Nigerian Journal of Technology (NIJOTECH)
Vol. 41, No. 3, May, 2022, pp.535-541
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
http://dx.doi.org/10.4314/njt.v41i3.13

A Proposed Framework for Face - Iris Recognition System using Enhanced Mayfly Algorithm

A. I. Oladimeji [1, *], A. W. Asaju-Gbolagade [2], K. A. Gbolagade [3]

[1] *Department of Computer Science, Aminu Saleh College of Education, Azare, Bauchi State, NIGERIA*
[2]*Department of Computer Science, University of Ilorin, Ilorin, Kwara State, NIGERIA*
[3]*Department of Computer Science, Kwara State University, Malete, Kwara State, NIGERIA*

Abstract
Fused biometrics systems have proven to solve some problems associated with unimodal systems but also face challenges in various aspects of their implementation such as difficulty in design, user acceptance is quite low, and the performance tradeoff. This framework tends to address some of these implementation challenges by using an enhanced mayfly algorithm, a modification of the existing mayfly algorithm that was recently proposed, as feature selection. Mayfly algorithm combines advantages of particle swarm optimization, genetic algorithm, and firefly algorithm, simulated in different experiments using varied benchmark function on conventional mayfly algorithm all tested to be capable of optimization, but despite its capabilities, some limitations such as slow convergent or premature convergent rate and possible imbalance between exploration and exploitation still remain unresolved, which necessitated enhancement for better performance. This framework will enhance the existing mayfly algorithm by expanding the search space which limited the ability of the conventional mayfly algorithm to be used to solve high-dimensional problem spaces such as feature selection and modify the selection procedure to model the attraction process as a deterministic process, that will be used for the feature selection procedure on fused face –iris recognition system. This will increase the capabilities of the mayfly algorithm and in turn, increase the recognition accuracy, and reduced the false acceptance rate, false rejection rate, and time complexity of the fused face–iris recognition system.

Keywords: Mayfly, Optimization, Face-Iris, Convergent rate

1.0 INTRODUCTION

These days, the requirement for the acknowledgment of people dependent on physical and/or behavioral characteristics could be a trend in places with high-security needs. The security domain utilizes different confirmation strategies to keep data ensured, the most recent strategy is biometrics which estimates the physical or social attributes of individuals [6].

Dunstone and Yager [3] depict a biometric formula as a correlation framework, taking biometric tests as data, and manufacturing as its output life of similarity. This comparability (called a matching score) is specific to an algorithm and is the fundamental output of the matching process.

Most biometric frameworks in continuous applications utilize a solitary biometric trademark. Unimodal biometric systems, which use single-source biometric rates, generally suffer due to several factors such as lack of oneness, non-universality, and noisy data, [4-14]. Subsequently, combination biometric systems or multi-model frameworks assume a critical part in giving precision, security, comprehensiveness, and cost-viability [13].

Researchers have proposed different feature selection procedures for the face and Iris-based recognition systems but desired recognition accuracy, recognition time, false acceptance rate, and false rejection rate have not been achieved so far. This framework, when implemented introduces a new enhanced feature selection method that will improve recognition accuracy, recognition time, false acceptance rate, and false rejection rate of the fusion of faces and Iris traits.

***Corresponding author (Tel:** +234 (0) 8062068600**)**

Email addresses: *oladimejiadeisaac@gmail.com* (A. I. Oladimeji), yusuf.aaw@unilorin.edu.ng (A. W. Asaju-Gbolagade) kazeem.gbolagade@kwasu.edu.ng (K. A. Gbolagade)

2.0 LITERATURE REVIEW

This Section presents an apt review of literature relevant to this paper.

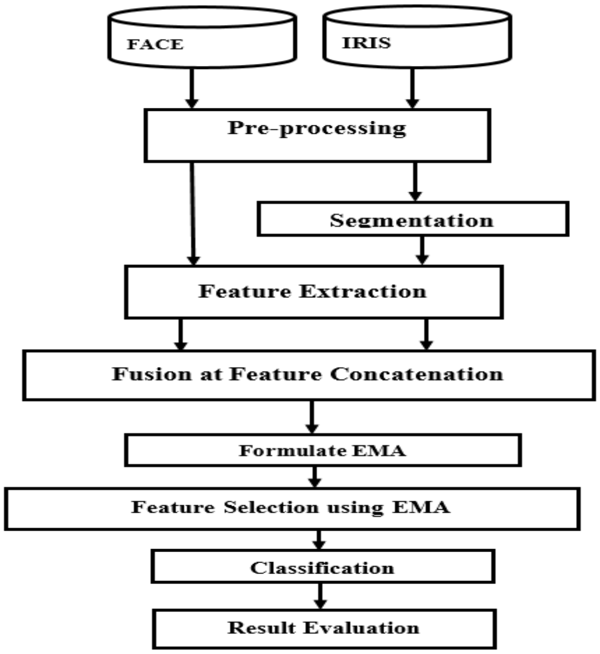

Figure. 1: Proposed framework for face - iris recognition system

2.1 Mayfly Algorithm

Mayfly algorithm incorporates the blend of provisions of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and firefly algorithm (FA), adopting and improving the global search of Particle Swarm Optimization (PSO) [19]. The mayfly algorithm is a hybrid optimization algorithm with high effectiveness, which models the mating example of mayflies. Mayflies are creepy crawlies that belong to the order Ephemeroptera, an ancient group of insects called Palaeoptera [19]. This optimization algorithm accepts that a mayfly is a grown-up subsequent to incubating and the fittest one survives disregarding the lifetime [16]. It is constantly expected to be that subsequent to bring forth from the egg, mayflies are as of now grown-ups and it is the fittest mayflies that endure, paying little mind to how long they live. It also noted that the position of each mayfly in the hunt space represents an implicit result to the problem. The mayfly optimization algorithm was lately proposed and published in the year 2020 [5].

Since its detailing, numerous researchers have utilized either the conventional mayfly algorithm or improved mayfly algorithm to proffer answers for optimization issues. Zhao and Gao [20] proposed the further developed mayfly optimization algorithm with the Chebyshev map, which could be a decent decision to supplant the irregular numbers in uniform appropriation associated with the first mayfly optimization algorithm. Gao et al., [21], present the OBL rule with the mayfly optimization algorithm. Abd Elaziz et al., [1] utilized a mayfly optimization algorithm with irregular vector utilitarian connection incorporated for execution expectation of sun-powered photovoltaic warm gatherer joined with electrolytic hydrogen creation framework.

Rajakumar et al., [8] proposed tuberculosis identification in chest X-beam utilizing Mayfly-algorithm improved double profound learning highlights, etc. The acquired outcome had sealing the high capacity of the mayfly algorithm. Xingmin et al., [17] proposed MPPT control dependent on further developed mayfly optimization algorithm under complex concealing conditions. The proposed apply the further developed Mayfly Optimization Algorithm (MA) to the greatest force the following control by presenting the gravity factor and restricting the inquiry space of male mayfly, the improved precision of the algorithm is upgraded, the vibration of the algorithm close to the MPP is diminished, and the event of untimely wonder is kept away from. The proposed reenactment results show that the improved MA algorithm can adequately unite to MPP under complex concealing conditions, and the yield productivity of photovoltaic exhibits can be kept up with above 99.96%.

Shaheen et al., [11] introduced an exact demonstration of PEM energy component improved turbulent Mayfly optimization algorithm. This exploration principally focuses on an exact displaying of the proton trade layer energy unit (PEMFC) that gives a great match between the reenactment results and those deliberate for all intents and purposes. Yi et al., [18] projected Dynamic Multi-peak MPPT for electrical phenomenon Power Generation underneath native Shadows supported improved mayfly optimization.

Zhao and Gao [20] proposed a negative mayfly optimization algorithm. In this proposal, every one of the people may way to deal with the authentic best directions and the worldwide best up-and-comers. This is a sensible idea for the design of refreshing conditions. Be that as it may, the refreshing conditions could likewise be deciphered with a contrary significance: every one of the people would flee from their own most noticeably awful verifiable directions and the worldwide most noticeably awful positions.

In the review of related works presented above, most of the procedures proposed by the authors are either combining the conventional mayfly algorithm with an existing algorithm or proposing an improvement of the mayfly algorithm to solve the optimization problem. The majority of these reviewed works proposed integration of already deployed legacy systems into a mayfly algorithm rather than developing an optimization system from the scratch. In this paper, a framework for a face-iris recognition system using an enhanced mayfly algorithm that is capable of improved recognition accuracy, recognition time, false acceptance rate, and false rejection rate of the fused faces and Iris traits is proposed.

2.1.1 Step by step presentation of Mayfly Algorithm

Step 1: Initialize the male mayfly population x_{ij}^0 (i=1,2, …, N) and velocities v_{ij}^0,
Initialize the female mayfly population y_{ij}^0 (i=1,2, …, M), Max_{iter} = max. no of iteration.

Step 2: Set iteration t = 1

Step 3: Evaluate the objective function values of male and female mayfly as
$f(x) = f(x_i^t)$. where $f: R^n \rightarrow R$ is the objective function which evaluate the quality of a solution
$f(x) = \sum_{k=2}^{m} \left[\sum_{i=1}^{n} \left(x_{i,k-1} - x_{i,k}\right)^2\right]$
Where x_i^t represent the features at *i=1,2, …, n* and *k=2,3, …, m*

Step 4: Find the personal best for each male and female as
$P_{best,iD}^t = x_i^t$ and global best as
$G_{best,iD} = min\{P_{best,iD}^t\}$

Step 5: Calculate gravity coefficient:
The gravity coefficient g can be a fixed number in the range of [0, 1], or it an be gradually reduced over the iterations, allowing the algorithm to exploit some specific areas, by being updated through the following equation:
$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}} - iter$
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.

Step 6: Update velocities and solution of males and females
$V_{max} = rand * (x_{max} - x_{min})\ where\ r\ \&\ \epsilon\ (0,1)$
where x_{max} and x_{min} are the search space limits for the fitness function,
$$v_{ij}^{\ t+1} = \begin{cases} v_{max}, & if\ v_{ij}^{\ t+1} > v_{max} \\ -v_{max}, & if\ v_{ij}^{\ t+1} < -v_{max} \end{cases}$$
$$v_{ij}^{\ t+1} = g * v_{ij}^{\ t} + \alpha_1\, e^{-\beta r_p^2}\left[pbest_{ij} - x_{ij}^{\ t}\right] + \alpha_2\, e^{-\beta r_g^2}\left[gbest_j - x_{ij}^{\ t}\right]$$
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 distances are calculated as:
$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n} (x_{ij} - X_{ij})^2}$$
Where x_{ij} is the j^{th} element of mayfly i and X_{ij} corresponds to $pbest_{ij}$ or $gbest$
$x_i^{\ t+1} = x_i^{\ t} + v_{ij}^{\ t+1}$
With $x_i^{\ 0} \sim U(x_{min}, x_{max})$ male mayfly
$y_i^{\ t+1} = y_i^{\ t} + v_{ij}^{\ t+1}$
With $y_i^{\ 0} \sim U(y_{min}, y_{max})$ female mayfly

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + \alpha_2\, e^{-\beta r_{mf}^2}(x_{ij}^{\ t} - y_{ij}^{\ t}) & if\ f(y_i) > f(x_i) \\ v_{ij}^t + fl * r & if\ f(y_i) \le f(x_i) \end{cases}$$
Where v_{ij}^t is the velocity of female mayfly i in dimension j = 1, …, 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, calculated using equation
$\mathbf{V} = \{\boldsymbol{V_1}, \boldsymbol{V_2}, \ldots, \boldsymbol{V_p}\}$.
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].

Step 7: Evaluate Solutions $f(x) = f(x_i^{t+1})$
where $f: R^n \rightarrow R$ is the objective function which evaluates the quality of a solution

Step 8: Mate the mayflies and evaluate offspring
$offsprint1 = L * male + (1 - L) * female$
$offsprint2 = L * male + (1 - L) * male$
where $male$ is the male parent, $female$ is the female parent and L is a random value within a specific range. Offspring's initial velocities are set to be zero

Step 9: Update $Pbest$ of population
$$pbest_i = \begin{cases} x_i^{t+1}, & if\ f(x_i^{t+1}) > f(pbest_i) \\ is\ kept\ the\ same, & otherwise \end{cases}$$

Step 10: Update $Gbest$ of population
The global best position $gbest$ at time step *t*, is defined as
$$gbest \in \{pbest_1, pbest_2, \ldots, pbest_N |\ f(cbest)\} = \min\{\{f(pbest_1),\ f(pbest_2), \ldots, f(pbest_N)|\}$$
Where N is the total number of male mayflies is the swarm.

Step 11: If t $< Max_{iter}$ then $t = t + 1$ and GOTO step 1 else GOTO step 12.

Step 12: Output optimum feature selected solution as $Gbest_{bD}$

$$Gbest_{bD} = x_b$$

3.0 METHODOLOGY

3.1 Proposed Framework

The proposed framework as shown in Figure 1, will be used as the organization to be followed in solving the research problems. The framework will begin with image acquisition via digital Cameras. Biometric features will be extracted from individual faces and iris after the application of suitable preprocessing techniques such as conversion to grayscale, image enhancement, image cropping, and image segmentation for each modality. The feature extracted will be fused at the feature extraction level using the feature concatenation method. The enhanced mayfly algorithm will be formulated from the conventional mayfly algorithm as feature selection. The optimal features will be selected using formulated enhanced mayfly algorithm. Metrics such as false acceptance rate, false rejection rate, recognition accuracy, equal error rate and computation time will be used as performance evaluation. Figure 2. Described the scheme of this framework.

3.2 Data Acquisition

A digital camera will be used to acquire face and iris biometric data of users from chosen experimental organization. Face and iris images of 190 subjects with 3 different samples will be captured with a size of 640 by 480 pixels. The two biometric traits will be downsized into 128 by 128 pixels without any alteration in the images. All images taken should have equal uniform illumination conditions and light color background. The dataset will be populated with 570 images per modality. 60% will be used to train the system and 40% will be used for authentication. The choice of dataset division will be based on the random sampling cross-validation method.

3.3 Formulation of an Enhanced Mayfly Algorithm

In this framework, an enhanced mayfly algorithm will be formulated from mayfly algorithm by introducing a roulette wheel selection procedure. In the existing mayfly algorithm, velocities must be reduced to better control the balance between exploration and exploitation abilities of the mayflies. The gravity coefficient of conventional mayfly algorithm 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. This makes it difficult for the mayfly algorithm to be used to solve high-dimensional problem spaces such as feature selection.

$$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}} - iter \tag{1}$$

This framework proposed a new gravity coefficient, which widens the search space in the range of [-1, 1].

$$g = g_{std} - \frac{(g_{std} - g_{\text{mean}}) * (iter_{max} - iter + 1)}{iter_{max}} - iter \tag{2}$$

The framework introduced roulette wheel selection procedure to model the attraction process as a deterministic process. That is, the probability of attracting the best female and best male of the next population is proportional to its fitness, the better the fitness is, the higher chance for best male to attract best female. The attraction between best female and best male can be depicted as spinning a roulette that has as many pockets as there are best female and best male in the current population, with sizes depending on their probability. Probability of attracting best female to best male is equal to p_i

$$p_i = rand \le \frac{f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{4}$$

Where $f(x_i^t)$ is the fitness of x_i, $rand \, \epsilon \, (0,1)$ and N is the size of the current population.

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + \alpha_2 \, e^{-\beta r_{mf}^2 (x_{ij}{}^t - y_{ij}{}^t)} & if \; f(y_i) > f(x_i) \\ v_{ij}^t + fl * p_i & if \; f(y_i) \le f(x_i) \end{cases} \tag{5}$$

Where v_{ij}^t is the velocity of female mayfly i in dimension j = 1, …, 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 deterministically by roulette wheel selection and p_i is a deterministic value. The roulette wheel selection is procedure as replacement for random selection used in conventional mayfly algorithm.

3.4 Feature Selection using Enhanced Mayfly Algorithm

The general formulation of an optimal feature selection problem that will be used in this framework are as follows:

$$\min_{Pbest,Gbest,F_f^d} \emptyset(y(F_f^d))$$

Subject to:

$$C1: \; 0 \leq (fa, ir, fit, Pbest, Gbest, F^d) \leq 1 \quad F^d \in F_e$$

$$C2: \; fit = \begin{cases} 1 & if\ fit \leq \overline{fit} \\ 0 & otherwise\ fit > \overline{fit} \end{cases} \quad (6)$$

where $fa \in R^n$, and $ir \in R^n$ are the vectors of the face feature f_{face}, and iris feature f_{iris} state variables, respectively. $\overline{fit}$ is the mean square error for fit.

The entire state vector is denoted as $y = [fa\ ir]$, where fa is the set of the feature vector of f_{face}, and ir is the set of the feature vector of f_{iris}. The problem will be defined on the feature's horizon $F_e = [F_o^d\ F_f^d]$. Where F_e consists of original feature of F_o^d of y and final feature F_f^d selected which is equivalent to F_{ij}^d.

The local and global best position feature-dependent control variables $P_{best}, G_{best} \in R^n$ and possibly the final feature F_f^d are decision variables for optimization. The goal of the optimization is to find the optimal set of decision variables to minimize the objective function $\emptyset$, that is, $\emptyset(y(F_f^d))$.

The search space for finding the optimum is restricted by constraints, which described an appropriate error fitness and feature parameter requirements to be fulfilled during feature selection at feature selection level. The framework considered feature constraint *C1* and fitness constraint *C2*. *C1* ensured that the feature values range between 0 and 1. *C2* certified that the fitness value for features to be selected was tagged as 1 and the irrelevant ones was tagged 0.

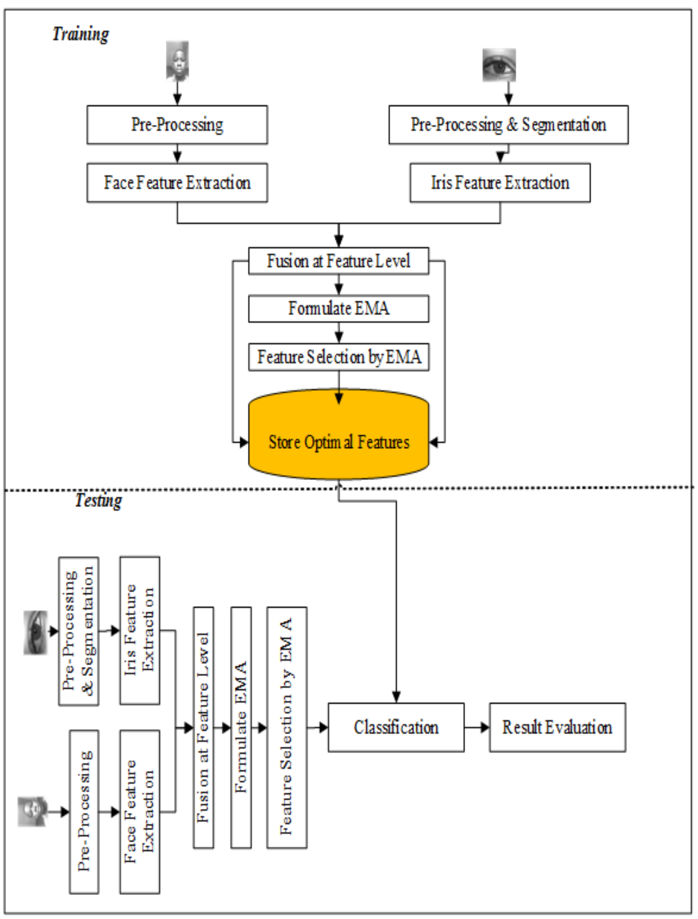

Figure 2: Architecture of proposed framework for Face -Iris recognition system

4.0 CONCLUSION

In this paper, a framework for face - iris recognition system using enhanced mayfly algorithm has been proposed. The proposed framework if implemented and adapted can proffered solutions to the attendant problems associated with recognition accuracy, recognition time, false acceptance rate, and false rejection rate of the fused faces and Iris traits. Improving the accuracy and computational time of the face and iris recognition system is the main focus of this paper.

Mayfly optimization algorithm that was recently proposed has demonstrated highly efficient capability in solving search space problems, but the conventional mayfly algorithm converges prematurely because of inaccurate balance between local and global searches. Also, the algorithm has low stability, which is caused by speed fluctuation. With the enhanced mayfly algorithm proposed in this paper, it would be able to solve the limitations observed in conventional mayfly algorithm and in turn improve the accuracy and computational time performance of fused face and iris recognition system. Future work will be to implement this proposed scheme, evaluate the time and accuracy performance of the system, and compare it with the conventional mayfly optimization algorithm.

REFERENCES

[1] Abd Elaziz, M., Senthilraja, S., Zayed, M. E., Elsheikh, A. H., Mostafa, R. R., and Lu, S." 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, 2021, p. 117055.doi:10.1016/j.applthermaleng.202.

[2] De Marsico, M., Galdi, C., Nappi, M., & Riccio, D. Firme "Face and Iris Recognition for Mobile Engagement. Image and Vision Computing", *Biometric Recognition*, 32(12), 2014, 1161–1172. doi:10.1016/j.imavis.2013.12.014

[3] Dunstone T. and Yager N. (eds), "Biometric System and Data Analysis". *Springer*, Boston, MA. 2009. https://doi.org/10.1007/978-0-387-77627-9_2

[4] Eskandari, M., & Toygar, Ö. "Selection of optimized features and weights on face-iris fusion using distance images. Computer Vision and Image Understanding", *Biometric Recognition*, 137, 2015, pp. 63–75, doi:10.1016/j.cviu.2015.02.011

[5] Juan Zhao and Zheng-Ming Gao, "The improved mayfly optimization algorithm with Chebyshev map", *Journal of Physics: Conference Series*, 2020, p. 012075 IOP Publishing doi:10.1088/1742-6596/1684/1/012075.

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

[7] Raghavendra, R., Raja, K. B., & Busch, C. "Exploring the Usefulness of Light Field Cameras for Biometrics: An Empirical Study on Face and Iris Recognition", *Institute of Electrical and Electronics Engineering Transactions on Information Forensics and Security*, 11(5), 922–936. doi:10.1109/tifs.2015.2512559

[8] Rajakumar, M.P. et al. 'Tuberculosis Detection in Chest X-ray Using Mayfly-algorithm Optimized Dual-deep-learning Features", 2021, pp. 1 – 14.

[9] Regouid, M., Touahria, M., Benouis, M., & Costen, N. "Multimodal biometric system for ECG, ear and iris recognition based on local descriptors", Multimedia *Tools and Applications*, 2019. doi:10.1007/s11042-019-7467-x

[10] Sue Chin Yow and Ahmad Nazri Ali, "Iris recognition system (IRS) using deep learning technique" *Journal of Engineering Science*, 15(2), 2019, pp. 125–144, https://doi.org/10.21315/jes2019.15.2.9

[11] Shaheen, M. A. M., Hasanien, H. M., El Moursi, M. S., & El-Fergany, A. A., "Precise modeling of PEM fuel cell using improved chaotic MayFly optimization algorithm, *International Journal of Energy Research*, doi:10.1002/er.6987

[12] Sharif M., Raza M., Shah J.H., Yasmin M and Fernandes S.L. "An Overview of Biometrics Methods. In: Singh A., Mohan A. (eds) Handbook of Multimedia Information Security*", Techniques and Applications. Springe*r, Cham. https://doi.org/10.1007/978-3-030-15887-3_2

[13] Tajinder Kuma, Shashi Bhushan and Surender Jangra, An Improved Biometric Fusion System of Fingerprint and Face using Whale Optimization, *International Journal of Advanced Computer Science and Applications*, 12(1), 2021.

[14] Omid Sharifi and Maryam Eskandari, "Optimal Face-Iris Multimodal Fusion Scheme Symmetry", 2016, 8, 48, doi:10.3390/sym8060048. www.mdpi.com/journal/symmetry

[15] Perez, C. A., Aravena, C. M., Vallejos, J. I., Estevez, P. A., & Held, C. M. "Face and iris localization using templates designed by particle swarm optimization", *Pattern Recognition Letters*, 31(9), pp. 857–868. doi:10.1016/j.patrec.2009.12.029

[16] Xiaokai Guo, Xianguo Yan & Kittisak Jermsittiparsert, "Using the modified mayfly algorithm for optimizing the component size and operation strategy of a high temperature PEMFC-powered CCHP". *Energy Reports*, 7, 2021, 1234–1245. www.elsevier.com/locate/egyr

[17] He Xingmin, He Baina, Zhao Yunwei, Rongxi Zhang, Jingru Dong, Yanchen and Jiang Renzhuo "MPPT control based on improved mayfly optimization algorithm under complex shading conditions" *International Journal of Emerging Electric Power Systems*, 22(6), 2021, pp. i-ii. https://doi.org/10.1515/ijeeps-2021

[18] Yi, L., Shi, H., Liu, J., Zhou, D., Liu, X., & Zhu, J. "Dynamic Multi-peak MPPT for Photovoltaic Power Generation Under Local Shadows Based on Improved Mayfly Optimization", *Journal of Electrical Engineering & Technology*,

doi:10.1007/s42835-021-00855-w

[19] Zervoudakis, K., & Tsafarakis, S. "A mayfly optimization algorithm", *Computers and Industrial Engineering*, 145, p. 106559.

[20] Zhao, J., & Gao, Z.-M., "The negative mayfly optimization algorithm" *Journal of Physics, Conference Series*, 1693, p. 012098. doi:10.1088/1742-6596/1693/1/012098

[21] Zheng-Ming GAO, Juan ZHAO, Su-Ruo LI and Yu-Rong HU, "The improved mayfly optimization algorithm with opposition-based learning rules", *Journal of Physics, Conference Series*, 1693 (2020) 012117, CISAI 2020 IOP Publishing doi:10.1088/1742-6596/1693/1/012117