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A THOROUGH STUDY OF NATURE INSPIRED OPTIMIZATION ALGORITHMS TO HANDLE STREAMING DATA

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Abstract: In the field of data analytics and machine learning, successfully processing streaming data is becoming increasingly difficult due to the volume of data created in real-time. Algorithms that draw inspiration from nature have become more and more popular for resolving challenging optimization issues, such as those involving streaming data. This paper offers an extensive analysis of several nature inspired optimization methods and their uses with streaming data. This study investigates how these methods might be modified and utilized to tackle the particular difficulties presented by streaming data and limitations to handle also including limited computational resources and idea drift. The study focuses more on limitations to handle streaming data by existing algorithms and how Ant colony, glowworm swarm optimization. Particle swarm optimization, genetic algorithms, pelican optimization techniques performed in various studies was mentioned. A comparative analysis of several nature inspired algorithms is also included in the study, with an emphasis on their advantages, disadvantages, and possible applications.

Keywords: Limitations to handle streaming data, Ant colony, glowworm swarm optimization, PSO, genetic algorithms, pelican optimization.

I. INTRODUCTION

Above all, nature is a collection of different species and serves as a habitat and ecosystem. These species differ in their behaviors, lifestyles, and modes of mobility. Nature-inspired algorithms are often defined as the study of these movements and their subsequent adaptation into algorithms. The goal of this project is to examine these nature-inspired models. The two primary categories of nature-inspired algorithms are Swarm Intelligence Algorithms and Evolutionary Algorithms. Darwin's principle of the survival of the fittest serves as the foundation for evolutionary algorithms, whereas swarm intelligence algorithms concentrate on the collective behavior of decentralized, continuous, self-organizing systems. The four nature-inspired algorithms under examination in this study are Bat, Genetic, Ant Colony Optimization, and Artificial Bee Colony. This survey was conducted to evaluate these four algorithms, and a table that highlights the aspects where one algorithm excels over the others was also made.

The emergence of streaming data sources, including internet transactions, social media feeds, and sensor networks, has revolutionized data collection, processing, and analysis methods. Because streaming data arrives continuously and quickly, it is difficult to process it using conventional batch methods. In order to handle the constantly evolving and dynamic nature of streaming data, scientists have resorted to optimization algorithms that draw inspiration from nature. These algorithms have demonstrated potential in handling the particular issues presented by streaming data, and they are inspired by a variety of natural events.

When it comes to avoiding local optima, nature-inspired optimization (NIO) algorithms outperform traditional optimization methods. As a result, the NIO algorithm emerged as a viable solution for a number of difficult real-world issues [1].

II. RELATED WORKS

A few reviews from previous decades are available. A thorough list of nature-inspired optimization methods was provided by Fister et al. [11] for the years 1992 through 2013. This paper established a taxonomy for NIO algorithms. In his review study, Yang proposed an additional taxonomy [12]. Kar [13] also provided an overview on the evolution of ten algorithms inspired by nature between the 1970s and 2015, with an emphasis on their use in particular contexts. The significance and enhancement in the functioning of the adaptability of the PSO, GSA, and ACO parameters were examined by Valdez et al. [14]. By evaluating the convergence performance on CEC'2014 (Institute of Electrical and Electronic Engineers, Congress on Evolutionary Computation 2014), Agarwal [15] carried out a thorough analysis of five NIO algorithms, including ABC, FA, FPA, CS, and BA. A thorough summary of the single-objective NIO algorithm for cluster analysis was provided by Nanda and Panda [16]. After carefully examining over three hundred publications of various kinds of bio-inspired algorithms, Molina et al. proposed a number of suggestions and areas for development for improved methodological practices [17]. Since this subject contains a large number of good NIOs and a wide range of themes, it is inevitable that all review papers published to yet have only covered a small portion of it.

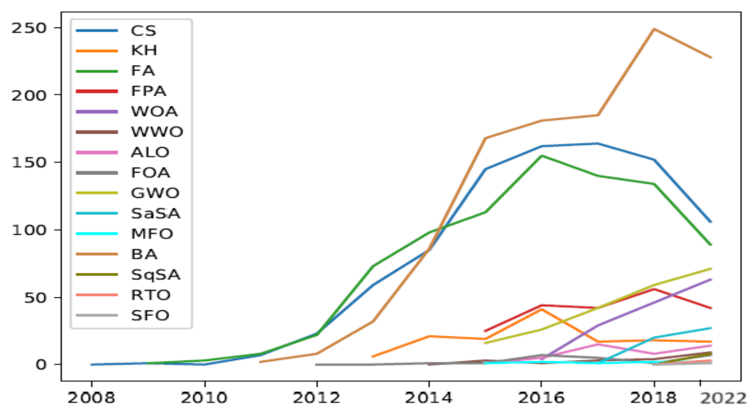

Figure 1. The Era of various Nature Inspired Optimization algorithms.

These articles also discuss the connections between them, and a comparative analysis is included. For training at RBF networks, Talal, R. and Alhanjouri compared the Bat Algorithm with PSO algorithm and, for the Travelling Salesman Problem, the Genetic Algorithm and Ant Colony Optimization. The performance analysis and valuation of ant colony optimization and genetic algorithms employing accuracy as a key component for facial feature extraction are covered in [8]. The authors of [9] claim that this paper's implementation and comparison of ACO, GA, and SA for TSP solution. All three algorithms yield an optimal solution; nevertheless, GA has been found to yield a superior result than ACO and SA. [10] discusses feature selection using ABC and GA.

Research comparing the performance of the ABC algorithm with the GA, DE, PSO, ES, ABS, and AB algorithms is presented in [10] on a sizable collection of unconstrained test functions. Maier worked on optimization issues related to the Water Distribution System in [11]. Two case studies were taken into account. According to their findings, ACOAs are used as a GA substitute. They came to the conclusion that when it comes to computing efficiency and the capacity to identify nearly global optimal solutions, ACOAs outperform GAs. When used to solve situations involving travelling salespeople and quadratic assignments, ACOAs outperformed other EAs, including GAs. The ABC algorithm was shown to be effective in [16] for resolving limited optimization issues.

III. LIMITATIONS OF THE STUDY

It is important to acknowledge the limits of the review process before delving into the explanation of NIO algorithms. First off, this evaluation has a narrow purview. As previously said, we restricted our attention to research articles that largely addressed continuous global optimization issues. Excluded from consideration are works pertaining to dynamic optimization, multimodal optimization, multi-objective optimization, and combinatorial optimization.

Second, this paper's analysis is based solely on what we understand. We didn't get in touch with the writers to make sure our knowledge of their work was accurate. Thirdly, there are two algorithms available for various NIOs: the original and the modified versions. The subjectivity issue cannot be completely eliminated when deciding which paper best exemplifies an NIO algorithm. Fourthly, several excellent papers pertaining to NIO algorithms might not be included in this study since they are not listed in the "Web of Science" index. Fifth, there are undoubtedly papers that we overlook because their keywords, abstract, or title did not lead us to include them in our collection. Lastly, the review is only current as of the drafting of this paper. Given that NIO has lately become a popular study area, it could alter. However, the literature search approach still guarantees a respectable degree of this review's thoroughness. As a result, we think the collection of publications is representative and that the analysis's conclusions can be applied generally.

Table 1. The study of NIO algorithms on time line.

NIO Name	Abbr.	Inspiration	Year	Ref
Sailfish Optimizer	SFO	Sailfish hunting.	2019	[2]
Black Widow Optimization Algorithm	BWOA	Black widow breeding.	2019	[3]
Squirrel Search Algorithm	S(q)SA	Squirrels foraging	2018	[5]
Salp Swarm Algorithm	S(a)SA	Salp swarm foraging	2017	[6]
Whale Optimization Algorithm	WOA	Whale foraging	2016	[8]
Root Tree Optimization	RTO	Tree roots growth	2016	[9]
Ant-lion Optimizer	ALO	The ant-lion hunting process	2015	[9]
Moth Flame Optimization	MFO	Moths navigation mechanism	2015	[10]
Water Wave Optimization	WWO	The shallow water theory	2014	[10]
Grey Wolf Optimizer	GWO	Grey wolf pack hunting	2014	[11]
Dispersive Files Optimization	DFO	Dispersive flies over foods	2014	[12]
Krill Herd	KH	Krill herd foraging behavior	2012	[12]
Flower Pollination Algorithm	FPA	Flowers pollination behavior	2012	[13]
Fruit Fly Algorithm	FOA	Fruit fly foraging	2011	[14]
Bat Algorithm	BA	Bats locating skills through sounds	2010	[15]
Firefly Algorithm	FA	Fireflies chasing the lights	2009	[16]
Cuckoo Search	CS	Cuckoos breeding behavior	2009	[16]

It makes sense for researchers to want to give NIOs a theoretical foundation. Holland [23] made a groundbreaking discovery when he applied Schema theory to logically describe the genetic algorithm. Nonetheless, the endeavour to establish a classical NIO was met with criticism due to its insufficient theoretical foundation [24]. Even worse, the challenges with fitness landscape analysis and stochastic search make it difficult to assess the computational complexity for any NIO [25]. Therefore, rather than estimating the computational complexity, we quantify the cost function evaluation counts in great detail.

Table1. The study of new NIO algorithms on time line.

New NIO Name	Abbr.	Inspiration	Year
Barnacles Mating Optimizer	BMO	Barnacles mating behavior.	2019
Poor and rich optimization algorithm	PRO	Efforts of the poor and the rich people to achieve wealth.	2019
Pathfinder algorithm	PFA	The leadership hierarchy of swarms to find best food area or prey.	2019
Falcon Optimization Algorithm	F(a)OA	The hunt behavior of falcons.	2019

Meerkats-inspired Algorithm	MEA	Meerkats social organizations.	2018
Farmland fertility	FF	Farmland fertility in nature.	2018
Coyote Optimization Algorithm	COA	The canis latrans species.	2018
Owl Optimization Algorithm	OOA	The decoy behavior of owls	2018
Interactive search algorithm	ISA	Modifies and combines iPSO and TLBO.	2018
Cheetah Based Optimization Algorithm	CBA	The social behavior of cheetah.	2018
Galactic Swarm Optimization	GCO	The motion of stars, galaxies and superclusters of galaxies.	2015

This paper offers a thorough analysis of optimization techniques for streaming data processing that draw inspiration from nature. We first go over the idea of streaming data and the difficulties it brings. Next, we investigate various algorithms that draw inspiration from nature and modify them for use in streaming data settings. Additionally, we offer a comparison of these algorithms and the streaming data analytics uses cases for each.

We examine Firefly and Particle Swarm Optimization in this study. Based on their features [1] examines the Bacterial Foraging Optimization Algorithm (BFO), the Bat Algorithm (BA), the Artificial Bee Colony, glowworm swarm optimization, PSO, genetic algorithms, pelican optimization and the Cuckoo Search.

In recent decades, optimization inspired by nature has become a modern technique. While some academics question its usefulness, others describe effective applications in a variety of sectors, including manufacturing, biomedical, and environmental engineering. In this work, we compile recently developed, nature-inspired optimization algorithms that have been suggested since 2008, present them cohesively, put them into practise, and assess their performance on benchmark functions. Additionally, we optimise these algorithms' behavioral characteristics.

IV. Nature Inspired Optimization ALGORITHMS

Artificial Bee Colony

A number of algorithms, including the bee system, marriage in honey bees, bee hive algorithm, bee ad hoc, bee colony optimization, the bees, ABC, virtual bees, and fitness scaled chaotic ABC, have been defined in recent years based on the intelligent behavior of honey bees. Of them, ABC appears to be applied more frequently to address various real-world issues. The real operation of ABC relies on the recruitment of high-quality food sources and the selection and behavior of foraging. The three primary components of a honey bee's foraging selection behavior are food sources, employed foragers, and jobless foragers. Additionally, finding high-quality nectar sources and removing lower-quality sources are crucial elements. The quality of food is greatly influenced by the food source's richness and remoteness.

Glow-Worm Swarm Optimization

Another insect-based optimization method known as glow-worm swarm optimization (GSO) was presented by Krishnan and Ghose. The biological traits and glow of glow-worms, or lightning bugs, served as the model for GSO. Glow-worms commonly exhibit the behavior of attracting prey to their partners. Glowworms employ their bioluminescence light for a variety of objectives.

The capacity of glow-worms to adjust the intensity of chemical, such as luciferin emission (similar to ant pheromones), allows them to light at various intensities. They attract prey during reproduction and use their shining ability to communicate with one another. When glowworms release a large amount of luciferin, they appear brighter and draw in more mates.

Firefly Algorithm

Another insect-based meta-heuristic method created by Yang is called FA [4]. Adaptive FA, discrete FA, multi objective FA, Lagrangian firefly algorithm, chaotic firefly algorithm, hybrid firefly algorithm, and memetic algorithm based on FA are some of the variations of FA that are employed in many disciplines. FA draws inspiration from fireflies' courtship rituals, which include reciprocal attraction and flashing. Swarm intelligence traits such as decision-making ability and self-organization are embodied by fireflies. In fireflies, the process of bioluminescence starts the flashing activity that helps attract a mate. Two crucial characteristics of fireflies are their attraction and brightness, or lighting. Fireflies' intense flashing indicates their desire to other fireflies. Nonetheless, a unisex characteristic of fireflies causes them to be mutually attracted to one another in the algorithm.

Antlion Optimizer

Antlion Optimizer (ALO), another insect-based NIC approach, was created by Mirjalili [4]. social and biological behaviors of insects, such as ants and antlions, provide as inspiration for ALO.Antlions are members of the netwinged (or neuropteran) Myrmeleontidae family of insects. The majority of an antlion's life cycle occurs during the larvae phase, which lasts for just three to five weeks in adults. Doodlebugs are another name for larvae, while dragonflies, which are rare and able to fly, are another name for adult antlions. ALO mimics the antlions' natural intelligent hunting process and mostly depicts their cooperative work of catching ants.

Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a computational approach in computer science that solves problems by repeatedly attempting to enhance a potential solution in relation to a predetermined quality criterion. It accomplishes this by utilizing a population of potential solutions, referred to as particles, and manipulating them in the search space in accordance with basic mathematical rules that control the particle's position and velocity. In addition to being led towards the best-known positions in the search space, which are updated when other particles find better positions, each particle's movement is also impacted by its local best-known position. It is anticipated that this will direct the swarm towards the optimal answers.

Genetic Algorithms

Natural selection and evolution serve as the foundation for the class of optimization algorithms known as genetic algorithms, or GAs. These algorithms are commonly employed to handle complex optimization issues in a variety of domains, such as artificial intelligence, machine learning, and data analysis. GAs work by mimicking the process of natural selection, in which individual’s potential solutions evolve over many generations in order to become more appropriate for a particular task. The basic ideas, essential elements, and applications of genetic algorithms in optimization tasks will all be covered in this essay. Their capacity to investigate intricate solution spaces, adjust to shifting conditions, and locate nearly ideal answers across a range of areas has led to their rise in popularity.

Pelican Optimization Algorithm

The underlying challenge of solving optimization problems in several scientific disciplines is optimization. This study presents the Pelican Optimization technique (POA), a new stochastic nature-inspired optimization technique. The primary concept of the planned POA's design is to mimic pelicans' natural hunting behavior. Pelicans are search agents in POA; they look for food sources. The POA mathematical model is offered for application in resolving optimization problems. Twenty-three objective functions of various unimodal and multimodal categories are used to assess POA's performance. While the optimization results for multimodal functions demonstrate the strong ability of POA exploration to locate the primary optimal area of the search space, the optimization results for unimodal functions demonstrate the high exploitation capacity of POA to approach the optimal solution.

V. LIMITATIONS TO HANDLING STREAMING DATA

Managing real-time data poses several difficulties when employing current algorithms, even ones that are modified from conventional batch processing. Several of the main restrictions consist of:

Concept Drift: When the underlying data distribution shifts over time, streaming data frequently shows signs of concept drift. A lot of current techniques are not appropriate for data that is changing since they presume a static data distribution. Constantly updating the model is necessary to adjust to concept drift, and this can be computationally costly.

Limited Computational Resources: Real-time processing of streaming data might be computationally demanding due to its frequent high rate of arrival. Existing algorithms might not be scalable or perform well since they are not optimised for these resource limitations.

Unbalanced Data: It is necessary to identify uncommon occurrences or interesting anomalies in streaming data. Unbalanced data may be difficult for traditional algorithms to manage, resulting in skewed models that favour the dominant class.

Time Sensitivity: When dealing with streaming data, prompt judgements are frequently required in order to adapt to shifting circumstances or new patterns. Processing delays could result from existing algorithms' lack of real-time decision-making functionality.

Data Quality and Noise: Errors, missing numbers, and outliers can all be present in streaming data. Inaccurate results and subpar model performance might arise from algorithms that are not resilient to these problems.

Storage Restrictions: Because of storage restrictions, it is frequently not possible to store previous data for batch processing in streaming systems. It's possible that existing algorithms that rely heavily on past data are inapplicable.

Online Learning: Since models must be updated constantly when new data is received, several conventional machine learning techniques are not appropriate for online learning. Batch algorithms can be difficult to modify for online learning, and they might miss the newest trends.

Interpretability of the Model: In order to support decision-making, streaming data models may need to be interpreted. It can be difficult to grasp the judgements made by some of the current algorithms due to their lack of transparency, especially complicated deep learning models.

Methodology Robustness: Models in streaming data are susceptible to attacks due to the possibility of adversarial or malicious input. It's possible that existing algorithms lack built-in robustness and security features.

Adaptive Sampling: To lessen the computing strain on flowing data, effective sampling techniques are essential. A lot of current algorithms don't use streaming scenario-specific adaptive sampling methods.

In an effort to overcome these constraints, scientists are always creating and refining algorithms made especially for streaming data, such as strategies for managing imbalanced data, online learning approaches, and idea drift detection. These strategies seek to optimise the use of data at hand and adjust to the peculiarities of streaming contexts.

Table 2. Study on streaming data with various existed approaches.

Method	Source Details	Observations	Limitations	Research approach
Naïve Bayes	Sonia 2017: REVIST	Higher accuracy even in 15% noise data	-	To compare various DDM
SVM on Haddop [13]	Pranamita Nanda 2017: IRJET	Reduce the time and code complexity, less memory	No proper implementation of Hadoop	To select the most appropriate induction model
Hetrostreams [14]	Jesmin 2016: ACM	Euclidian distance and majority votes,	More computational	To find the k value

		reduce the cost of search	complexity	
MCNN [15]	Mark Tennant 2016: Elsevier	Micro cluster-based inherently parallel adaptive classifier, calculates statistical summary	Difficult to implement	Parallel implementation
RANMTPR [15]	Tomoyasu 2011: IEEE	Can be used for multiple class data set, one pass incremental learning	Less percentage of interpretation and hard to implement	To learn from multiple class labels
BPTT [16]	Fan He 2017	No need to store all of history parts, Information is stored in each connection of neural network	Usage of Kalman filter's fast convergence, causes overfitting problem	To handle concept drift
KME [17]	Siqi Ren 2017: Elsevier	Reduces labeling cost	Less diversity between the base classifiers	To detect multiple drifts
MLP [18]	Anand Gupta: 2017	Multi-class classifier is combined with multi-class deep learning	Overfitted data set in the first level and more time consumption in the second level	To handle class imbalance
Predict—Detect [19]	Tegjyot 2017: Elsevier	Handled adversarial concept drift, reduces the labeling cost	Difficult to detect adversarial concept drift	To handle concept drift
DOED [19]	Parneeta et al. 2015: Springer	Usage of Naïve Bayes and Hoeffding tree as classifiers improves accuracy	Attribute independency is not always possible with all data	To handle concept drift
DDD [12]	Leandro 2011: IEEE	Improve the prequential accuracy in the presence of drift	Usage of old concept increases memory usage	To handle drift
Ensemble [11]	Haixun 2002: ACM	An instance-based pruning, cost-sensitive learning, uses weight-based method for	Hard to implement	To handle concept drift

		prediction accuracy		
SEA [14]	Nick Street 2001: ACM	Needs constant memory and adjusts quickly to concept drift. Any time learning method	Accuracy reduces with noisy data. Not suitable for high-speed data streams	To learn stream data at any time
VFDT-Hadoop [18]	Sharmishta Desai, 2017: IEEE	Lesser memory and faster using optimal HB value for an efficient tree pruning	Hadoop Map reduce is not a suitable platform for streaming data	To reduce processing time
ECVFT [10]	Gang Liu 2013: IEEE	Examples are cached before execution and no information gain is calculated	Attributes with more information may be lost	To identify the types of drift

VI. SUMMARY OF THE CURRENT SURVEY

We have noticed that while assessments of individual NIOAs [4] are rather popular, there aren't many attempts to evaluate different NIOAs using the same broad criteria. A small number of surveys [6] that were dubbed "horizontal NIOAs reviews" used the narrative literature review methodology to address a number of NIOAs, covering their fundamental ideas, variations, and application domains. Chakraborty [6] expounded on eight bio-inspired optimization algorithms (BIOAs), which can be categorised into two groups: insect-based algorithms, which draw inspiration from ants, bees, fireflies, and glow-worms, and animal-based algorithms, which draw inspiration from bats, monkeys, lions, and wolves; Kar [8] provided an in-depth analysis of the principles, advancements, and applications of twelve BIOAs, comprising neural networks, GA, PSO, ACO, ABC, bacterial foraging (BFO) algorithm, CS, FA, shuffled frog leaping algorithm (SFLA), BA, flower pollination (FP) algorithm, and artificial plant optimization algorithm (APOA), Parpinelli [3] condensed the principles, application fields, and meta-heuristics information of nine BIOAs, including bees algorithm, ABC, marriage in honey-bees optimization (MBO) algorithm, BFO, and glow-worm swarm optimization A number of benchmark functions were used in certain literature to compare the performance of NIOAs in addition to the reviews mentioned above. Chu [9] only examined three BIOAs, including PSO, ACO, and ABC, on three benchmark functions; AbWahab [7] compared seven BIOAs, including GA, ACO, PSO, DE, ABC, GSOA, and CS, using a variety of statistical tests.

Table 3. Comparison of data streams limitations with various NIO algorithms.

Parameters	PSO	GA	AC	GSO	PO	ABC	BA	IA	FA	GSA	GWO	HS
Concept Drift	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Limited Computational Resources	X	✓	X	✓	✓	✓	✓	✓	✓	✓	✓	✓
Unbalanced Data	✓	✓	✓	✓	X	X	✓	X	X	✓	X	✓
Time Sensitivity	X	✓	✓	-	✓	✓	✓	✓	✓	✓	-	✓
Data Quality and Noise	✓	✓	✓	✓	✓	✓	X	✓	✓	✓	✓	✓
Storage Restrictions	✓	✓	X	✓	X	✓	-	✓	✓	✓	✓	✓
Online Learning	X	✓	✓	✓	-	✓	✓	-	X	✓	X	✓
Methodology Robustness	✓	✓	✓	✓	✓	-	✓	✓	✓	✓	-	✓
Adaptive Sampling	✓	✓	✓	-	✓	✓	✓	✓	✓	✓	✓	✓

(PSO: Particle Swarm Optimization, GA: Genetic Algorithm, ABC: Artificial Bee Colony, BA: Bat Algorithm, IA: Immune Algorithm, FA: Firefly Algorithm, CS: Cuckoo Search, DE: Differential Evolution, GSA: Gravitational Search Algorithm, GWO: Grey Wolf Optimizer, HS: Harmony Search)

All things considered, the aforementioned survey works offer helpful resources for NIOAs yet, these analyses lack thoroughness and nuance. For instance, the survey work [8] just presents the fundamentals, variations, and uses of many BIOAs; it does not compare their performances, which is a crucial step towards the development and use of BIOAs. A few reviews [9] go over BIOAs' performance comparison.

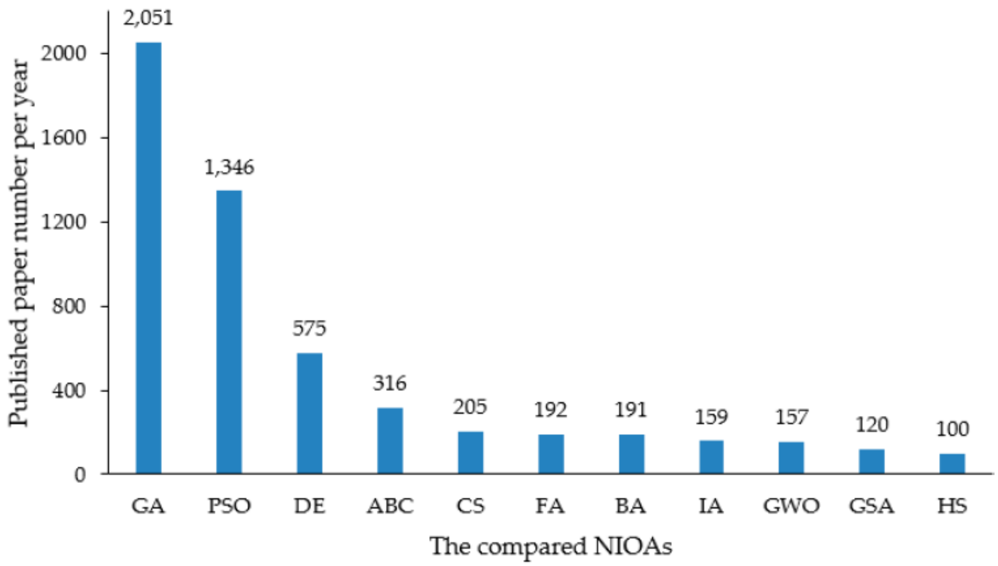

Figure 2. Research works on NIOS and Number of papers published up to 2022.

But because the selected BIOAs are incomplete, the majority of benchmark functions are low-dimensional, and the experimental findings are only represented by mean error (comparison of convergence speed is not taken into consideration), the comparison in [7] for the seven BIOAs is insufficient. Only three BIOAs are compared in the review in [9] on three benchmark functions; the experimental work and comparison algorithms are quite limited. In addition to the aforementioned issues, there are two more issues: the selection criteria is unclear and certain NIOAs are not well-liked. Additionally, not all of the survey studies mentioned above has extracted and discussed the prevalent hard problems faced by NIOAs [9]. These include, to name a few, the common traits and variations among NIOAs, the difficulties and potential paths facing the field of NIOAs, and the methodical compilation of techniques for progress for each selected NIOA.

VI.CONCLUSION

Using nature inspired optimization algorithms is a promising way to address the difficulties presented by constantly changing and continuous data streams in the era of streaming data. This thorough study offers insights into the application and adaption of algorithms inspired by nature for streaming data settings, along with a performance comparison. Naturalistic algorithms have enormous potential for real-time, flexible, and effective data processing as streaming data analytics develops. Using the NIO algorithms, we optimize the behavioral parameters of different NIO algorithms. While some optimized values that deviate from the proposed parameters can offer higher performance than the recommended parameters, the majority of optimized parameters are compatible with the authors' suggested parameters. Note that this review is limited by numerous factors that it cannot address. Discrete metaheuristics, which may have more uses than continuous algorithms, are not covered in this study.

REFERENCES

[1] Chandrasegar Thirumalai, Himanshu Kar, “Memory Efficient MultiKey (MEMK) generation scheme for secure transportation of sensitivedata over Cloud and IoT devices,” IEEE IPACT 2017.

[2] Nazri Mohd. Nawi, Abdullah Khan, and Mohammad Zubair Rehman:” A New Back-Propagation Neural Network Optimized with Cuckoo Search Algorithm”. Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia (UTHM).SPRINGER. pp. 413–426, 2013.

[3] S. Shadravan, H. Naji, and V. Bardsiri, “The sailfish optimizer: A novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems,” Engineering Applications of Artificial Intelligence, vol. 80, pp. 20 – 34, 2019.

[4] M. Jain, V. Singh, and A. Rani, “A novel nature-inspired algorithm for optimization: Squirrel search algorithm,” Swarm and Evolutionary Computation, vol. 44, pp. 148 – 175, 2019.

[5] M. A. E. Aziz, A. A. Ewees, and A. E. Hassanien, “Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation,” Expert Systems with Applications, vol. 83, pp. 242 – 256, 2017.

[6] M. M. Mafarja and S. Mirjalili, “Hybrid whale optimization algorithm with simulated annealing for feature selection,” Neurocomputing, vol. 260, pp. 302 – 312, 2017.

[7] I. Aljarah, H. Faris, and S. Mirjalili, “Optimizing connection weights in neural networks using the whale optimization algorithm,” Soft Computing, vol. 22, no. 1, pp. 1–15, Jan 2018.

[8] Y. Labbi, D. B. Attous, H. A. Gabbar, B. Mahdad, and A. Zidan, “A new rooted tree optimization algorithm for economic dispatch with valve-point effect,” International Journal of Electrical Power & Energy Systems, vol. 79, pp. 298 – 311, 2016.

[9] A. Wadood, S. Gholami Farkoush, T. Khurshaid, C.-H. Kim, J. Yu, Z. W. Geem, and S.-B. Rhee, “An optimized protection coordination scheme for the optimal coordination of overcurrent relays using a nature-inspired root tree algorithm,” Applied Sciences, vol. 8, no. 9, 2018.

[10] S. Mirjalili, “The ant lion optimizer,” Advances in Engineering Software, vol. 83, pp. 80 – 98, 2015.

[11] S. Mirjalili, P. Jangir, and S. Saremi, “Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems,” Applied Intelligence, vol. 46, no. 1, pp. 79–95, Jan 2017.

[11] M. Raju, L. C. Saikia, and N. Sinha, “Automatic generation control of a multi-area system using ant lion optimizer algorithm based pid plus second order derivative controller,” International Journal of Electrical Power & Energy Systems, vol. 80, pp. 52 – 63, 2016.

[13] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” Knowledge-Based Systems, vol. 89, pp. 228 – 249, 2015.

[14] W. Yamany, M. Fawzy, A. Tharwat, and A. E. Hassanien, “Mothflame optimization for training multi-layer perceptrons,” in 2015 11th International Computer Engineering Conference (ICENCO), Dec 2015, pp. 267–272.

[15] Y.-J. Zheng, “Water wave optimization: A new natureinspired metaheuristic,” Computers & Operations Research, vol. 55, pp. 1 – 11, 2015.

[16] S. Mirjalili, S. Saremi, S. M. Mirjalili, and L. dos S. Coelho, “Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization,” Expert Systems with Applications, vol. 47, pp. 106 – 119, 2016.

[16] S. Mirjalili, “How effective is the grey wolf optimizer in training multilayer perceptrons,” Applied Intelligence, vol. 43, no. 1, pp. 150–161, Jul 2015.

[44] S. Saremi, S. Z. Mirjalili, and S. M. Mirjalili, “Evolutionary population dynamics and grey wolf optimizer,” Neural Computing and Applications, vol. 26, no. 5, pp. 1257–1263, Jul 2015.

[17] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, “Multi-verse optimizer:a nature-inspired algorithm for global optimization,” Neural Computing and Applications, vol. 27, no. 2, pp. 495–513, Feb 2016.

[18] M. M. al-Rifaie, “Dispersive flies optimization,” in 2014 Federated Conference on Computer Science and Information Systems, Sep. 2014, pp.529–538.

[19] S. Fidanova, Ed., Dispersive Flies Optimization and Medical Imaging. Cham: Springer International Publishing, 2016.

[20] A. H. Gandomi and A. H. Alavi, “Krill herd: A new bio-inspired optimization algorithm,” Communications in Nonlinear Science and Numerical Simulation, vol. 17, no. 12, pp. 4831 – 4845, 2012.

[21] G.-G. Wang, A. H. Gandomi, and A. H. Alavi, “Stud krill herd algorithm,” Neurocomputing, vol. 128, pp. 363 – 370, 2014.

[22] G.-G. Wang, L. Guo, A. H. Gandomi, G.-S. Hao, and H. Wang, “Chaotic krill herd algorithm,” Information Sciences, vol. 274, pp. 17 – 34, 2014.

[23] G.-G. Wang, A. H. Gandomi, A. H. Alavi, and G.-S. Hao, “Hybrid krill herd algorithm with differential evolution for global numerical optimization,” Neural Computing and Applications, vol. 25, no. 2, pp. 297–308, Aug 2014.

[24] G.-G. Wang, A. H. Gandomi, and A. H. Alavi, “An effective krill herd algorithm with migration operator in biogeography-based optimization,” Applied Mathematical Modelling, vol. 38, no. 9, pp. 2454 – 2462, 2014.

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