic penalty function approach for mechanical components design," *International Journal of Parallel, Emergent and Distributed Systems*, Vol. 33, No. 6, pp. 570–588, Nov. 2018, https://doi.org/10.1080/17445760.2016.1242728

[61] M. H. Zafar, N. M. Khan, A. F. Mirza, and M. Mansoor, "Bio-inspired optimization algorithms based maximum power point tracking technique for photovoltaic systems under partial shading and complex partial shading conditions," *Journal of Cleaner Production*, Vol. 309, p. 127279, Aug. 2021, https://doi.org/10.1016/j.jclepro.2021.127279

[62] H. Abouadane, A. Fakkar, D. Sera, A. Lashab, S. Spataru, and T. Kerekes, "Multiple-power-sample based P&O MPPT for fast-changing irradiance conditions for a simple implementation," *IEEE Journal of Photovoltaics*, Vol. 10, No. 5, pp. 1481–1488, Sep. 2020, https://doi.org/10.1109/jphotov.2020.3009781

[63] Z. Alqaisi and Y. Mahmoud, "Comprehensive study of partially shaded PV modules with overlapping diodes," *IEEE Access*, Vol. 7, pp. 172665–172675, Jan. 2019, https://doi.org/10.1109/access.2019.2956916

[64] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf optimizer," *Advances in Engineering Software*, Vol. 69, pp. 46–61, Mar. 2014, https://doi.org/10.1016/j.advengsoft.2013.12.007

[65] K. Majumdar, P. K. Roy, and S. Banerjee, "Implementation of multi-objective chaotic mayfly optimisation for hydro-thermal – solar-wind scheduling based on available transfer capability problem," *International Transactions on Electrical Energy Systems*, Vol. 31, No. 11, Aug. 2021, https://doi.org/10.1002/2050-7038.13029

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