International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v10i10.5731
***Article Received**: 28 July 2022 **Revised**: 05 September 2022 **Accepted**: 12 September 2022*

Unity Attractors Inspired Programmable Cellular Automata and Barnacles Swarm Optimization-Based Energy Efficient Data Communication for Securing IoT

[1] P. Hemalatha, [2] K. Dhanalakshmi
[1]Assistant Professor, Department of Computer Science and Engineering
IFET College of Engineering
Villupuram, Tamilnadu, India
hemadec4@gmail.com
[2]Professor, Department of Computer Science and Engineering,
PSNA College of Engineering and Technology
Dindigul, Tamilnadu, India
dhanalakshmikrs@gmail.com

Abstract: Wireless Sensor Networks (WSNs) is the innovative technology that covers wide range of application that possesses high potential merits such as long-term operation, unmonitored network access, data transmission, and low implementation cost. In this context, Internet of Things (IoT) have evolved as an exciting paradigm with the rapid advancement of cellular mobile networks, near field communications and cloud computing. WSNs potentially interacts with the IoT devices based on the sensing features of web devices and communication technologies in sensors. At this juncture, IoT need to facilitate huge amount of data aggregation with security and disseminate it to the reliable path to make it reach the required base station. In this paper, Unity Attractors Inspired Programmable Cellular Automata and Barnacles Swarm Optimization-Based Energy Efficient Data Communication Mechanism (UAIPCA-BSO) is proposed for Securing data and estimate the optimal path through which it can be forwarded in the IoT environment. In specific, Unity Attractors Inspired Programmable Cellular Automata is adopted for guaranteeing security during the data transmission process. It also aids in determining the optimal path of data transmission based on the merits of Barnacles Swarm Optimization Algorithm (BSOA), such that data is made to reach the base station at the required destination in time. The simulation results of UAIPCA-BSO confirmed minimized end-to-end delay , accuracy and time taken for malicious node detection, compared to the baseline approaches used for comparison.

Keywords: Internet of Things (IoT), Barnacles Swarm Optimization Algorithm (BSOA), Unity Attractors, Programmable Cellular Automata, Wireless Sensor Networks (WSNs).

1. Introduction

Optimization technique is to identify the best group of variables or characteristics that satisfy the limitations and accomplish the fitness function, whether for diminution or maximization goals. Typically, tasks or problems that need to be handled are used to define the fitness function, which can be expressed in terms of costs, effectiveness, profitability, etc. Various strategies or algorithms have been utilized to tackle optimization problems, from complex computers to morpho methods. Complex computational methods use contour data of the associated variables to obtain the best solution. Although these methods are still in use nowadays by a variety of users to tackle optimization algorithms, they frequently face the issue of near-optimal trapping, are useless for unsolved difficulties, and require computational cost methodologies [1]. The popularity of morpho strategies, on the other hand, hand, is growing, particularly in engineering design problems, due to their capacity to break free from the optimization algorithm by relying on straightforward ideas. It mimics natural phenomena and can be applied to various issues from different disciplines. Basic schema is typically motivated by specific concepts and is comparatively short. They can be split into four categories algorithms based on physics, human behaviour, swarm intelligence, and evolvement [2]. The Barnacle Mating Optimizer (BMO), a revolutionary bio-inspired conceptual algorithm that imitates the mating behaviour of crustaceans, is proposed in this paper. BMO fits into the category of optimization computation.

The researchers are aware of no prior research on this topic in the optimization survey. The efficiency of the BMO is proven and assessed using 23 theoretical design parameters and an actual application of the electrical design issue. The results show that the BMO is quite advantageous compared to the most cutting-edge optimization techniques. It is important to note that the authors in [3] published the first studies connected to the evolution of BMO, and Sulaiman et al. also covered the integration of BMO into issues with economic load dispatch. A microbially EA called Sulaiman first developed the barnacle mating optimizer (BMO) in 2020 [4]. BMO can seek promising opportunities in the search area and offers the advantage of fewer parameters. Nevertheless, the No Free Lunch (NFL) Hypothesis demonstrates mathematically that there isn't a method for every optimal control problem [5] in the machine learning domain. In other words, discussing which solution is superior is useless even without a specific issue. The NFL theorem and this motivation drive our use of Stochastic mutations, stochastic modelling, and specular reflection to increase BMO efficiency for the first time. In principle, a better algorithm can aid in selecting probable features from a set of elements in a particular machine-learning task. It can enhance the effectiveness and information processing of the provided models of machine learning. Or, it is employed to fix the parameter estimation issue that plagues the majority of model-based machine learning algorithms. The proposed algorithm is tested for different performance metrics against existing systems. Experimental results shows that the propounded method outperforms existing optimization methods.

2. Literature Review

For classification tasks, training algorithms and machine learning models are now applied. Wan et al. proposed the two-dimensional maximal embedding difference, a unique manifold learning approach that relies on local structure (2DMED). The best spatial vectors were immediately retrieved using this technique from 2D picture grids. Additionally, it could avoid constructing a reverse matrix thanks to the difference trace. According to experimental findings, 2DMED has reasonable recognition rates on digitized facial and calligraphy databases [6]. A unique use of 2D classifier locality preserving projections (2DDLPP) with fuzzy set theory is fuzzy 2D classifier locality preserving points (F2DDLPP). This technique improved the translation into a lesser space's discriminating power. F2DDLPP can choose the most beneficial characteristics for classification by comparison and analysis [7]. In 2017, localized graph anchoring methods were improved using the decision boundary criteria and fuzzy set theories. It worked well as a face recognition method [8]. There are numerous learning algorithms for various supervised learning issues. Several SVM variables can be used to regulate multiple aspects of the algorithm's effectiveness. In general, there are three fundamental ways to adjust these settings. By using bidirectional trials, several scientists test various combinations to optimize these characteristics. The automated selecting approach requires prior knowledge of the impact of variables on enhancing its performance. Another popular approach is grid search, used when there are less than three parameters. Because there are so many different parametric permutations, this method is exceedingly sluggish. MAs are the third strategy. An optimal solution can be created from the parameter subproblem. Here, the optimization cost is the fitness value of the fitness equation, and the governing equations are constants. FS can help increase the accuracy and aid in developing an effective classification algorithm. Some renowned research areas execute FS while also taking SVM parameters into account. Following is a presentation of such examples.

In [9], Huang et al. integrated discontinuous and continual PSO to choose the features and adjust the SVM parameters simultaneously. To speed up the calculation, a parallel and distributed structure were used to develop PSOSVM. To accomplish the same objective in 2018, Aljarah et al. [10] presented a hybrid approach based on the GOA. In terms of increasing the SVM classifier accuracy, the testing findings showed that GOA outperformed grid search, PSO, genetic algorithm (GA), multi-verse optimizer (MVO), grey wolf optimizer (GWO), firefly algorithm (FF), bat algorithm (BA), and cuckoo search (CS). Al-Zoubi et al. utilized the SSA-SVM technique to 3 common medical problems in 2020. This model proved more effective in solving common diagnostic issues than other methods in terms of correctness, recall, and precision [11]. Hussein et al. recently used HHO with SVM and kNN to pick biochemical descriptors and analyze individual activity. HHO-SVM outperformed other approaches in terms of performance.

Additionally, HHO-SVM outperformed HHO-kNN in terms of performance as rounds increased [12]. In this optimization field, instances of native MAs that are used include GA [13], ant colony algorithm optimization (ACO) [14], required to teach optimization (TLBO) [15], brainstorm optimization (BSO) [16], and others. Gauthama Raman et al. [17] expanded GA by introducing spectral graph methods that will allow HG-GA. The search for the optimal strategy was ramped up, and entrapment at the locally optimal was avoided by exploiting the hyperclique feature of the directed graph to construct the random number. The HG-GA-SVM model was

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v10i10.5731
***Article Received**: 28 July 2022 **Revised**: 05 September 2022 **Accepted**: 12 September 2022*

utilized to deal with an intrusion detection system (IDS), and it was contrasted against GA-SVM, PSO-SVM, BGSA-SVM, random forest, and Bayes net. The HG-GA-SVM demonstrated outstanding results regarding classifier efficiency (an increase of about 2%), recognition rate, rate of false alarms and runtime. Memetic algorithm-based SVM (M-SVM), which Baliarsingh et al. [18] suggested, was motivated by the integration of social engineering optimizer (SEO) in emperor penguin optimizer (EPO). EPO served as a foundation for global optimization, whereas SEO was seen as a local search approach. Binary-class data and multi-class datasets were used to analyze the experiment. According to statistical findings, the proposed strategy is superior to previous techniques for selecting features and microarray data classification. Investigators have never ceased investigating, according to the review of the literature. The NFL theory suggested a novel approach to address this issue.

3. Proposed Unity Attractors Inspired Programmable Cellular Automata and Barnacles Swarm Optimization-Based Energy Efficient Data Communication Mechanism (UAIPCA-BSO)

In this section, the proposed UAIPCA-BSO is explained with respect to the role Unity Attractors Inspired Programmable Cellular Automata (UAIPCA) towards the process of guaranteeing security and Barnacles Swarm Optimization (BSOA) used for identifying the potential IoT nodes that need to be selected for efficient data communication.

3.1 Unity Attractors Inspired Programmable Cellular Automata (UAIPCA)

This incorporated UAIPCA is determined to be highly ideal for different application like the data dissemination of IoT which necessitates the process of error-correcting codes, arithmetic operator design, signature analysis**,** pseudo-exhaustive pattern generation and pseudorandom generation. This UAIPCA is used in several cryptographic applications that include message authentication, secret sharing, public key cryptography and symmetric cryptography. In specific, UAIPCA is a cryptographic algorithm that permits users to verify the specific properties associated with an encrypted value without disclosing the actual message. This scheme can be combined with Fully Homomorphic Encryption (FHE) capabilities in the encryption process for converting them into a Verifiable FHE Scheme (VFHES). This UAIPCA includes three main phases namely: i) Pre-Treatment ii) Input Preparation and iii) Computation and verification of output. Gennaro et al. have defined the notion associated with the UAIPCA as a reliable protocol that represents a challenge and response mechanism between two entities under cooperation. This protocol is responsible for preserving collaboration between the entities for calculating a function fn: $\{0,1\} \rightarrow (0,1)$ that incurs polynomial execution time.

In the process of pre-treatment, the client is responsible for derive some definite complementary information related to the function fn: $\{0,1\} \rightarrow (0,1)$. The auxiliary information derived in this phase is open and exchanged with the server (prover). The residual auxiliary information is considered as private and is available with the client. Then, in the input Preparation phase, the client uses the input functionfn: $\{0,1\} \rightarrow (0,1)$ for computing the auxiliary information. The specific auxiliary information calculated by applying the function fn: $\{0,1\} \rightarrow (0,1)$ is made public and the rest is considered as private (secret) and is available with the client. In addition, the information which is made public is forwarded to the server for calculating functions on the considered inputs.

In the third phase, the computation and Verification of Output is achieved. In this phase, the server computes the output related to the function fn: $\{0,1\} \rightarrow (0,1)$based on the shared inputs and public information corresponding to the function in the former two phases. The computed result is reverted to the client with an aim of verifying accuracy based on the computation of actual values associated with the output. Accuracy verification is performed through the decoding process carried out by the server based on the private information computed in the former phases. Further, the method of UAIPCA involves less number of interactions between the challenger and the prover by using only two messages. In this phase, a message is exchanged from the challenger to the prover, while the second message is sent vice-versa during different stages of the protocol.

In other words, UAIPCA is considered as a protocol that permits a client to authorize a computation to the server with the assurance that the calculation will be performed correctly. In this context, UAIPCA is suitable for performing verification of encryption for permitting the prover to convince an auditor entity (aggregating node), as homomorphic encryption is capable of delegating calculations that could be performed over the encrypted data with the help of a remote server.

3.2 Barnacles Swarm Optimization-Based Energy Efficient Data Communication

The proposed BSOA is proposed based on the inspiration derived based on the micro-organism named Barnacles that exists from the times of Jurassic. The Barnacles exhibit two typical characteristics during their lifetime process. In the earlier stage, the Barnacles possesses the capability of swimming. On the other hand, they get attach to the objects on the water and grow a shell in the adult stage. Majority of the barnacles falls on the category of

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v10i10.5731
***Article Received**: 28 July 2022 **Revised**: 05 September 2022 **Accepted**: 12 September 2022*

hermaphroditic since they possess the organs for male and female reproduction. The steps adopted in the implementation of BSOA algorithm is explained as follows.

In the initialization process, the candidate solution (barnacles) is considered as a population vector which is typically expressed in Equation (1)

$$B_{CS} = \begin{pmatrix} SA_1^1 & \cdots & SA_1^{NC} \\ \vdots & \ddots & \vdots \\ SA_n^1 & \cdots & SA_n^{NC} \end{pmatrix} \qquad (1)$$

Where, 'n' and 'NC' represents the search agents (population size or barnacles count) and number of control variables considered for exploration. The control variables defined in Equation (1) need to satisfy the lower and upper thresholds of the problem specified in Equation (2) and (3)

$$U_{Th} = [U_{Th(1)}, U_{Th(2)}, \ldots\ldots, U_{Th(n)}] \qquad (2)$$

$$L_{Th} = [L_{Th(1)}, L_{Th(2)}, \ldots\ldots, L_{Th(n)}] \qquad (3)$$

Where, U_{Th} and L_{Th} indicates the lower and upper thresholds considered fir evaluating the potentiality of each i^{th} variable used for controlling the population of search agents.

Initially, the vector B_{CS} is evaluated and process of sorting is facilitated for identifying the best solutions determined so far as the best search agent.

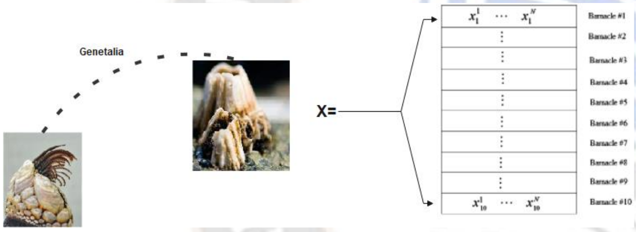

Figure 1. Mating of BMO having length of pl=10

BMO stresses the allele frequency of adults to create the offspring relying on the Hardy-Weinberg rule due to the lack of specific formulas to determine the germination process of crustaceans. It is vital to emphasise that the exploration and exploration processes are significantly influenced by the height of their genitalia (pl). According to Figure 1, which is based on the assumption that pl = 10, Benthic #1 can only breed with one of Crustaceans #2–#10. Then the process of selection depends on the penis's length possesses by the barnacles (exploration of the search space). This process of selection is achieved based on the assumptions, that includes, i) it is randomly conducted but it completely depends on the length of exploration (penis length), ii) It only ensures the process of solution crossover from one solution with another solution, iii) It permits the process of self-crossover or distinct crossover during the process of selection, iv) whenever the fitness value of the parents considered during selection is greater than the penis length (p), then perform the process of exploitation based on Equation (4) and (5)

$$B_{CS(Parent-1)} = Rnd(n) \qquad (4)$$

$$B_{CS(Parent-2)} = Rnd(n) \qquad (5)$$

Where, $B_{CS(Parent-1)}$and $B_{CS(Parent-2)}$ indicates the parent solution considered for the process of selection.

At this juncture, the process of reproduction is more different than most of the evolutionary-inspired algorithms. Thus, the process of reproduction inherited in BSOA completely depends on Equation (6)

$$B_{CS(i)} = pB_{CS(i)}^{NC} + qB_{CS(i)}^{NC} \qquad (6)$$

Where, p indicates the pseudo random number which is distributed uniformly between the value of 0 and 1 by satisfying the condition $q = 1 - p$.

Further, the process of exploration is imposed such that the selection of candidate solution completely depends on as initially assigned value of pl as specified in Equation (7)

$$B_{CS(i)} = Rnd * B_{CS(i)}^{NC} \qquad (7)$$

Where, 'Rnd' represents the random value that ranges between 0 and 1. The above-mentioned Equation (7) is used for the generation of new candidate solution from the selected mating parent solution determined from the search space. These final determined offspring candidate solutions are again evaluated based on fitness function during the procedure of exploration. Moreover, process of sorting is imposed over the best 50% solution such that the impotent solutions are prevented during the searching process.
Therefore, the arranging process is performed for choosing the 50% top solutions that fit the size of the population, and the unwanted results are eliminated.

Algorithm 1: Steps included in the proposed BSOA algorithm used for efficient data communication

Input: Maximum number of iterations $(\boldsymbol{Iter_{Max}})$, $p,\ i,\ Counter\ U_{Th}$ and L_{Th}.

Output: The set of nodes (solution) which is selected for achieving efficient data communication.

Step 1: Initially generate a population (B_{CS}) that depicts the complete number of nodes in the network environment.

Step 2: Utilize the fitness function and compute the fitness value associated with each candidate solution of (B_{CS}).

Step 3: Arrange the candidate solution of (B_{CS}) depending on the fitness value possessed by each solution.

Step 4: Determine the best solution and label it as $P - B_{CS}$

Step 5: While $\boldsymbol{Iter_{Curr} < Iter_{Max}}$ do

Step 6: Introduce the process of selection based on Equation (4) and (5)

Step 7: If the fitness value (parent solution) < penis parameter (p) then

Step 8: For each of the variable do

Step 9: Use Equation (6) for attaining the generation of offspring

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v10i10.5731
***Article Received**: 28 July 2022 **Revised**: 05 September 2022 **Accepted**: 12 September 2022*

Step 10: End For
Step 11: Else
Step 12: For each of the variable do
Step 13: Introduce the process of generating offspring based on Equation (7)
Step 14: End For
Step 15: End If
Step 16: If the threshold violation is identified
Step 17: Then again calculate the fitness of the candidate solution
Step 18: Again, identify the best solution and update it as $New\ (P - B_{CS})$
Step 19: $\boldsymbol{Iter_{Curr} = Iter_{Curr} + 1}$
Step 20: End while
Step 21: Return $P - B_{CS}$

The aforementioned BSOA algorithm (Figure 2) is adopted for selecting reliable IoT devices through which the data can be forwarded from the source to the destination.

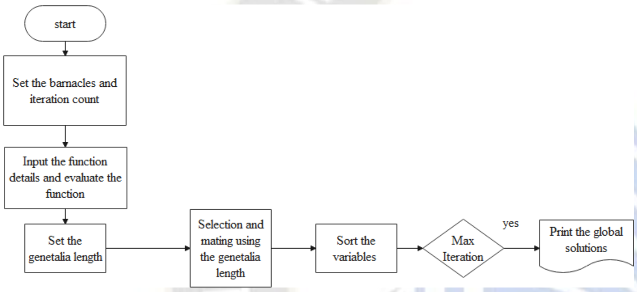

Figure 2. Flowchart of Barnacles Swarm Optimization

4. Results and discussion

Accuracy is an essential factor in measuring the performance of the learning model. We conduct experiments with the proposed scheme, and the results are compared with the existing IDS security models like Support vector machines [19], PSO[20], FFSO[21] , GA[22] as shown in figure 3 . To carry out the task, the values such as True positive (the number of accurate classifications of attacks), True Negative (the number of accurate classifications of trusted nodes), False Positive(Number of false classifications of attacks), False Negative(Number of false classifications of trusted nodes) are determined. Based on the values described above, the accuracy can be found out by the following equation 8.

$$Accuracy = \frac{True\ positive + true\ negative}{True\ positive + True\ negative + False\ positive + False\ Negative} \quad (8)$$

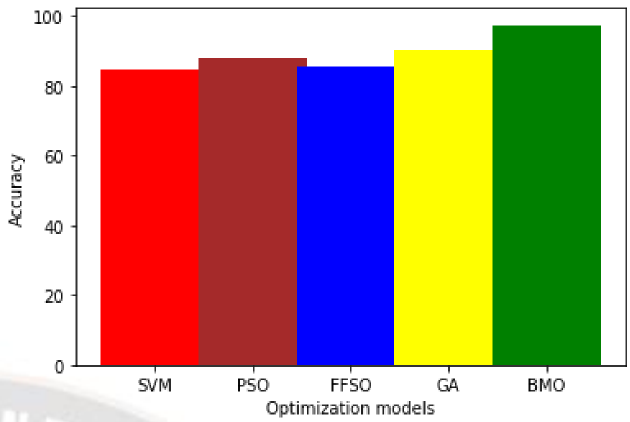

Figure 3. Accuracy Graph

It is determined by counting the number of network nodes that are depleted. The low voltage backups and maybe some potential drifts may cause the nodes to fail when they begin transmitting data for an extended period. For data transfer, the present methods are always designed to select the node with lesser function values. The lower-level nodes may occasionally halt due to the overuse of the same nodes. BMO planned to choose the node based on the remaining energy. As a result, the system's design extends the network's lifespan by carrying out data transfer in a balanced manner. The many cases of a network lifetime when the total number of nodes is increased at specific intervals are shown in Figure 4.

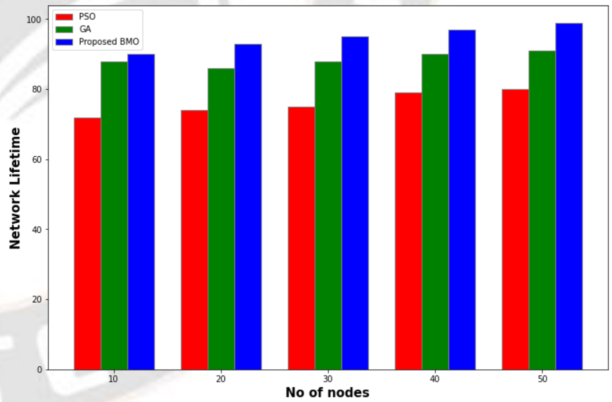

Figure 4. Network lifetime

The value of the counter that each node keeps track of impacts how long it takes to identify a rogue node. Every time a generally given the total score of 0, it increases its buffer capacity by one and flags the transmitted node as hostile on the source nodes. When a node is identified as malicious, it communicates the news to every other node within its coverage area. As the number of nodes grows, it takes longer to find the malicious nodes. It happens because more neighbors participate in monitoring and transmitting, which lengthens the time it takes to forecast node activity. The simulation begins with ten nodes and continues until there are 100 nodes as shown in figure 5.

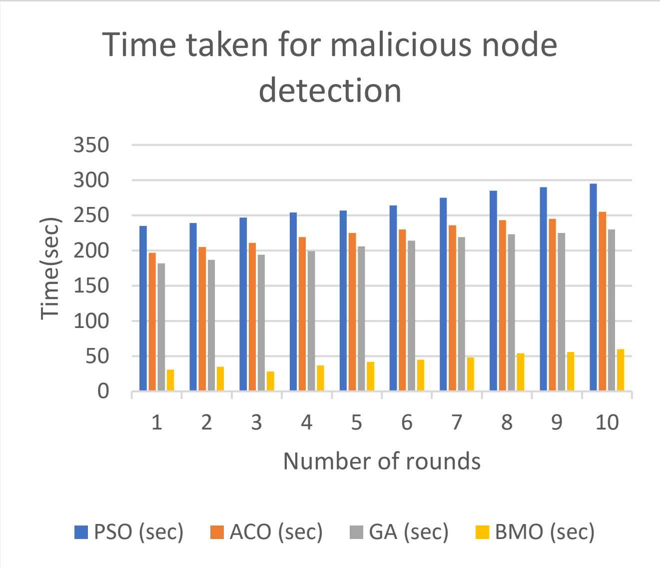

Figure 5. Time taken for malicious node detection

Conclusion

This research uses a brand-new bio-inspired optimization technique modeled after barnacle life. The suggested algorithm imitated the way barnacles mate. The findings demonstrated that BMO delivered competitive outcomes compared to various latest algorithms, notably GA and PSO, in determining the globally optimum values for multimodal functions. The ability to explore cross features and the capability of avoiding local maxima in composite elements. Furthermore, the creation of a multimodal and multiobjective variant of BMO can be developed in the foreseeable future for complex engineering problems.

References

[1]. Saremi, S., Mirjalili, S., Lewis, A., 2017. Grasshopper optimisation algorithm: Theory and application. Adv. Eng. Softw. 105, 30–47. http://dx.doi.org/10.1016/j.advengsoft.2017.01.004.

[2]. Mirjalili, S., Lewis, A., 2016. The whale optimization algorithm. Adv. Eng. Softw. 95, 51–67. http://dx.doi.org/10.1016/j.advengsoft.2016.01.008.

[3]. Sulaiman, M.H., Mustaffa, Z., Saari, M.M., Daniyal, H., Daud, M.R., Razali, S., Mohamed, A.I., 2018a. Barnacles mating optimizer: A bio-inspired algorithm for solving optimization problems. In: 2018 19th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD). pp. 265–270. http://dx.doi.org/10.1109/SNPD.2018.8441097.

[4]. Sulaiman MH, Mustafa Z, Saari MM, Daniyal H (2020) Barnacles Mating Optimizer: A new bio-inspired algorithm for solving engineering optimization problems. Eng Appl Artif Intell 87:103330

[5]. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82.

[6]. Wan M, Li M, Yang G, Gai S, Jin Z (2014) Feature extraction using two-dimensional maximum embedding diference. Inf Sci 274:55–69 .

[7]. Ernst Huenges, & Mohamed K. Hassan. (2022). Architecture Framework of High Throughput for the Soft Decision Decoding. Acta Energetica, (02), 15–20. Retrieved from http://actaenergetica.org/index.php/journal/article/view/464

[8]. Wan M, Yang G, Gai S, Yang Z (2017) Two-dimensional discriminant locality preserving projections (2DDLPP) and its application to feature extraction via fuzzy set. Multimed Tools Appl 76:355–371 .

[9]. Wan M, Lai Z, Yang G, Yang Z, Zhang F, Zheng H (2017) Local graph embedding based on maximum margin criterion via fuzzy set. Fuzzy Sets Syst 318:120–131.

[10]. Huang C, Dun J (2008) A distributed PSO-SVM hybrid system with feature selection and parameter optimization. Appl Soft Comput 8:1381–1391

[11]. Aljarah I, Al-Zoubi AM, Faris H, Hassonah MA, Mirjalili S, Saadeh H (2018) Simultaneous feature selection and support vector machine optimization using the grasshopper optimization algorithm. Cognit Comput 10:478–495

[12]. Al-Zoubi AM, Heidari AA, Habib M, Faris H, Aljarah I, Hassonah MA (2020) Salp Chain-Based Optimization of Support Vector Machines and Feature Weighting for Medical Diagnostic Information Systems. In: Faris H, Aljarah I (eds) Mirjalili S. Evolutionary machine learning techniques. algorithms for intelligent systems. Springer, Singapore.

[13]. Jan Soliński, & Dr. Nitin Sherje. (2022). A Low Voltage Novel High-Performance Hybrid Full Adder for VLSI Circuit. Acta Energetica, (03), 09–14. Retrieved from http://actaenergetica.org/index.php/journal/article/view/471

[14]. Houssein EH, Hosney ME, Oliva D, Mohamed WM, Hassaballah M (2020) A novel hybrid Harris hawks optimization and support vector machines for drug design and discovery. Comput Chem Eng 133:106656

[15]. Zhao M, Fu C, Ji L, Tang K, Zhou M (2011) Feature selection and parameter optimization for support vector machines: a new approach based on genetic algorithm with feature chromosomes. Expert Syst Appl 38(5):5197–5204

[16]. Zhang X, Chen W, Wang B, Chen X (2015) Intelligent fault diagnosis of rotating machinery using support vector machine with ant colony algorithm for synchronous feature selection and parameter optimization. Neurocomputing 167:260–279

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 10 Issue: 10
DOI: https://doi.org/10.17762/ijritcc.v10i10.5731
***Article Received**: 28 July 2022 **Revised**: 05 September 2022 **Accepted**: 12 September 2022*

[17]. . Das SP, Padhy S (2018) A novel hybrid model using teaching– learning-based optimization and a support vector machine for commodity futures index forecasting. Int J Mach Learn Cybern 9:97–111

[18]. Tuba E, Strumberger I, Bezdan T, Bacanin N, Tuba M (2019) Classifcation and feature selection method for medical datasets by brain storm optimization algorithm and support vector machine. Procedia Comput Sci 162:307–315

[19]. Gauthama Raman MR, Somu N, Kirthivasan K, Liscano R, Shankar Sriram VS (2017) An efcient intrusion detection system based on hypergraph – Genetic algorithm for parameter optimization and feature selection in support vector machine. Knowl Based Syst 134:1–12

[20]. Baliarsingh SK, Ding W, Vipsita S, Bakshi S (2019) A memetic algorithm using emperor penguin and social engineering optimization for medical data classifcation. Appl Soft Comput 85:105773

[21]. Ioannou, Christiana, and Vasos Vassiliou. "Network Attack Classification in IoT Using Support Vector Machines." Journal of Sensor and Actuator Networks 10, no. 3 (2021): 58.

[22]. Dohare, Indu, and Karan Singh. "PSO-DEC: PSO based deterministic energy efficient clustering protocol for IoT." Journal of Discrete Mathematical Sciences and Cryptography 22, no. 8 (2019): 1463-1475.

[23]. Hemalatha, P., Dhanalakshmi, K., Cellular automata based energy efficient approach for improving security in iot, Intelligent Automation and Soft Computing this link is disabled, 2022, 32(2), pp. 811–825

[24]. Singh, Samayveer, Aridaman Singh Nandan, Aruna Malik, Rajeev Kumar, Lalit K. Awasthi, and Neeraj Kumar. "A GA-Based Sustainable and Secure Green Data Communication Method Using IoT-Enabled WSN in Healthcare." IEEE Internet of Things Journal 9, no. 10 (2021): 7481-7490.