PERFORMANCE COMPARISON OF MAYFLY ALGORITHM AND ENHANCED MAYFLY ALGORITHM ON FUSED FACE – IRIS RECOGNITION SYSTEM

OLADIMEJI Adegbola Isaac[1], ASAJU-GBOLAGADE Ayisat Wuraola[2] GBOLAGADE Kazeem Alagbe[3]
[1] Department of Computer Science, Aminu Saleh College of Education, Azare, Nigeria
[2]Department of Computer Science, University of Ilorin, Ilorin, Nigeria
[3]Department of Computer Science, Kwara State University, Malete, Nigeria
[1]oladimejiadeisaac@gmail.com, [2]yusuf.aaw@unilorin.edu.ng [3] kazeem.gbolagade@kwasu.edu.ng

Keywords: Mayfly Algorithm, Optimization, Fused Face – Iris

Abstract: *Since the formulation of the Mayfly optimization algorithm in 2020, many researchers have proposed either improvement or used the conventional Mayfly optimization algorithm to proffer solutions to the optimization problems. In the Mayfly algorithm, the gravity coefficient which works similar to Particle Swarm Optimization's inertia weight assists the achievement of a sufficient balance between exploration and exploitation. The gravity coefficient was fixed and gradually reduced over the iterations, allowing the existing Mayfly algorithm to exploit specific areas in the search space. This makes it difficult for the Mayfly algorithm to be used to solve high-dimensional problem spaces such as feature selection. In this paper, the new gravity coefficient widens the search space. The experimental result shows that the enhanced Mayfly algorithm (EMA) technique has ensured optimal computational efficiency in terms of its recognition accuracy, recognition time, false acceptance rate, and false rejection rate compared with the conventional Mayfly algorithm (MA). This result implies that the enhanced Mayfly algorithm would indeed increase the capability of the original Mayfly algorithm.*

I. INTRODUCTION

The main motive behind optimization is to find the best solution for a function or it can be said that optimization is a process of finding the best solution for a function (either its minimum or its maximum value) as noted by Konstantinos and Stelios [9]. Previously, mathematical or numerical methods were used for solving optimization problems in which the final solution is obtained by reaching a zero-derivative point. But solving a non-linear non-convex problem with lots of variables and constraints using mathematical or numerical methods is so difficult and almost impossible, reason is as the number of dimensions increases, the search space also increases exponentially [9, 8]. In this paper, a performance evaluation of the Mayfly optimization (MA) algorithm and enhanced Mayfly algorithm (EMA) is presented.

II. RELATED LITERATURE

Since the formulation of the Mayfly optimization algorithm, many researchers have either used it to solve optimization issues or improved on the original Mayfly algorithm to enhance its capabilities.

Zheng-Ming Gao et al [14] presented an advanced Mayfly optimization algorithm, a reasonable modification for the velocity updating equations was proposed grounded on the idea of moving toward each other as able as they can. Simulation results proved that the bettered Mayfly optimization algorithm would perform better than the original Mayfly algorithm.

Zhao and Zheng-Ming Gao [8], proposed bettered Mayfly optimization algorithm with a Chebyshev map. The proposed bettered Mayfly algorithm with the Chebyshev map would be a good choice to replace the arbitrary figures in invariant distribution involved in the original Mayfly algorithm.

Zheng-Ming Gao et al [14], presented an advanced Mayfly optimization algorithm with opposition-based learning rules. The proposed stress that not only the stylish campaigners or the stylish literal circles would perform well in guiding the individualities in masses to find the stylish result, the worst and the worst literal circles would also work well in doing so. Similar situations could be directly treated as dyads of resistance and satisfied by the ancient Chinese Yin-Yang gospel, which the opposition-based learning (OBL) rule was directly deduced from. The proposed simulation trial results showed that the advanced Mayfly optimization algorithm with opposition-based learning (OBL) rules would perform better than usual.

Lingzhi et al., [11], present dynamic multi-peak MPPT for Photovoltaic Power Generation under Local Shadows Based on Enhanced Mayfly Optimization. A Chaos Mayfly Optimization with Levy Flight and Adaptive Algorithm (CMOFA) is proposed to track the maximum power points of PV arrays under partial shading. Firstly, sin chaos is used to initialize the population, then adaptive adjustment of inertia weights is introduced and the learning factor is changed to enhance the local search ability of the algorithm. Simulation results show that CMOFA is not only able to avoid local shading and dynamic shading changes, but also has a significant improvement in convergence speed and search accuracy compared with conventional intelligent algorithms.

Shaheen et al., [13], proposed precise modeling of PEM energy cells using an improved chaotic Mayfly optimization algorithm. The proposal presents a recently developed optimization system “Chaotic Mayfly optimization algorithm” (CMOA) for carrying the proton exchange membrane energy cell (PEMFC) parameters. It substantially targets accurate modeling of the PEMFC that provides a good match between the simulation results and those measured virtually. findings of the simulations of the proposed CMOA are compared with other findings attained by other optimization styles. Applying the CMOA results in an accurate development of the PEMFC model.

Bhattacharyya et al. [3], proposed Mayfly-Harmony Search (MA-HS) grounded on two meta-heuristics videlicet Mayfly Algorithm and Harmony Search. The trial result proved the robustness of the algorithm by applying it to three high-dimensional microarray datasets.

Zhao and Gao, [16] proposed the multi-start Mayfly optimization algorithm, the multi-start methods were introduced to the Mayfly optimization algorithm and the male mayflies would be reinitialized the same as the at the beginning. Simulation trials vindicated that the multi-start Mayfly algorithm would perform better than the original Mayfly algorithm.

Zhao and Gao, [15] introduced the Monte Carlo system, and further simulation trials on non-symmetric standard functions, which were proved to be delicate to optimize for some optimizers were carried out. The study finds out the difference between the bare-bones Mayfly optimization and the traditional Mayfly optimization algorithm which would rely on another opportunity for individuals to update their positions. In the bare-bones Mayfly optimization algorithm, individualities would have another chance to update their positions with stochastic rules. The study concluded that if the individualities had multiple choices to update their positions, their capabilities of optimizing might be increased. Simulation trials and results indicated that the bare-bones Mayfly algorithm would perform better than the conventional Mayfly algorithm.

Donghui et al. [4], used a modified interpretation of the Mayfly Optimization algorithm to recover and develop the effectiveness of the CCHP system. The results indicate that the proposed optimal CCHP system offers good results and elevation toward the compared algorithms in both terms of environmental and effectiveness.

Juan and Zheng-Ming [7], proposed a negative Mayfly optimization algorithm. the male mayflies would update their velocities according to the worst campaigners together with their worst trajectories. Unlike the normal positive interpretation, in the negative Mayfly algorithm, the male mayflies would run away from their worst trajectories and the global worst candidates. Simulation trials showed that both the negative Mayfly algorithm and Mayfly algorithms would work well in optimizing both the unimodal and multimodal standard functions, indeed for the non-symmetric bone.

Gao and Zhao [5], proposed the guaranteed convergence Mayfly optimization algorithm. The study noted that the streamlining equations of velocities for individualities in the Mayfly optimization algorithm were not the same as that for individualities in the particle swarm optimization algorithm, there was still a similarity among the equations. Thus, when the masses were approaching the local or global optima, the individualities would be trapped in local optima in the same way. Consequently, the guaranteed convergence enhancement should also be introduced to the Mayfly algorithm.

II.I. Conventional Mayfly Optimization Algorithm

The Mayfly optimization algorithm was just proposed and published in 2020 by Konstantinos Zervoudakis and Stelios Tsafarakis [8]. The traditional Mayfly optimization algorithm includes the combination of features of particle swarm optimization (PSO), genetic algorithm (GA), and firefly algorithm (FA). The mayfly optimization (MO) algorithm was proposed to simulate the social behavior, especially the mating process displayed by the mayflies in nature. Zervoudakis and Tsafarakis [2] translated the mating process and flight behavior of mayflies as a mathematical model to be used in solving the optimization problem [1].

In the Mayfly algorithm, it is assumed that a Mayfly is a grown-up after hatching and the fittest one survives disregarding the continuance. Also, the position of each Mayfly in the search space represents an implicit result of the problem [1].

II.II. Multimodal Biometric

Harsh and Pawan [6], stress that the integration of biometrics in the diurnal life provokes the need to design secure authentication systems. The biometric authentication by multimodal schemes promotes the matching accuracy of the authentication process and accomplishes further trustability and security than the unimodal biometric system because it takes a combination of different behavioral or physiological characteristics of the person into account to distinguish that person [2]. Mina and Önsen [12], emphasize the main aim of multimodal biometric systems as to improve the recognition accuracy by minimizing the limitations of unimodal systems.

The benefits of multimodality to unimodal biometric systems has makes it possible to reduce certain limitations of unimodal biometric systems, such as the impossibility of acquiring data from certain people or intentional fraud, while improving recognition performance [10].

Through fusing a few biometrics considering no standard for their determination, numerous researchers had a go at proposing multimodal biometric frameworks, so by fusing iris and face, will have a multimodal biometric system. The determination or selection of biometrics is through test and error since there are no rules for this [10].

More attention was given to feature extraction compared to the attention given to feature selection. The enhanced algorithm to be formulated in this study will be used for feature selection of the fused face- iris recognition system, and the performance of the enhanced Mayfly algorithm will be compared with the conventional Mayfly algorithm.

III. METHODOLOGY

In the conventional Mayfly algorithm (MA), the gravity coefficient g which works similar to PSO's inertia weight as described in Equation (1), assists the achievement of a sufficient balance between exploration and exploitation. To calculate the gravity coefficient, velocities must be reduced to better control the balance between the exploration and exploitation abilities of the mayflies. The gravity coefficient was fixed in the range of [0, 1] and gradually reduced over the iterations, allowing the existing algorithm to exploit specific areas in the search space by being updated through the equation (2). Due to this, it is difficult for the Mayfly algorithm (MA) to be used to solve high-dimensional problem spaces such as feature selection.

$$\bar{X}_i = \bar{X}_i - \bar{X} \quad (1)$$

$$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}} - iter \quad (2)$$

where g_{max} and g_{min} are the maximum and minimum values that the gravity coefficient can take, $iter$ is the current iteration of the algorithm and $iter_{max}$ is the maximum number of iterations.

In this study, a new gravity coefficient g is introduced to exploit large specific areas and will make it possible for the new enhanced Mayfly algorithm (EMA) to be used for high dimensional problem spaces.

The new gravity coefficient g widens the search space in the range of [-1, 1].

$$g = g_{std} - \frac{(g_{std} - g_{\text{mean}}) * (iter_{max} - iter + 1)}{iter_{max}} - iter \quad (3)$$

where g_{std} and g_{mean} are the standard deviation and mean values that the gravity coefficient can take, $iter$ is the current iteration of the algorithm and $\text{iter}_{\boldsymbol{max}}$ is the maximum number of iterations.

In this study, modification of the movement of male and female mayflies' phases is enhanced. In the conventional Mayfly algorithm (MA), Males' gathering in swarms, implies that the position of each male Mayfly is adjusted according to both its own experience and that of its neighbors.

The velocity of a male Mayfly was calculated as:

$$v_{ij}{}^{t+1} = g * v_{ij}{}^{t} + \alpha_1 e^{-\beta r_p^2}\left[pbest_{ij} - x_{ij}{}^{t}\right] + \alpha_2 e^{-\beta r_g^2}\left[gbest_j - x_{ij}{}^{t}\right] \quad (4)$$

Where β is a fixed visibility coefficient that is used to limit a Mayfly's visibility to others, r_p is the Cartesian distance between x_i and $pbest_{ij}$ and r_g is the Cartesian distance between x_i and $gbest$. It is important for the functioning of the algorithm that the best mayflies in the swarm continue to perform their characteristic up-and-down nuptial dance. Hence, the best mayflies must keep changing their velocities, which in such a case was calculated as

$$v_{ij}^{t+1} = v_{ij}^{t} + fl * r \quad (5)$$

where fl is the random walk coefficient and r is a random value in the range [-1, 1]. This up and down movement introduces a stochastic element to the algorithm.

Unlike males, female mayflies do not gather in swarms [2]. They instead fly toward males to breed. Whereas the attraction process used was randomized, consequently, their velocities are calculated as Equation

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2 e^{-\beta r_{mf}^2 (x_{ij}{}^{t} - y_{ij}{}^{t})} & if\ f(y_i) > f(x_i) \\ v_{ij}^{t} + fl * r & if\ f(y_i) \leq f(x_i) \end{cases} \quad (6)$$

Where v_{ij}^{t} is the velocity of female Mayfly i in dimension $j = 1, \ldots, n$ at time step t, $y_{ij}{}^{t}$ the position of female Mayfly i in dimension j at time step t, α_2 is a positive attraction constant and β is a fixed visibility coefficient, while r_{mf} is the Cartesian distance between male and female mayflies. Finally, fl is a random walk coefficient, used when a female is not attracted by a male, so it flies randomly and r is a random value in the range of [-1, 1]. This study, introduced another selection procedure to model the attraction process as a deterministic process.

IV. RESULTS AND DISCUSSION

To determine the performance of the developed algorithm, the MATLAB implementation of both algorithms was carried out on a Core i3 laptop computer with 2.00GHz of RAM. The fused face – iris recognition system experimented with a total of 570 images using a digital camera to acquire face and iris biometric data of users from the chosen experimental organization, out of which 60% images were used in training the database and 40% images were used for testing the created database.

Both the Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) were experimented with by implementing both at the feature selection stage with the two biometric traits downsized into 128 by 128 pixels without any alteration in the images.

With both the Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA), the following parameters were taken into consideration namely:

1. Recognition accuracy
2. Recognition time
3. False acceptance rate
4. False rejection rate

Tables 1 and 2 presented performance evaluated based on recognition accuracy, recognition time, false acceptance rate, and false rejection rate with respect to the application of enhanced Mayfly algorithm (EMA) and Mayfly algorithm (MA) on fused face -iris. The accuracies generated by fused face - iris were analyzed at threshold values of 0.20, 0.35, 0.50 and 0.76 respectively.

Out of all threshold values considered as obtainable in Table 1 and Table 2, it was noticed that recognition accuracy with introduction of fused iris-face at threshold value 0.76 and above was 97.36% and 95.18% higher in values than other thresholds for enhanced Mayfly algorithm (EMA) and Mayfly algorithm (MA) respectively.

Hence, the fused iris - face at 0.76 thresholds performed better in accuracy compared with other thresholds value. Also, the enhanced Mayfly algorithm (EMA) and Mayfly algorithm (MA) had 1.79% and 3.51% false acceptance rates and 2.92% and 5.26% false rejection rates respectively at 0.76 thresholds. Figure 1, 2, 3, and 4 shows the comparison of the Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.20, 0.35, 0.50, and 0.76 threshold value with respect to recognition Accuracy, recognition time, force acceptance rate, and force rejection rate respectively.

This result shows the high performance of the enhanced Mayfly algorithm over the original Mayfly algorithm taking into consideration all parameters used.

Table 1. *Result of Fused face- iris with Enhanced Mayfly Algorithm (EMA).*

Threshold	FAR (%)	FRR (%)	ACC (%)	Time (sec)
0.20	17.5	1.17	94.74	184.07
0.35	12.3	1.75	95.61	181.61
0.50	7.02	2.34	96.49	183.26
0.76	1.79	2.92	97.36	181.52

Table 2. *Result of Fused face - iris with Mayfly Algorithm (MA).*

Threshold	FAR (%)	FRR (%)	ACC (%)	Time (sec)
0.20	17.54	3.51	92.98	211.77
0.35	14.04	4.09	93.42	221.55
0.50	8.77	4.68	94.3	229.52
0.76	3.51	5.26	95.18	213.75

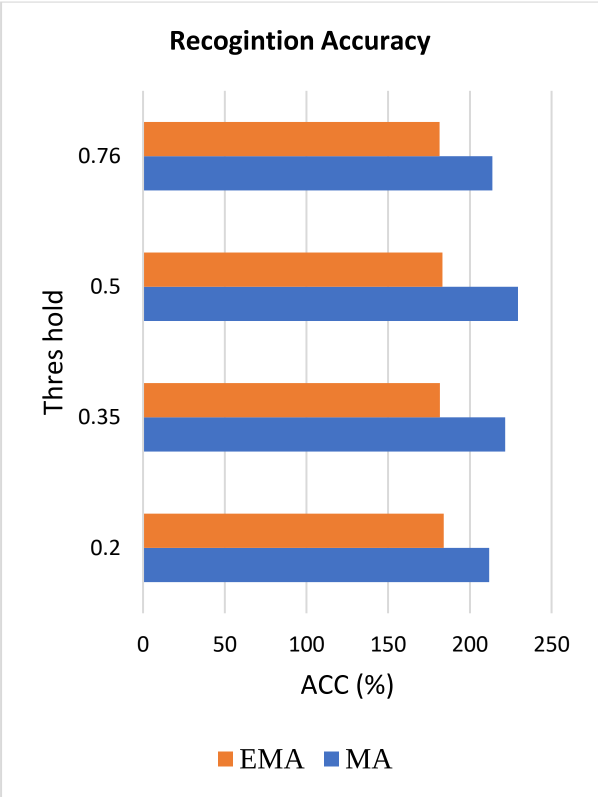

Figure 1. *Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.20, 0.35, 0.50, and 0.76 threshold values (Recognition Accuracy).*

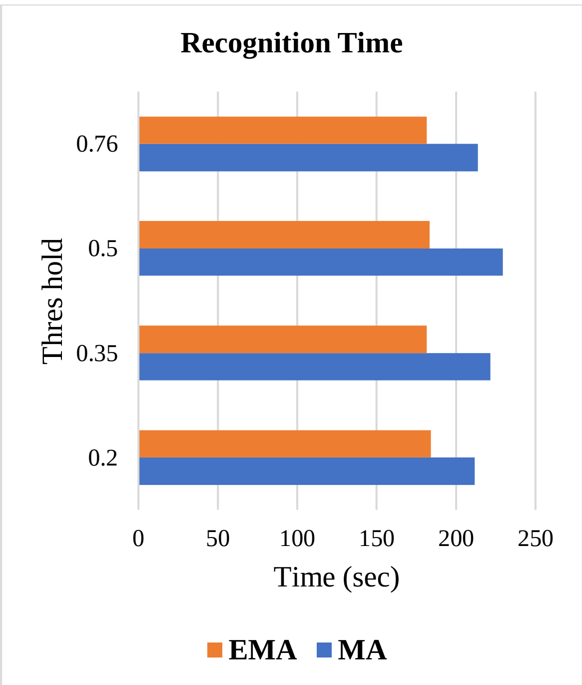

Figure 2. *Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.20, 0.35, 0.50 and 0.76 threshold value (Recognition Time).*

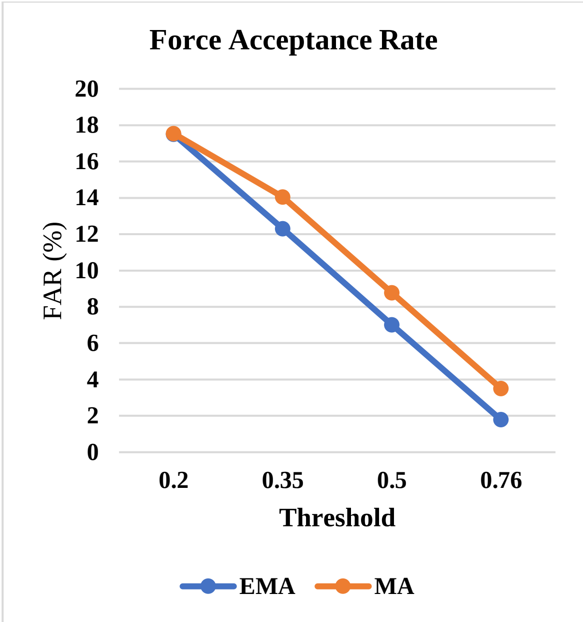

Figure 3. *Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.20, 0.35, 0.50 and 0.76 threshold (False Acceptance Rate).*

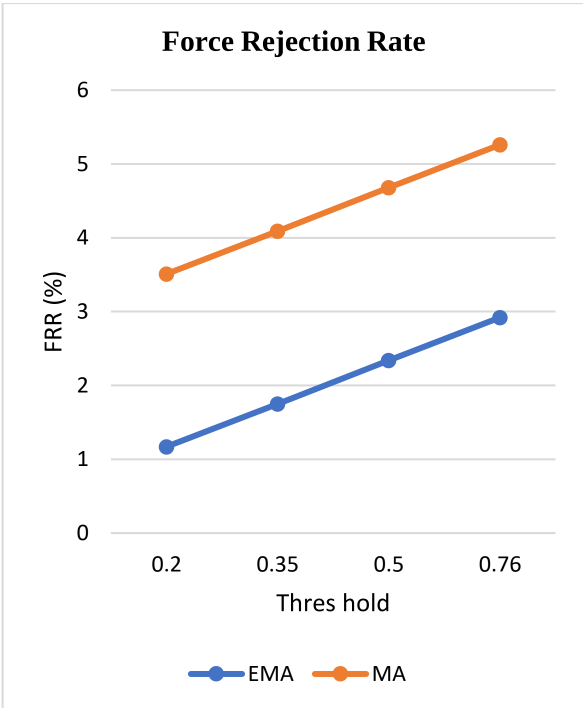

Figure 4. *Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.20, 0.35, 0.50 and 0.76 threshold (False Rejection Rate).*

V. CONCLUSION

The experimental results obtained revealed that the fused face - iris under enhanced Mayfly algorithm (EMA) technique gave 97.36% in terms of recognition accuracy, 1.79% false acceptance rate, 2.92% false rejection rate, and 181.52s recognition time compare with fused face - iris using original Mayfly algorithm (MA) which gave 95.18% in terms of recognition accuracy, 3.51% false acceptance rate, 5.26% false rejection rate, and 213.75s recognition time at the threshold of 0.76.

It can be concluded that the developed enhanced Mayfly algorithm (EMA) technique has ensured optimal computational efficiency in terms of its accuracy and time compare with the conventional Mayfly algorithm (MA).

REFERENCES

[1] Abd Elaziz, M., Senthilraja, S., Zayed, M. E., Elsheikh, A. H., Mostafa, R. R., & Lu, S. (2021). 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, 193, 117055. doi: 10.1016/j.applthermaleng.2021.

[2] Anter Abozaid, Ayman Haggag, Hany Kasban and Mostafa Eltokhy, 2018. Multimodal biometric scheme for human authentication technique based on voice and face recognition fusion. Multimedia Tools and Applications (2019) 78: 16345–16361, https://doi.org/10.1007/s11042-018-7012-3

[3] Bhattacharyya, T., Chatterjee, B., Singh, P. K., Yoon, J. H., Geem, Z. W., & Sarkar, R. (2020). Mayfly in Harmony: A New Hybrid Meta-Heuristic Feature Selection Algorithm. IEEE Access, 8, 195929–195945. doi:10.1109/access.2020.3031718

[4] Donghui Wei, Jinghong Ji, Junlong Fang, Nasser Yousefi, (2021). Evaluation and optimization of PEM Fuel Cell-based CCHP system based on Modified Mayfly Optimization Algorithm, Energy Reports, Volume 7, 2021, Pages 7663-7674, ISSN 2352-4847, https://doi.org/10.1016/j.egyr.2021.10.118.

[5] Gao, Z.-M., Li, S.-R., Zhao, J., & Hu, Y.-R. (2020). The guaranteed convergence Mayfly optimization algorithm. 2020 7th International Forum on Electrical Engineering and Automation IFEEA). doi:10.1109/ifeea51475.2020.00179

[6] Harsh Sinha and Pawan K. Ajmera, (2019) Upgrading security and protection in ear biometric The Institution of Engineering and Technology Volume 8, Issue 4, July 2019, p. 259 – 266. DOI: 10.1049/iet-bmt.2018.5081 , Print ISSN 2047-4938, Online ISSN 2047-4946

[7] Juan Zhao and Zheng-Ming Gao (2020). The negative Mayfly optimization algorithm *J. Phys.: Conf. Ser.* 1693 012098

[8] Juan Zhao and Zheng-Ming Gao (2020). The improved Mayfly optimization algorithm with Chebyshev map. Journal of Physics: Conference Series. 1684 012075. doi: 10.1088/1742-6596/1684/1/012075.

[9] Konstantinos Zervoudakis and Stelios Tsafarakis, (2020). A Mayfly optimization algorithm [J]. Computers &Industrial Engineering, 2020, 145: 106559. https://doi.org/10.1016/j.cie.2020.106559

[10] Lemmouchi Mansoura, Athamena Noureddine, Ouarda Assas and Abdessemed Yassine, (2019). Multimodal Face and Iris Recognition with Adaptive Score Normalization using Several Comparative Methods. Indian Journal of Science and Technology, Vol 12 (7), DOI: 10.17485/ijst/2019/v12i7/140755, February 2019, ISSN (Online): 0974-5645.

[11] Lingzhi Yi, Hao Shi, Jiangyong Liu, Dongfang Zhou, Ximeng Liu and Jiang Zhu, (2021). Dynamic Multi-peak MPPT for Photovoltaic Power Generation Under Local Shadows Based on Improved Mayfly Optimization. Journal of Electrical Engineering & Technology https://doi.org/10.1007/s42835-021-00855-w.

[12] Mina Farmanbar and Önsen Toygar, (2015). Feature selection for the fusion of face and palmprint biometrics. SIViP DOI 10.1007/s11760-015-0845-6

[13] Mohamed A. M. Shaheen, Hany M. Hasanien, M. S. El Moursi and Attia A. El-Fergany, (2021). Precise modeling of PEM fuel cell using improved chaotic Mayfly optimization algorithm. Int J Energy Res. 2021; 1–16. wileyonlinelibrary.com/journal/er © 2021 John Wiley & Sons Ltd. DOI: 10.1002/er.6987

[14] Zheng-Ming GAO, Juan ZHAO, Su-Ruo LI and Yu-Rong HU, (2020). The improved Mayfly optimization algorithm. Journal of Physics: Conference Series 1684 (2020) 012077 IOP Publishing doi: 10.1088/1742-6596/1684/1/012077

[15] Zhao J. and Z. -M. Gao, (2020). Bare bones Mayfly optimization algorithm, 2020 *2nd International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI)*, 2020, pp. 238-241, doi: 10.1109/MLBDBI51377.2020.00051

[16] Zhao, J., & Gao, Z.-M. (2020). The multi-start Mayfly optimization algorithm. 2020 7th International Forum on Electrical Engineering and Automation (IFEEA). doi:10.1109/ifeea51475.2020.00184