Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

Article

An Exhaustive Review of Bio-Inspired Algorithms and its Applications for Optimization in Fuzzy Clustering

Fevrier Valdez[1], Oscar Castillo[1,*] and Patricia Melin[1]

[1] Division Graduate of Studies, Tijuana Institute of Technology, Calzada Tecnologico S/N, Tijuana, 22414, BC, Mexico. Tel.: 664 607 8400

* Correspondence: ocastillo@tectijuana.mx; Tel.: 664 607 8400

Abstract: In recent years, new metaheuristic algorithms have been developed taking as reference the inspiration on biological and natural phenomena. This nature-inspired approach for algorithm development has been widely used by many researchers in solving optimization problem. These algorithms have been compared with the traditional ones algorithms and have demonstrated to be superior in complex problems. This paper attempts to describe the algorithms based on nature, that are used in fuzzy clustering. We briefly describe the optimization methods, the most cited nature-inspired algorithms published in recent years, authors, networks and relationship of the works, etc. We believe the paper can serve as a basis for analysis of the new are of nature and bio-inspired optimization of fuzzy clustering.

Keywords: FUZZY; CLUSTERING; OPTIMIZATION ALGORITHMS

1. Introduction

Optimization is a discipline for finding the best solutions to specific problems. Every day we developed many actions, which we have tried to improve to obtain the best solution; for example, the route at work can be optimized depending on several factors, as traffic, distance, etc. On other hand, the design of the new cars implies an optimization process with many objectives as wind resistance, reduce the use of fuel, maximize the potency of motor, etc. These best solutions are found by adapting the parameters of the algorithm to give either a maximum or a minimum value for the solution. Therefore, in the last years many optimization methods have been developed with the aim of improving existing solutions.

Nowadays, many optimization algorithms based on nature can be found in the literature, it is calculated there are more than 150 different algorithms, and improved algorithms for finding the best results on the optimization problems [1–11]. However, it is not our aim to analyze all methods. Instead, our approach will be on the bio-inspired algorithms that are dealing with fuzzy clustering. Therefore, we have selected only a few algorithms in this review. Although, we have worked with different algorithms in different ways, for example, with parameter adaptation using fuzzy logic, original methods, the selected methods were chosen because they have demonstrated are good alternative for solving many optimization problems, and we have experience working with them. However, we focused with the applications about optimization fuzzy clustering.

Nature inspired algorithms can be classified as those based on biology and those inspired on natural phenomena. The algorithms based on biology can be further divided into those based on evolution and those based on swarm behavior. The evolutionary algorithms include the Genetic Algorithms, Differential Evolution, Cultural Evolution, Evolutionary Strategies, Genetic Programming. The swarm category includes Particle Swarm Optimization, Ant Colony Optimization [12], Artificial Bees [13], Termites [14], Bats [15], Birds [16], Cats [17], Bacterial Foraging [18], Cuckoo Search [19], Firefly algorithm [20] and others. Also, there are algorithms based on the physical laws; for example,

 doi:10.20944/preprints202103.0282.v1

Simulated Annealing, the Gravitational Search algorithm and the Big Bang Big Crunch algorithm.

2. Literature Review

In this section, we made a general review about the methods using optimization fuzzy clustering with different bio-inspired optimization methods. However, in the following sections a deep study is developed doing specific queries of Web of Science, and the tool VoSviewer to calculate the clusters of the analyzed works. InTable 1, is presented a list with the most popular bio-inspired optimization algorithms based on swarms, physics, populations, chemistry and evolution. This table shows many methods in chronological orders that have been used since 1975 to date. However, only are some methods but can be useful to expand the knowledge about these methods and to observe the inspiration type. We made the query in Web of Science: 'Optimization fuzzy clustering', we found a total of 2208 papers with this topic. However, in this paper only is presented a description of the most recent works, but with the query above mentioned can be seen the updated works. Figure 1, shows the countries with major number of publications.

Recently, multi-view clustering research has attracted considerable attention because of duo the rapidly increasing demand for unsupervised analysis of multi-view data in practical applications. In [21], was presented a novel Two-level Weighted Collaborative Multi-view Fuzzy Clustering (TW-Co-MFC) approach to address the aforementioned issues. In this method, TW-Co-MFC, a two-level weighting strategy is devised to measure the importance of views and features, and a collaborative working mechanism is introduced to balance the within-view clustering quality and the cross-view clustering consistency.

Also, in [22], authors proposed the image segmentation using Bat Algorithm with Fuzzy C Means clustering. The proposed segmentation technique was evaluated with existing segmentation techniques. On the other hand, in [23], the authors presented a hybridization of SKH and RKFCM clustering optimization algorithm for efficient moving object exploration.

Another recent study on this area is shown in [24], where the authors presented a hybrid interval type-2 semi-supervised possibilistic fuzzy c-means clustering and particle swarm optimization for satellite image analysis.

Also, in [25] a fuzzy based unequal clustering and context aware routing procedure with glow-worm swarm optimization was developed in random way point based dynamic wireless sensor networks. Based on fuzzy systems the unequal clustering is formed and the optimal cluster head is nominated to convey the information from cluster member to base station to increase the system lifespan and to decrease the energy consumption.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

Table 1: Popular Bio-inspired Optimization Algorithms based on swarms, physics, populations, chemistry and evolution.

Year	Algorithms and references
2021	Horse herd optimization algorithm [26]
2020	Mayfly Optimization Algorithm [27]
2020	Chimp Optimization Algorithm [28]
2020	Coronavirus Optimization Algorithm [29]
2020	Water strider algorithm [30]
2020	Newton metaheuristic algorithm [31]
2020	Black Widow Optimization Algorithm [32]
2019	Harris hawks optimization [33]
2019	Sailfish Optimizer [34]
2019	Spider Monkey Optimization [35]
2017	Grasshopper Optimisation Algorithm [36]
2017	Fractal Based Algorithm [37]
2017	Bacterial Foraging Inspired Algorithm [18]
2017	Rain-fall Optimization Algorithm [38]
2016	Dragonfly algorithm [39]
2016	Sperm Whale Algorithm [40]
2015	Water Wave Optimization [41]
2015	Ant Lion Optimizer [42]
2014	Symbiotic Organisms Search [43]
2013	Egyptian Vulture Optimization Algorithm [44]
2013	Dolphin echolocation [45]
2012	Great Salmon Run [46]
2012	Big Bang-Big Crunch [47]
2012	Flower Pollination Algorithm [48]
2011	Spiral Optimization Algorithm [49]
2011	Galaxy-based Search Algorithm [50]
2010	Japanese Tree Frogs [51]
2010	Bat Algorithm [15]
2010	Termite Colony Optimization [14]
2010	Firefly Algorithm [20]
2009	Cuckoo Search [19]
2009	Glowworm Swarm Optimization [52]
2009	Bee Colony Optimization [53]
2009	Gravitational Search Algorithm [54]
2008	Fast Bacterial Swarming Algorithm [55]
2007	River Formation Dynamics [56]
2007	Imperialistic Competitive Algorithm [57]
2008	Roach Infestation Optimization [58]
2006	The bees Algorithm [13]
2006	Cat Swarm Optimization [17]
2004	BeeHive [59]
2003	Queen-Bee Evolution [60]
2001	Harmony Search Algorithm [61]
1995	Particle Swarm Optimization [16]
1992	Genetic Programming [62]
1992	Ant Colony Optimization [12,63]
1989	Tabu Search [64]
1975	Genetic Algorithms [65]

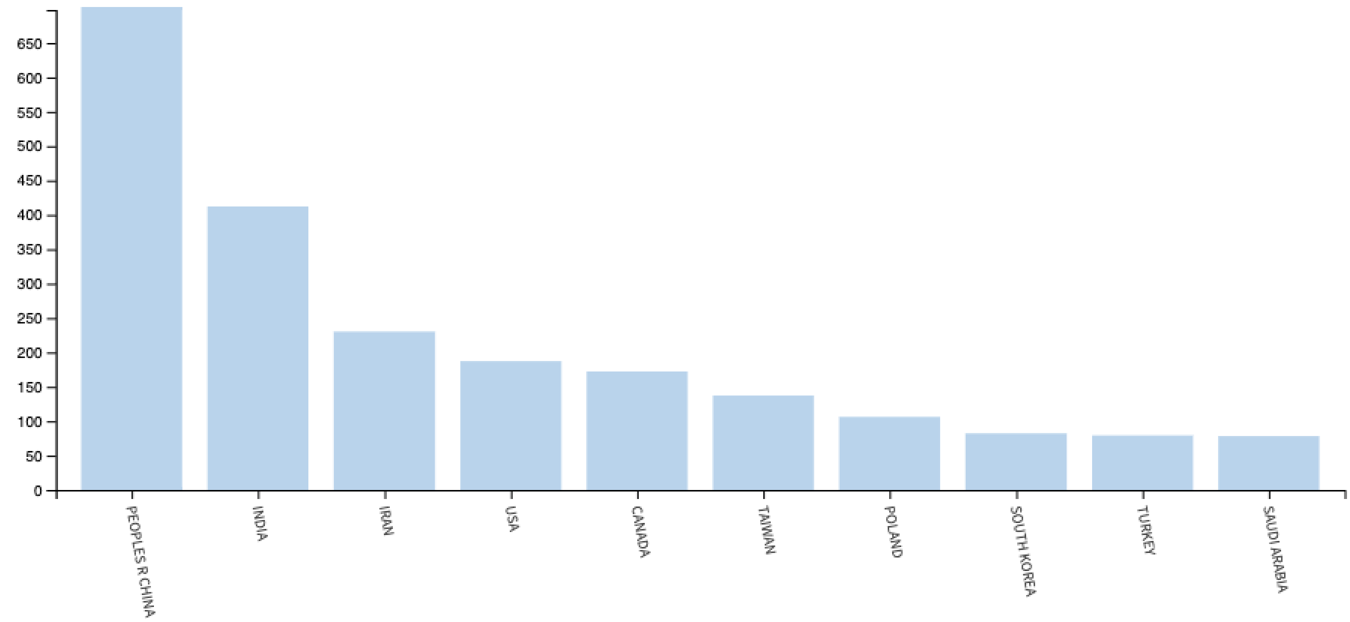

Figure 1. 2,208 papers of Web of Science for topic: (Optimization fuzzy clustering) by Countries.

3. Bio-Inspired Optimization Methods

This section presents the algorithms used as reference in this study. After making a complete review of the methods above mentioned. We decide to include, in making our study, some important and relevant methods along the history. Though, there are many algorithms, it is impossible to include all methods. However, with these selected methods it is possible to give us an idea of the relationship of authors, citations, cluster of work networks with specific queries from high impact journals and other important information. The main aim of this section is to briefly outline the basic concepts of several bio-inspired optimization algorithms for a better comprehension of the importance of this area. The selected algorithms are presented in the following sub-sections.

3.1. Genetic Algorithms

John Holland, from the University of Michigan initiated his key work on genetic algorithms at the beginning of the 1960s. His first achievement was the publication of Adaptation in Natural and Artificial Systems in 1975, developing a popular method in the evolutionary computation field, known as genetic algorithm. In the simple genetic algorithm, the representation used is a bit string. Each position in the string is assumed to represent a particular feature of an individual, and the value stored in that position represents how that feature is coded in the solution. Usually, the string is "evaluated as a collection of structural features of a solution that have little or no interactions". The analogy may be drawn directly to genes in biological organisms. Each gene represents an entity that is structurally independent of other genes. The main reproduction operator used is bit-string crossover, in which two strings are used as parents and new individuals are formed by swapping a sub-sequence between the two strings. Another popular operator is bit-flipping mutation, in which a single bit in the string is flipped to form a new offspring string. A variety of other operators have also been developed, but are used less frequently. A primary distinction that may be made between the various operators is whether or not they introduce any new information into the population. Crossover, for example, does not while mutation does. All operators are also constrained to manipulate the string in a manner consistent with the structural interpretation of genes. For example, two genes at the same location on two strings may be swapped between parents, but not combined based on their values. Traditionally, individuals are selected to be parents probabilistically based upon their fitness values, and the offspring that are created replace the parents. For example, if N parents are selected, then N offspring are generated which replace the parents in the next generation [65].

3.2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as the Genetic Algorithms (GA). The system is initialized with a random population solutions and searches for optima by updating generations. However, unlike the GA, the PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current best particles [1,11,66].

Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

3.3. Cuckoo Search Algorithm

Cuckoo Optimization Algorithm is based on the life of a bird called 'cuckoo'. The basis of this novel optimization algorithm is specific breeding and egg laying of this bird. Adult cuckoos and eggs are used in this modeling. The cuckoos which are adult lay eggs in other birds' habitat. These eggs grow and become a mature cuckoo if they are not found and not removed by host birds. The immigration of groups of cuckoos and environmental specifications hopefully lead them to converge and reach the best place for reproduction and breeding. The objective function is in this best place [19]. CSA is a new continuous over all aware search based on the life of a cuckoo bird. Similar to other meta heuristic, CSA begins with a main population, a group of cuckoos. These cuckoos lay some eggs in the habitat of other host birds. A random group of potential solutions is generated that are considered to represent the habitat in CSA.

3.4. Bat Algorithm

Bat algorithm (BA) is a bio-inspired algorithm inspired on bat behavior and BA has been found to be very efficient. If we idealize some of the echolocation characteristics of, we can develop various bat-inspired algorithms or bat algorithms. For simplicity, we now use the next idealized rules:

1. All bats use echolocation to sense distance, and they also 'know' the difference between food/prey and background barriers in some unknown way.

2. Bats fly randomly witch velocity v_i at position x_i witch a fixed frequency , varying wavelength and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission r [0, 1], depending on the proximity of their target.

3. Although loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

For simplicity, the frequency f is in [0, {max}], the new solutions and velocity at a specific time step t are represented by a random vector drawn from a uniform distribution [15].

4. Experimental Results

In this section, is presented the obtained results with the different tools available in the literature for building the networks clusters, relationships, citations, with the analyzed methods. To validate the queried information of Web of Science, the VosViewer

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

tool [67] was used. However, this type of studies can be made by other similar tools to make bibliometric analysis. For example, Bibliometrix [68] is a free tool that provides various routines for importing bibliographic data from SCOPUS and Clarivate Analytics' Web of Science databases; Bibliotool [69], is a set of python scripts written by Sebastian Grauwin. They can read ISI data in CSV format and do some studies including co-occurrence map and bibliographic coupling; finally, CiteSpace [70] is a free Java-based software for visualizing and analyzing trends and patterns in the scientific literature. It is designed as a tool for progressive knowledge domain visualization.

4.1. Study with Genetic Algorithms

In this section, is presented the obtained results of the queries in Web of Science with the topic 'optimization fuzzy clustering with genetic algorithms'. First, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc. Figure 2, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 92 keywords, the total strength of the co-ocurrence links with other keywords was calculated. On VosViewer, if the keyword 'genetic algorithm' is selected, we can appreciate the number of clusters is 7 for this selection, with 88 links, and 141 occurrences.

Figure 3, represents the selection of the keyword 'genetic algorithm' that corresponding to the information obtained from Figure 2.

Figure 4, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 2 and Figure 3. It can be seen how the number of citations and papers with the analyzed topic has been increasing in recent years.

Also, with this information was possible to observe, the record by authors, where in Figure 5, it can be appreciated that two authors are the leaders in this area with the topic 'optimization fuzzy clustering with genetic algorithms'.

4.2. Study with Particle Swarm Optimization

In this section, is presented the obtained results of the queries in Web of Science with the topic 'optimization fuzzy clustering with genetic algorithms'. First, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc.Figure 6, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 116 keywords, the total strength of the co-ocurrence links with other keywords was calculated. On VosViewer, if the keyword 'particle swarm optimization' is selected, we can appreciate the number of cluster is 8 for this selection, with 108 links, and 234 occurrences.

Figure 7, represents the selection of the keyword 'genetic algorithm' that corresponding to the information obtained from Figure 6.

Figure 8, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 6 and Figure 7. It can be seen how the number of citations and papers with the analyzed topic has been increasing in recent years.

 doi:10.20944/preprints202103.0282.v1

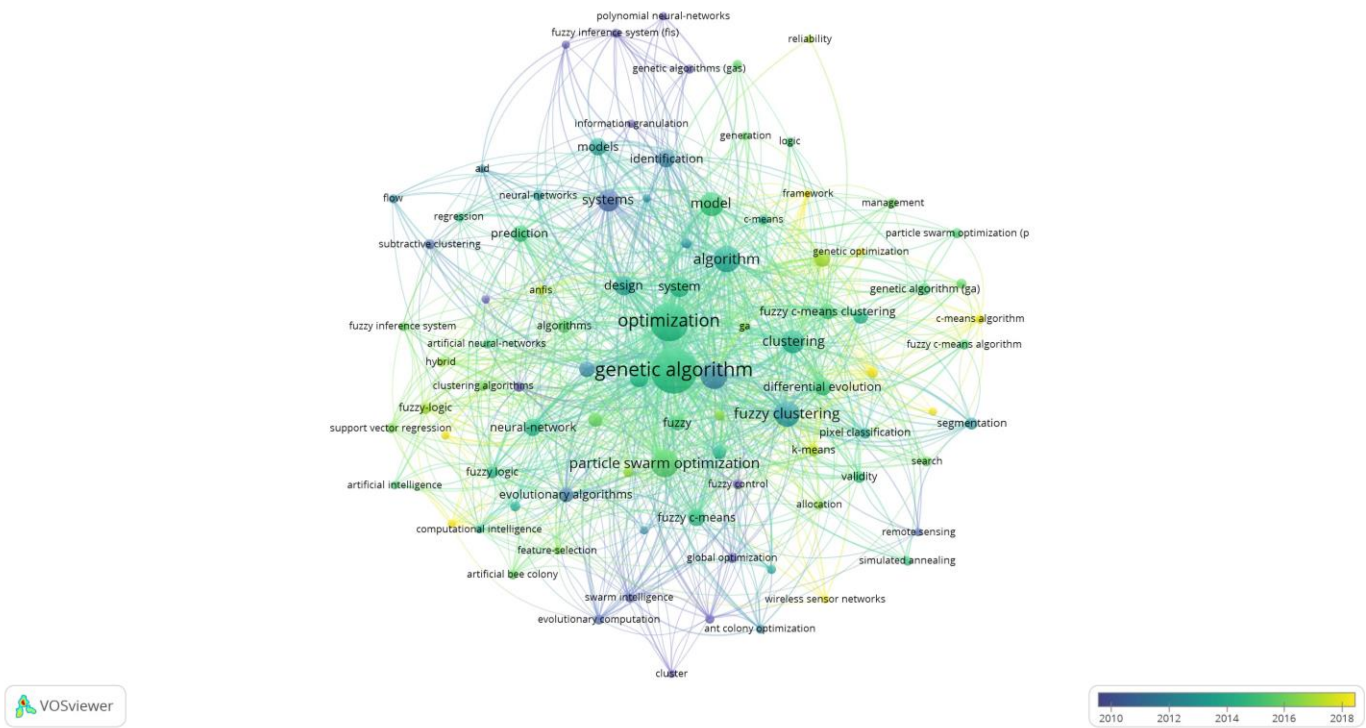

Figure 2. Total cluster obtained with the search ’optimization fuzzy clustering with genetic algorithms’ from VOS viewer

Also, with this information was possible to observe, the records by authors, where in Figure 9, it can be appreciated that two authors are the leaders in this area with the topic ’optimization fuzzy clustering with particle swarm optimization’.

4.3. Study with Cuckoo Search Algorithm

In this section, we present the obtained results of the queries in Web of Science with the topic ’optimization fuzzy clustering with Cuckoo Search Algorithm’. The main difference with the other analyzed algorithms was that only 23 papers were found with the reviewed topic. Also, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc.Figure 10, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 3 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, we can appreciate the number of clusters is 2 as can be seen in Figure 10 with only 1 link. With these results, it can be seen that this method has not been widely used or combined with fuzzy clustering.

Figure 11, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 10. It can be seen how the number of citations and papers are less than the other analyzed methods.

Also, with this information was possible to observe, the records by authors, where in Figure 9, it can be appreciated that two authors are the leaders in this area with the topic ’optimization fuzzy clustering with cuckoo search algorithm’.

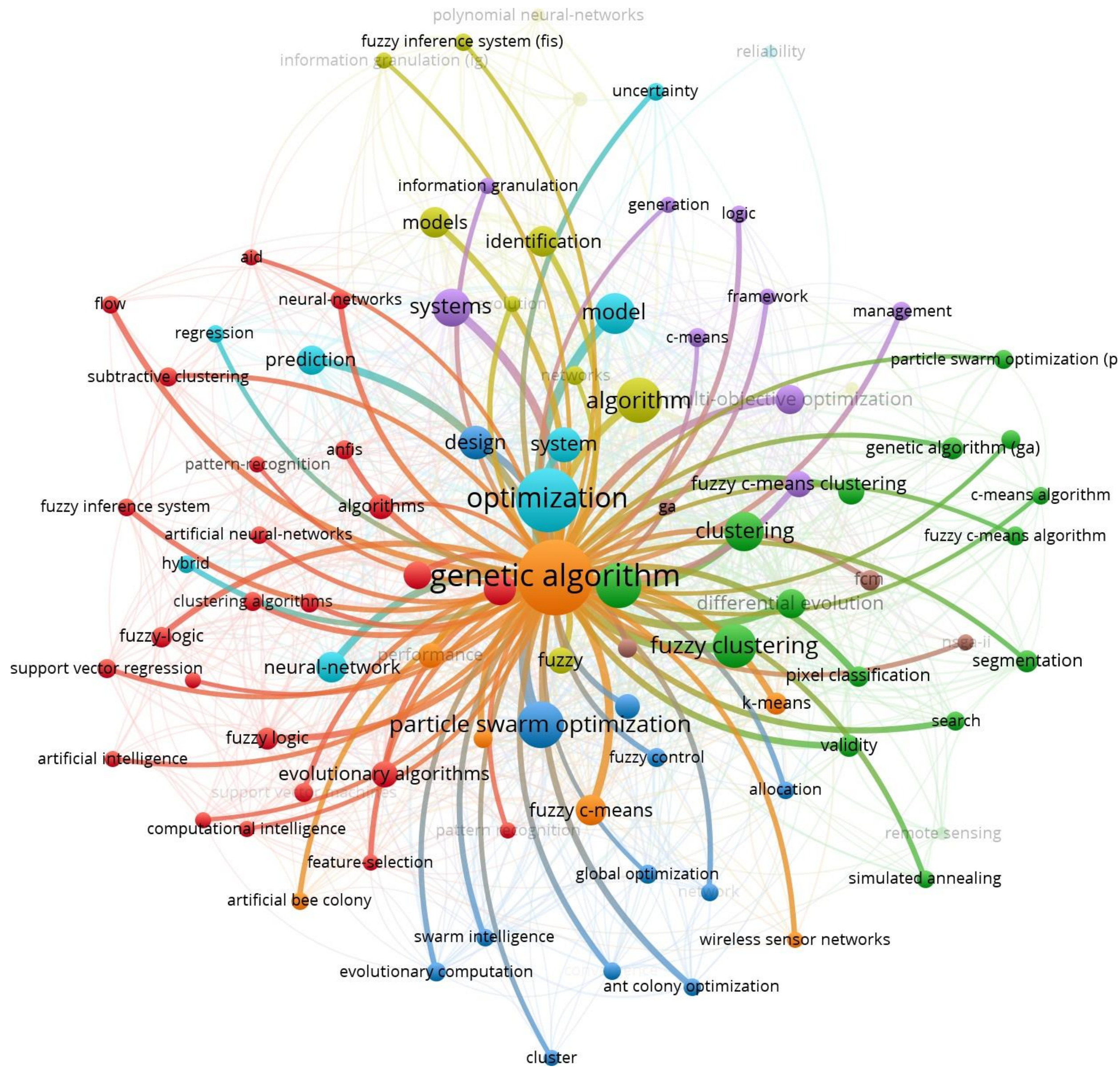

Figure 3. Represent the selection of the keyword 'genetic algorithm'.

4.4. Study with Bat Algorithm

In this section, is presented the obtained results of the queries in Web of Science with the topic 'optimization fuzzy clustering with Bat Algorithm'. The main difference with the other analyzed algorithms was that only 23 papers were found with the reviewed topic. Also, it was necessary to access the web of science, and then make the desired queries. Once the information was extracted, and using the Vos Viewer tool, it was possible to calculate the related works, citations, authors, etc.Figure 13, represents a map based on network data collected from the bibliographic database in Web of Science. The type of analysis represented in this Figure is by co-occurrence, the unit of analysis was by keywords, the minimum number of documents of an author was 5, minimum number of citations was 0, the counting method was full counting, minimum number of occurrences of a keyword was 5; and finally, for each of the 3 keywords, the total strength of the co-occurrence links with other keywords was calculated. On VosViewer, we can appreciate the number of clusters is 1 as can be seen in Figure 13 with only 1 link.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

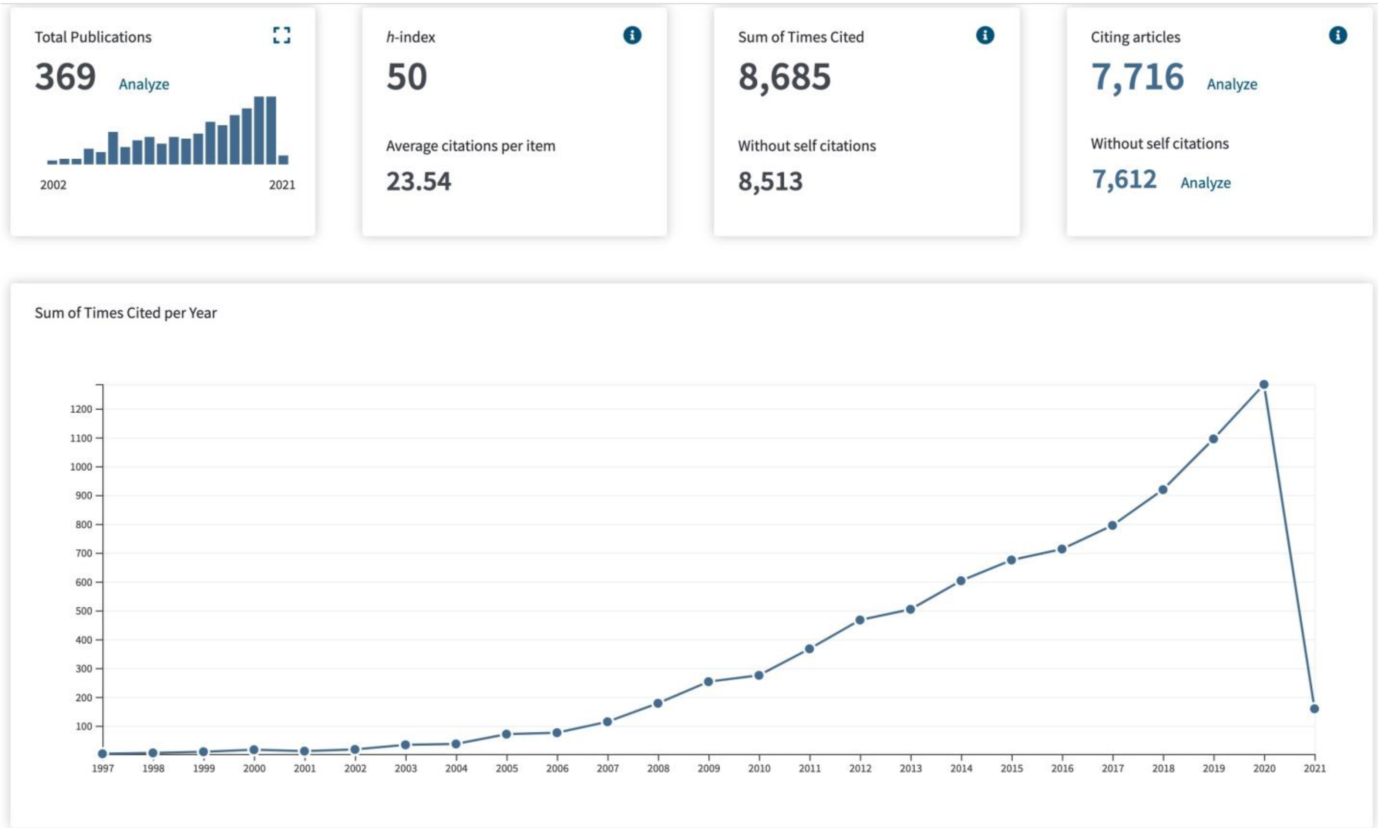

Figure 4. Citation report for 369 results from Web of Science Core Collection

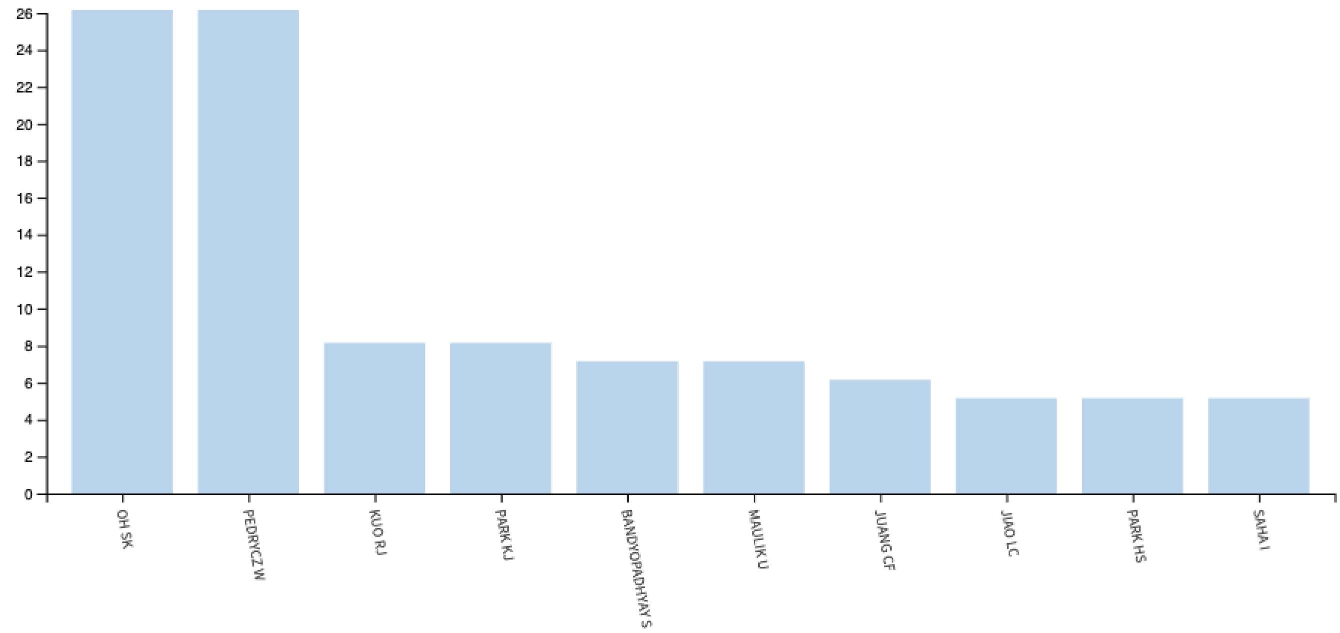

Figure 5. Record by authors for TOPIC: (optimization fuzzy clustering with genetic algorithms)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

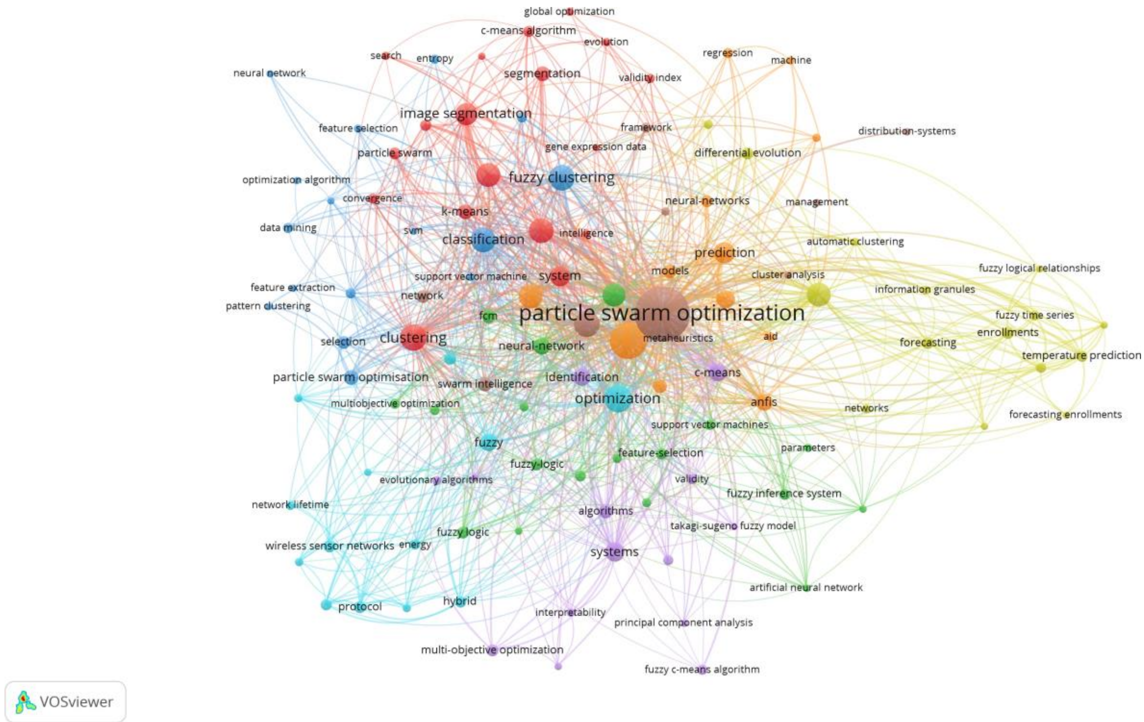

Figure 6. Total cluster obtained with the search 'optimization fuzzy clustering with particle swarm optimization' from VOS viewer

With these results, it can be seen that this method has not been widely used or combined with fuzzy clustering.

Figure 14, shows the total of papers collected from Web of Science and that were used to make the calculus above described in Figure 13. It can be seen how the number of citations and papers are less than the other analyzed methods.

Also, with this information was possible to observe, the record by authors, where in Figure 15, it can be appreciated that two authors are the leaders in this area with the topic 'optimization fuzzy clustering with bat algorithm'.

4.5. Analysis by authors

In this section is presented an analysis by authors, considering the total cites from web of science, we can appreciate that the author with more works in this area with the analyzed algorithms in this paper is Witold Pedrycz from the University of Alberta, Canada. According with the information collected of Web of Science,Figure 16 shows the total of the publications of this author.

Figure 17, was calculated in Vos Viewer and represents the relationship authors with Witold Pedrycz in the area of fuzzy clustering. The graph, was made considering the global work with a total of 1001 works collected from Web of Science.

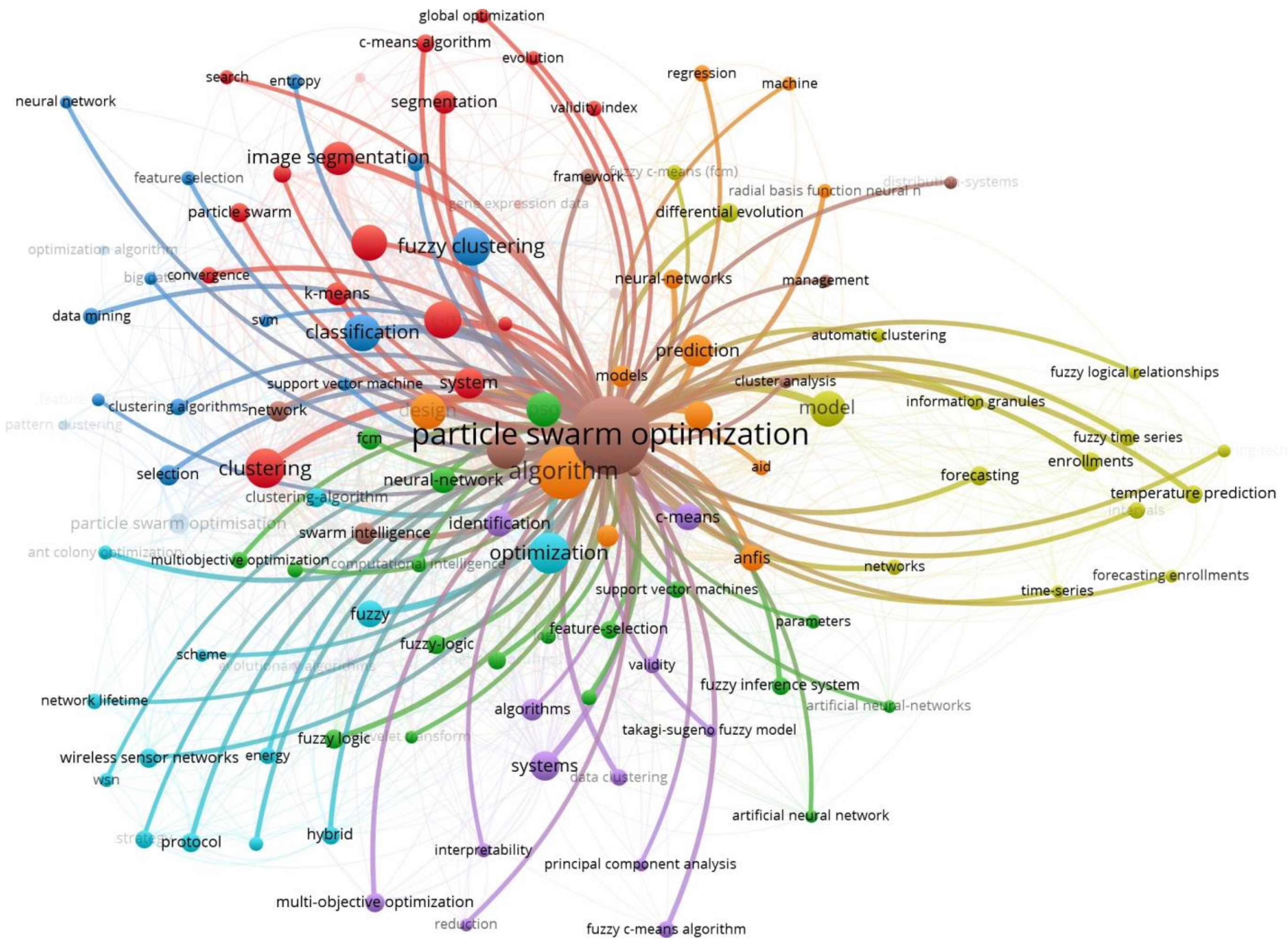

Figure 7. Representing the selection of the keyword 'particle swarm optimization'.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

Figure 8. Citation report for 508 results from Web of Science Core Collection

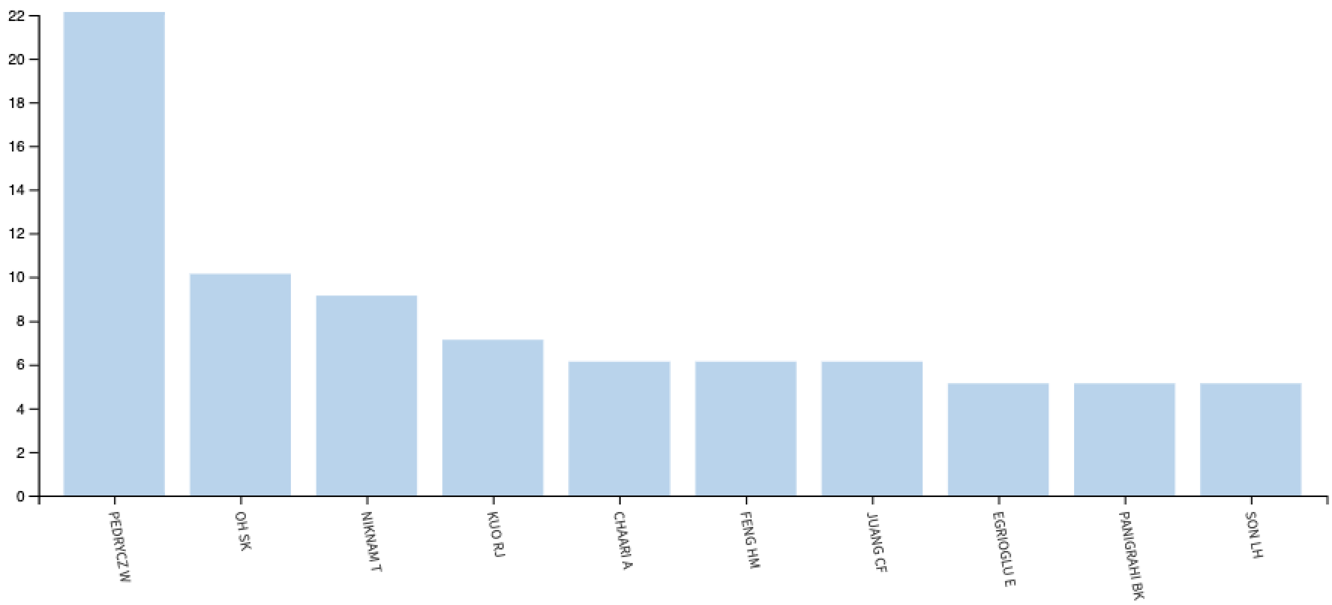

Figure 9. Record by authors for TOPIC: (optimization fuzzy clustering with particle swarm optimization)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

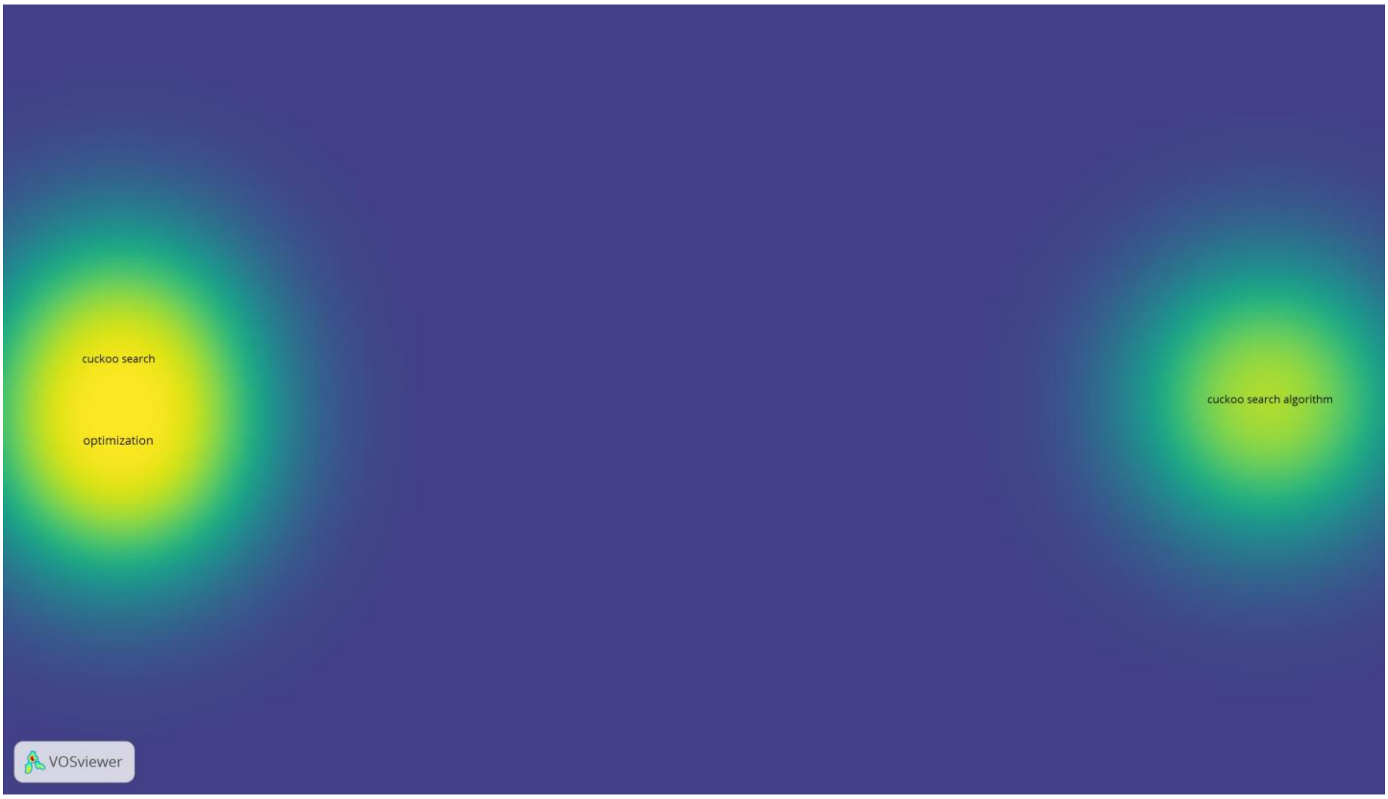

Figure 10. Total cluster obtained with the search 'optimization fuzzy clustering with cuckoo search optimization' from VOS viewer

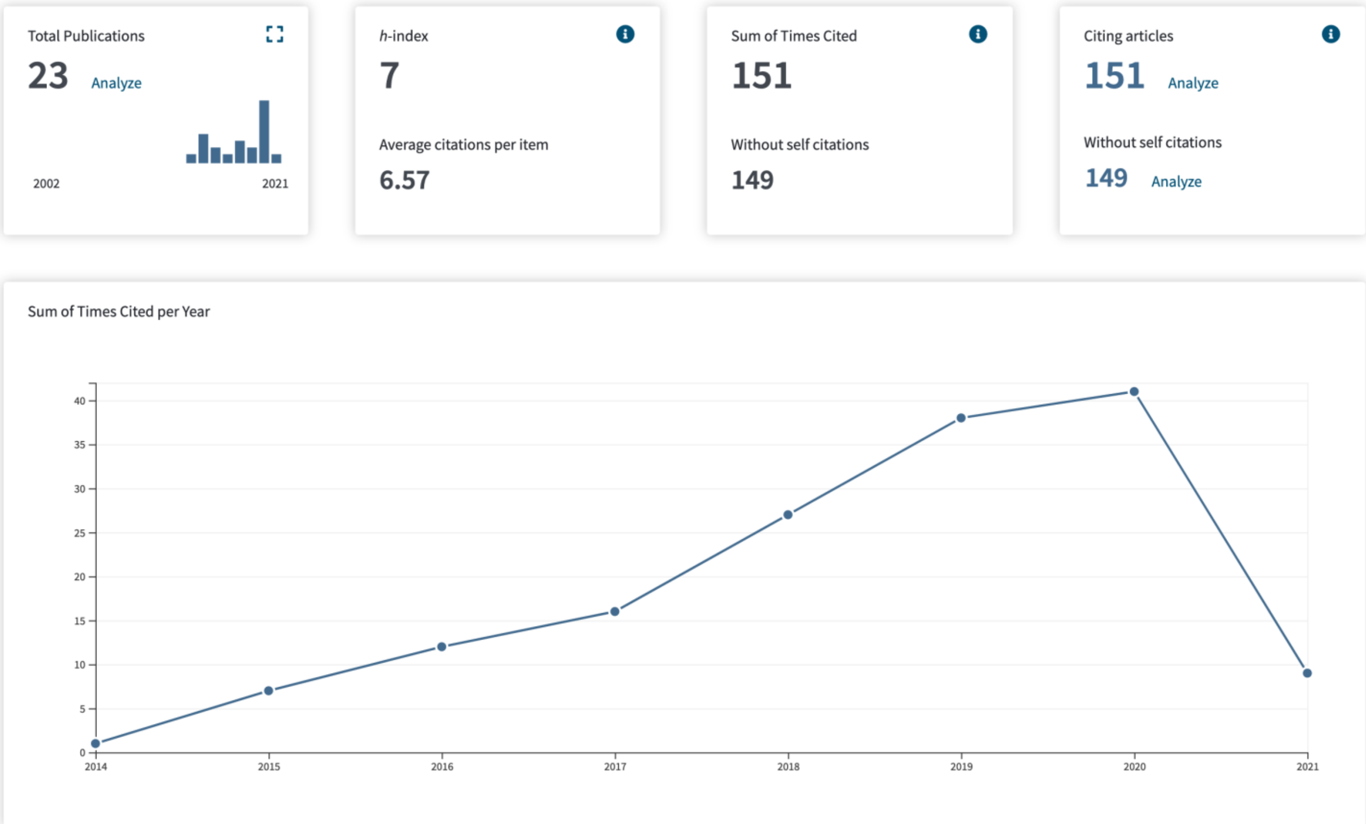

Figure 11. Citation report for 23 results from Web of Science Core Collection

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

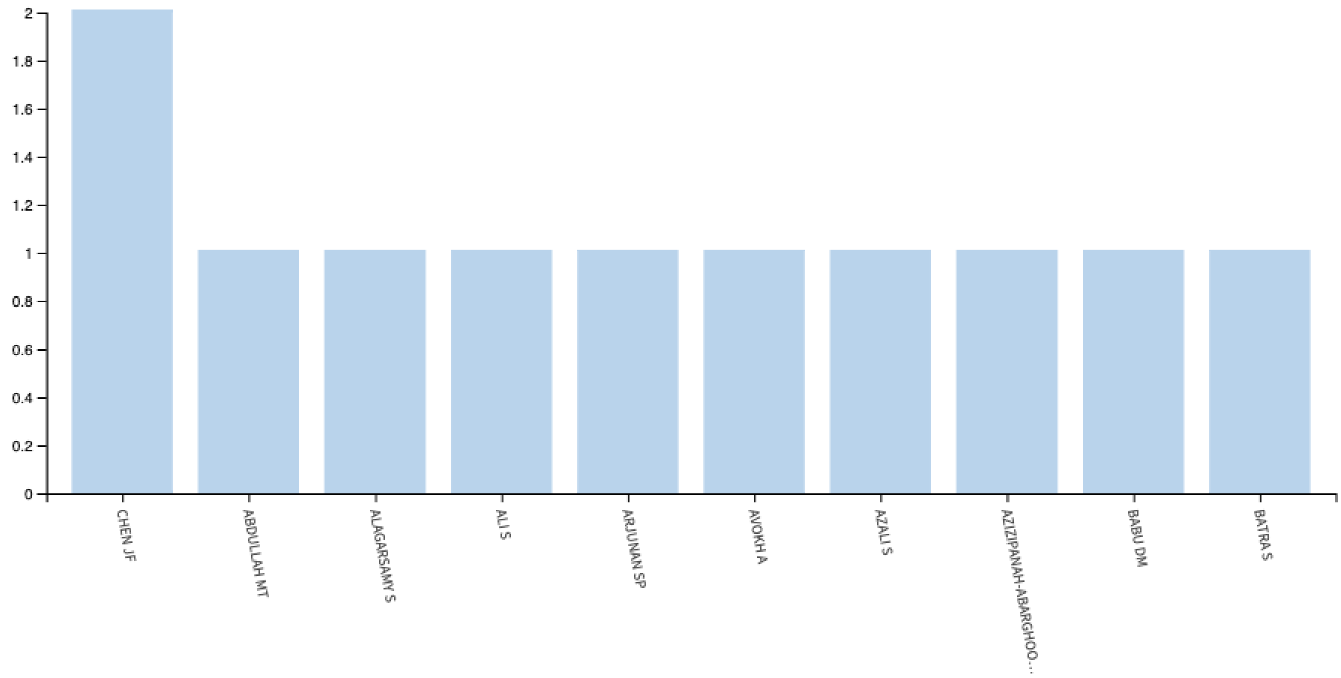

Figure 12. Record by authors for TOPIC: (optimization fuzzy clustering with cuckoo search algorithm)

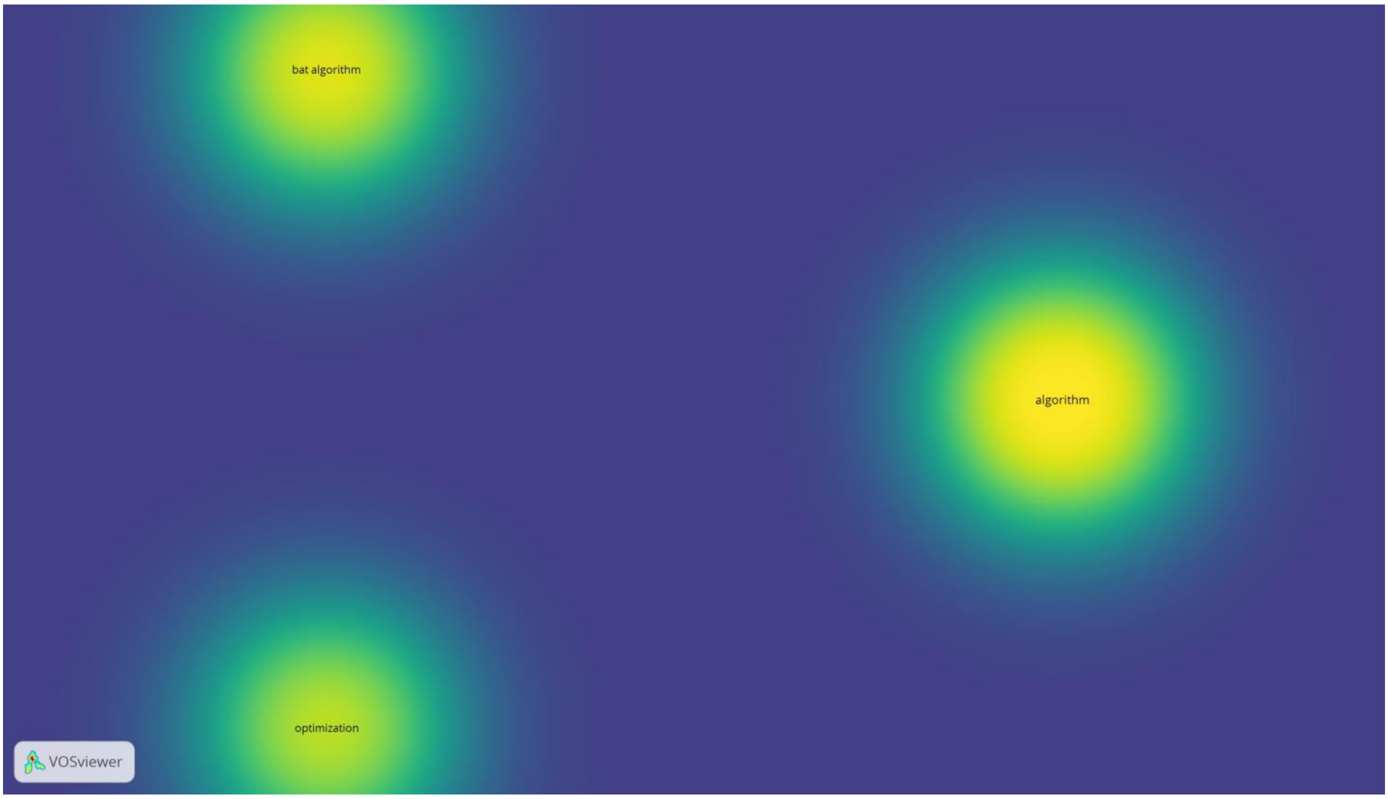

Figure 13. Total cluster obtained with the search 'optimization fuzzy clustering with cuckoo search optimization' from VOS viewer

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 10 March 2021 doi:10.20944/preprints202103.0282.v1

Figure 14. Citation report for 23 results from Web of Science Core Collection

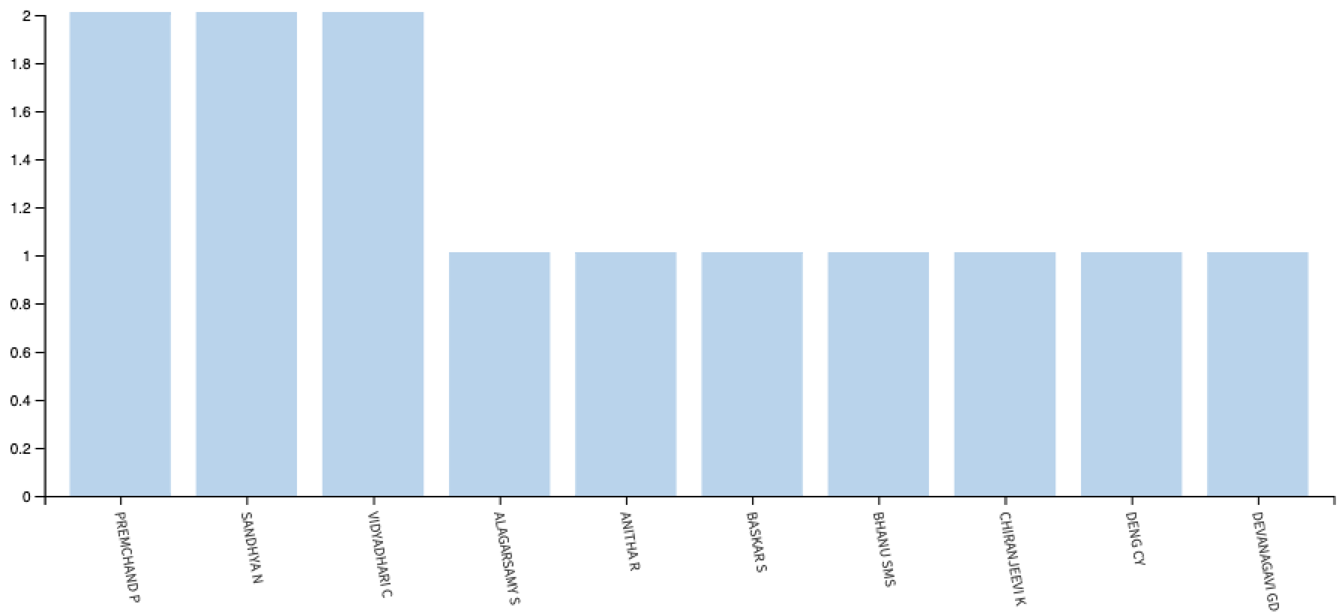

Figure 15. Record by authors for TOPIC: (optimization fuzzy clustering with bat algorithm)

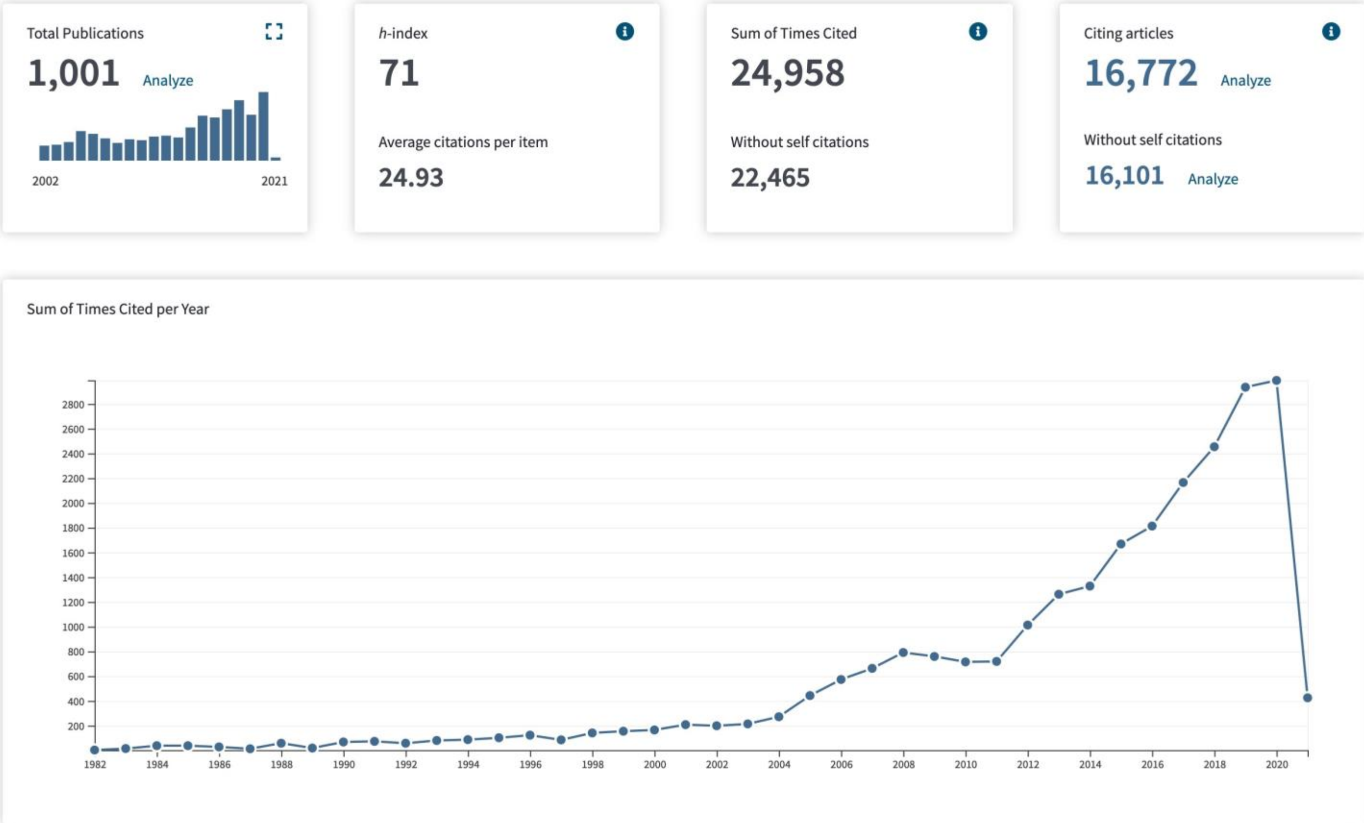

Figure 16. Citation report for1,001 results from Web of Science Core Collection by the author Witold Pedrycz.

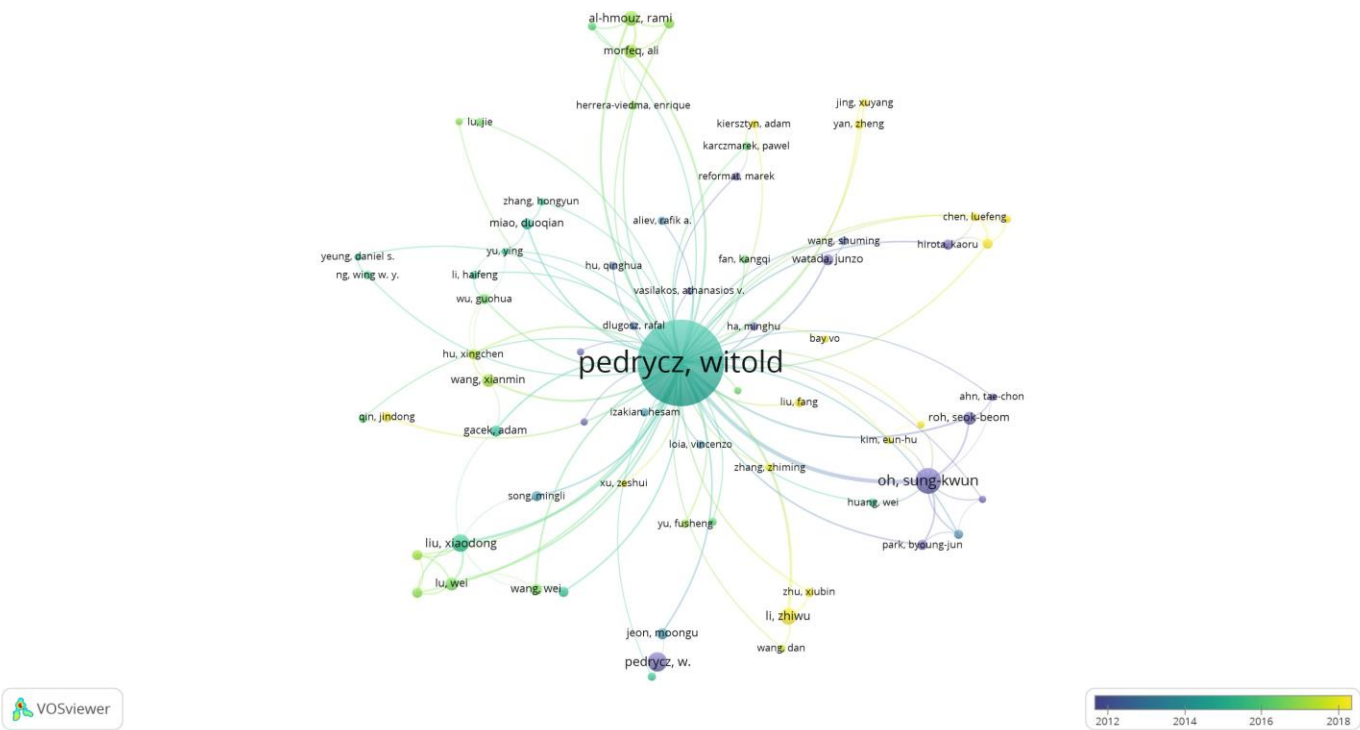

Figure 17. Clusters by authors on Vos Viewer

5. Conclusions

After reviewing the state of the art about area optimization fuzzy clustering with optimization methods. We decided to make an analysis, considering four optimization methods, which we have used in the last year. With all collected information of Web of Science, Vos Viewer tool, we can observe that Genetic Algorithms and Particle Swarm Optimization are two very popular methods that the authors have been using in the last years. On the other hand, Cuckoo Search and Bat Algorithm, are two methods newer than the other two. However, not many authors have attempted to make fuzzy clustering using these two methods. Also, we were able to review the author with more works in this area. As a future work, this review can be extended analyzing other optimization methods with fuzzy clustering. The type of queries can be made by authors, keywords, occurrences, etc. However, with the paper can be reviewed the software and tools used and can be extracted all the information here presented.

Funding: This paper did not receive funding.

Acknowledgments: The authors would like to thank CONACYT and Tecnológico Nacional de Mexico/Tijuana Institute of Technology for the support during this research work.

References

1. Reyes-Sierra, M.; Coello, C. Multi-Objective Particle Swarm Optimizers: A Survey of the State-of-the-Art. *International Journal of Computational Intelligence Research* **2006**, *2*, 287–308.
2. Valdez, F.; Melin, P.; Castillo, O. A survey on nature-inspired optimization algorithms with fuzzy logic for dynamic parameter adaptation. *Expert Syst. Appl.* **2014**, *41*, 6459–6466.
3. Fister, I.; Fister, I.; Yang, X.S.; Brest, J. A comprehensive review of firefly algorithms. *Swarm and Evolutionary Computation* **2013**, *13*, 34–46.
4. Chen, M.R.; Huang, Y.Y.; Zeng, G.Q.; Lu, K.D.; Yang, L.Q. An improved bat algorithm hybridized with extremal optimization and Boltzmann selection. *Expert Systems with Applications* **2021**, p. In Press.
5. Odili, J.B.; Noraziah, A.; Babalola, A.E. Flower pollination algorithm for data generation and analytics - a diagnostic analysis. *Scientific African* **2020**, *8*, 1–9.
6. Gao, S.; Gao, Y.; Zhang, Y.; Li, T. Adaptive cuckoo algorithm with multiple search strategies. *Applied Soft Computing* **2021**, p. 107181.
7. Valdez, F. A review of optimization swarm intelligence-inspired algorithms with type-2 fuzzy logic parameter adaptation. *Soft Comput.* **2020**, *24*, 215–226.
8. Yue, C.; Suganthan, P.N.; Liang, J.; Qu, B.; Yu, K.; Zhu, Y.; Yan, L. Differential evolution using improved crowding distance for multimodal multiobjective optimization. *Swarm and Evolutionary Computation* **2021**, *62*, 1–10.
9. Wang, Y.; Gao, S.; Yu, Y.; Cai, Z.; Wang, Z. A gravitational search algorithm with hierarchy and distributed framework. *Knowledge-Based Systems* **2021**, *218*, 106877.
10. Yan, Z.; Zhang, J.; Zeng, J.; Tang, J. Nature-inspired approach: An enhanced whale optimization algorithm for global optimization. *Mathematics and Computers in Simulation* **2021**, *185*, 17–46.
11. Bonyadi, M.R.; Michalewicz, Z. Particle Swarm Optimization for Single Objective Continuous Space Problems: A Review. *Evolutionary Computation* **2017**, *25*, 1–54.
12. Colorni, A.; Dorigo, M.; Maniezzo, V. Distributed Optimization by Ant Colonies. 1992.
13. Pham, D.T.; Ghanbarzadeh, A.; Koç, E.; Otri, S.; Rahim, S.; Zaidi, M. - The Bees Algorithm — A Novel Tool for Complex Optimisation Problems; Elsevier Science Ltd: Oxford, 2006; pp. 454–459.
14. Hedayatzadeh, R.; Salmassi, F.A.; Keshtgari, M.; Akbari, R.; Ziarati, K. Termite colony optimization: A novel approach for optimizing continuous problems. 2010 18th Iranian Conference on Electrical Engineering, 2010, pp. 553–558.
15. Yang, X.S. A New Metaheuristic Bat-Inspired Algorithm. Nature Inspired Cooperative Strategies for Optimization (NICSO 2010); González, J.R.; Pelta, D.A.; Cruz, C.; Terrazas, G.; Krasnogor, N., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2010; pp. 65–74.
16. Kennedy, J.; Eberhart, R. Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks, 1995, Vol. 4, pp. 1942–1948.
17. Chu, S.C.; wei Tsai, P.; Pan, J.S. Cat Swarm Optimization. PRICAI 2006: Trends in Artificial Intelligence; Yang, Q.; Webb, G., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2006; pp. 854–858.
18. Lindfield, G.; Penny, J. Bacterial Foraging Inspired Algorithm. *Introduction to Nature-Inspired Optimization* **2017**, pp. 101–117.
19. Yang, X.; Deb, S. Cuckoo Search via Lévy flights. 2009 World Congress on Nature Biologically Inspired Computing (NaBIC), 2009, pp. 210–214.
20. Yang, X.S. Firefly Algorithm, Stochastic Test Functions and Design Optimisation. *International Journal of Bio-inspired Computation* **2010**, *2*, 78–84.

21. Hu, J.; Pan, Y.; Li, T.; Yang, Y. TW-Co-MFC: Two-level weighted collaborative fuzzy clustering based on maximum entropy for multi-view data. *Tsinghua Science and Technology* **2021**, *26*, 185–198.
22. Jai Shankar, B.; Murugan, K.; Obulesu, A.; Finney Daniel Shadrach, S.; Anitha, R. MRI Image Segmentation Using Bat Optimization Algorithm with Fuzzy C Means (BOA-FCM) Clustering. *Journal of Medical Imaging and Health Informatics* **2021**, *11*, 661–666.
23. Mahalingam, T. A hybridization of SKH and RKFCM clustering optimization algorithm for efficient moving object exploration. *Multimedia Tools and Applications* **2021**, pp. 1–32.
24. Mai, D.S.; Ngo, L.T.; Trinh, L.H.; Hagras, H. A hybrid interval type-2 semi-supervised possibilistic fuzzy c-means clustering and particle swarm optimization for satellite image analysis. *Information Sciences* **2021**, *548*, 398–422.
25. Vinodhini, R.; Gomathy, C. Fuzzy Based Unequal Clustering and Context-Aware Routing Based on Glow-Worm Swarm Optimization in Wireless Sensor Networks: Forest Fire Detection. *Wireless Personal Communications* **2021**.
26. MiarNaeimi, F.; Azizyan, G.; Rashki, M. Horse herd optimization algorithm: A nature-inspired algorithm for high-dimensional optimization problems. *Knowledge-Based Systems* **2021**, *213*, 1–17.
27. Zervoudakis, K.; Tsafarakis, S. A mayfly optimization algorithm. *Computers & Industrial Engineering* **2020**, *145*, 106559.
28. Khishe, M.; Mosavi, M.R. Chimp optimization algorithm. *Expert Systems with Applications* **2020**, *149*, 113338.
29. Martínez-Álvarez, F.; Asencio-Cortés, G.; Torres, J.F.; Gutiérrez-Avilés, D.; Melgar-García, L.; Pérez-Chacón, R.; Rubio-Escudero, C.; Riquelme, J.C.; Troncoso, A. Coronavirus Optimization Algorithm: A Bioinspired Metaheuristic Based on the COVID-19 Propagation Model. *Big Data* **2020**, *8*, 308–322.
30. Kaveh, A.; Eslamlou, A.D. Water strider algorithm: A new metaheuristic and applications. *Structures* **2020**, *25*, 520–541.
31. Gholizadeh, S.; Danesh, M.; Gheyratmand, C. A new Newton metaheuristic algorithm for discrete performance-based design optimization of steel moment frames. *Computers & Structures* **2020**, *234*, 106250.
32. Hayyolalam, V.; Kazem, A.A.P. Black Widow Optimization Algorithm: A novel meta-heuristic approach for solving engineering optimization problems. *Engineering Applications of Artificial Intelligence* **2020**, *87*, 103249.
33. Heidari, A.A.; Mirjalili, S.; Faris, H.; Aljarah, I.; Mafarja, M.; Chen, H. Harris hawks optimization: Algorithm and applications. *Future Generation Computer Systems* **2019**, *97*, 849–872.
34. Shadravan, S.; Naji, H.R.; Bardsiri, V.K. The Sailfish Optimizer: A novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems. *Engineering Applications of Artificial Intelligence* **2019**, *80*, 20–34.
35. Sharma, H.; Hazrati, G.; Bansal, J.C. Spider Monkey Optimization Algorithm. Evolutionary and Swarm Intelligence Algorithms; Bansal, J.C.; Singh, P.K.; Pal, N.R., Eds.; Springer International Publishing: Cham, 2019; pp. 43–59.
36. Saremi, S.; Mirjalili, S.; Lewis, A. Grasshopper Optimisation Algorithm: Theory and application. *Advances in Engineering Software* **2017**, *105*, 30–47.
37. Kaedi, M. Fractal-based Algorithm: A New Metaheuristic Method for Continuous Optimization. *International journal of artificial intelligence* **2017**, *15*, 76–92.
38. Kaboli, S.H.A.; Selvaraj, J.; Rahim, N.A. Rain-fall optimization algorithm: A population based algorithm for solving constrained optimization problems. *Journal of Computational Science* **2017**, *19*, 31–42.
39. Mirjalili, S. Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. *Neural Comput. Appl.* **2016**, *27*, 1053–1073.
40. Ebrahimi, A.; Khamehchi, E. Sperm whale algorithm: An effective metaheuristic algorithm for production optimization problems. *Journal of Natural Gas Science and Engineering* **2016**, *29*, 211–222.
41. Zheng, Y.J. Water wave optimization: A new nature-inspired metaheuristic. *Computers & Operations Research* **2015**, *55*, 1–11.
42. Mirjalili, S. The Ant Lion Optimizer. *Advances in Engineering Software* **2015**, *83*, 80–98.
43. Cheng, M.Y.; Prayogo, D. Symbiotic Organisms Search: A new metaheuristic optimization algorithm. *Computers & Structures* **2014**, *139*, 98–112.
44. Sur, C.; Sharma, S.; Shukla, A. Egyptian Vulture Optimization Algorithm – A New Nature Inspired Meta-heuristics for Knapsack Problem. *Advances in Intelligent Systems and Computing* **2013**, *209 AISC*, 227–237.
45. Kaveh, A.; Farhoudi, N. A new optimization method: Dolphin echolocation. *Advances in Engineering Software* **2013**, *59*, 53–70.
46. Mozaffari, A.; Fathi, A.; Behzadipour, S. The great salmon run: A novel bio-inspired algorithm for artificial system design and optimisation. *International Journal of Bio-Inspired Computation* **2012**, *4*, 286–301.
47. Zandi, Z.; Afjei, E.; Sedighizadeh, M. Reactive power dispatch using Big Bang-Big Crunch optimization algorithm for voltage stability enhancement. 2012 IEEE International Conference on Power and Energy (PECon), 2012, pp. 239–244.
48. Yang, X.S. Flower Pollination Algorithm for Global Optimization. Unconventional Computation and Natural Computation; Durand-Lose, J.; Jonoska, N., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2012; pp. 240–249.
49. Tamura, K.; Yasuda, K. Primary study of spiral dynamics inspired optimization. *IEEJ Transactions on Electrical and Electronic Engineering* **2011**, *6*, 98–100.
50. Shah-Hosseini, H. Principal components analysis by the galaxy-based search algorithm: A novel metaheuristic for continuous optimisation. *International Journal of Computational Science and Engineering* **2011**, *6*, 132–140.
51. Pibernat, H.; Blum, C. Distributed Graph Coloring: An Approach Based on the Calling Behavior of Japanese Tree Frogs. *Swarm Intelligence* **2012**, *6*, 117–150.

 doi:10.20944/preprints202103.0282.v1

52. Krishnanand, K.N.; Ghose, D. Glowworm Swarm Optimisation: A New Method for Optimising Multi-Modal Functions. *Int. J. Comput. Intell. Stud.* **2009**, *1*, 93–119.
53. Teodorović, D. Bee Colony Optimization (BCO). Innovations in Swarm Intelligence; Lim, C.P.; Jain, L.C.; Dehuri, S., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2009; pp. 39–60.
54. Rashedi, E.; Nezamabadi-pour, H.; Saryazdi, S. GSA: A Gravitational Search Algorithm. *Information Sciences* **2009**, *179*, 2232–2248.
55. Chu, Y.; Mi, H.; Liao, H.; Ji, Z.; Wu, Q.H. A Fast Bacterial Swarming Algorithm for high-dimensional function optimization. 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), 2008, pp. 3135–3140.
56. Rabanal, P.; Rodríguez, I.; Rubio, F. Using River Formation Dynamics to Design Heuristic Algorithms. LNCS, 2007, Vol. 4618, pp. 163–177.
57. Atashpaz-Gargari, E.; Lucas, C. Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. 2007 IEEE Congress on Evolutionary Computation, 2007, pp. 4661–4667.
58. Havens, T.C.; Spain, C.J.; Salmon, N.G.; Keller, J.M. Roach Infestation Optimization. 2008 IEEE Swarm Intelligence Symposium, 2008, pp. 1–7.
59. Wedde, H.F.; Farooq, M.; Zhang, Y. BeeHive: An Efficient Fault-Tolerant Routing Algorithm Inspired by Honey Bee Behavior. Ant Colony Optimization and Swarm Intelligence; Dorigo, M.; Birattari, M.; Blum, C.; Gambardella, L.M.; Mondada, F.; Stützle, T., Eds.; Springer Berlin Heidelberg: Berlin, Heidelberg, 2004; pp. 83–94.
60. Jung, S. Queen-bee evolution for genetic algorithms. *Electronics Letters* **2003**, *39*, 575–576.
61. Geem, Z.W.; Kim, J.H.; Loganathan, G.V. A New Heuristic Optimization Algorithm: Harmony Search. *Simulation* **2001**, *76*, 60–68.
62. Koza, J. Genetic programming as a means for programming computers by natural selection. *Statistics and Computing* **1994**, *4*, 87–112.
63. Dorigo, M. Optimization, Learning and Natural Algorithms. *PhD Thesis, Politecnico di Milano* **1992**.
64. Glover, F. Tabu Search—Part I. *ORSA Journal on Computing* **1989**, *1*, 190–206.
65. Holland, J.H. Genetic Algorithms and Adaptation. Adaptive Control of Ill-Defined Systems; Selfridge, O.G.; Rissland, E.L.; Arbib, M.A., Eds.; Springer US: Boston, MA, 1984; pp. 317–333.
66. Kennedy, J.; Eberhart, R. Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks, 1995, Vol. 4.
67. Perianes-Rodriguez, A.; Waltman, L.; van Eck, N.J. Constructing bibliometric networks: A comparison between full and fractional counting. *Journal of Informetrics* **2016**, *10*, 1178–1195.
68. Aria, M.; Misuraca, M.; Spano, M. Mapping the Evolution of Social Research and Data Science on 30 Years of Social Indicators Research. *Social Indicators Research* **2020**, *149*.
69. Grauwin, S.; Szell, M.; Sobolevsky, S.; Hövel, P.; Simini, F.; Vanhoof, M.; Smoreda, Z.; Barabasi, A.L.; Ratti, C. Identifying and modeling the structural discontinuities of human interactions. *Scientific Reports* **2017**, p. 46677.
70. Chen, C.; Ibekwe-Sanjuan, F.; Hou, J. The Structure and Dynamics of Co-Citation Clusters: A Multiple-Perspective Co-Citation Analysis. *Journal of the American Society for Information Science and Technology* **2010**, *61*, 1386–1409.

Author biography

Fevrier Valdez is a researcher of the National System of Researchers Level 1 in Mexico recognized by CONACYT. His main interests are Intelligence Computing, Swarm Intelligence, Bio- Inspired Computing, Evolutionary Computing, Fuzzy Logic, Neural Networks, Intelligence Control and Parallel Computing. Actually the Ph.D. Fevrier Valdez is developing research in the bio inspired and nature computing. This researching is of great relevance to international level which had allowed an international recognition. Is professor-researcher of full time in the Tijuana Institute of Technology.

With his academic production, the professor has achieved to publish papers in several international journals, world congress and some chapters of books which are described as follows. His productivity is 51 papers in indexed journals in the JCR, 60 chapters of books, 69 congress memories and 4 books. Also, one research was recognized as a Best Paper Award Second Place with the paper "Backpropagation Method with Type-2 Fuzzy Weight Adjustment for Neural Network Learning" in the Congress North American Fuzzy Information Processing Society 2012, Berkeley CA, USA. The Dr. Valdez, nowdays he is reviewer of papers in the international journals like Applied Soft Computing, Information Sciences, IEEE Transactions on Fuzzy Systems e IEEE Transactions on Neural Networks, Hindawi, NeuroScience, etc.

 doi:10.20944/preprints202103.0282.v1

Oscar Castillo holds the Doctor in Science degree (Doctor Habilitatus) in Computer Science from the Polish Academy of Sciences (with the Dissertation “Soft Computing and Fractal Theory for Intelligent Manufacturing”). He is a Professor of Computer Science in the Graduate Division, Tijuana Institute of Technology, Tijuana, Mexico. In addition, he is serving as Research Director of Computer Science and head of the research group on Hybrid Fuzzy Intelligent Systems. Currently, he is President of HAFSA (Hispanic American Fuzzy Systems Association) and Past President of IFSA (International Fuzzy Systems Association). Prof. Castillo is also Chair of the Mexican Chapter of the Computational Intelligence Society (IEEE). He also belongs to the Technical Committee on Fuzzy Systems of IEEE and to the Task Force on “Extensions to Type-1 Fuzzy Systems”. He is also a member of NAFIPS, IFSA and IEEE. He belongs to the Mexican Research System (SNI Level 3). His research interests are in Type-2 Fuzzy Logic, Fuzzy Control, Neuro-Fuzzy and Genetic-Fuzzy hybrid approaches. He has published over 300 journal papers, 10 authored books, 50 edited books, 300 papers in conference proceedings, and more than 300 chapters in edited books, in total more than 940 publications with h index of 77 according to Google Scholar. He has been Guest Editor of several successful Special Issues in the past, like in the following journals: Applied Soft Computing, Intelligent Systems, Information Sciences, Soft Computing, Non-Linear Studies, Fuzzy Sets and Systems, JAMRIS and Engineering Letters. He is currently Associate Editor of the Information Sciences Journal, Journal of Engineering Applications on Artificial Intelligence, International Journal of Fuzzy Systems, Journal of Complex and Intelligent Systems, Granular Computing Journal and Intelligent Systems Journal (Wiley). He was Associate Editor of Journal of Applied Soft Computing and IEEE Transactions on Fuzzy Systems. He has been elected IFSA Fellow in 2015 and MICAI Fellow in 2016. Finally, he recently received the Recognition as Highly Cited Researcher in 2017 and 2018 by Clarivate Analytics and Web of Science.

Patricia Melin is a Professor of Computer Science in the Graduate Division, Tijuana Institute of Technology, Tijuana, Mexico, since 1998. In addition, she is serving as Director of Graduate Studies in Computer Science and is head of the research group on Hybrid Neural Intelligent Systems (2000-present). She holds the Doctor in Science degree (Doctor Habilitatus D.Sc.) in Computer Science from the Polish Academy of Sciences. Prof. Melin has published nearly 800 publications in indexed journals, book chapters, and conference proceedings, as well as nearly 50 books, and as consequence of this she has achieved more than 17000 citations with an H index of 72 in Google Scholar. In addition, she has been awarded the Highly Cited Researcher recognition in the area of Computer Science in 2017 and 2018 by Clarivate Analytics-Web of Science because she is in the top 1% cited author in this area. She has also been advisor of more than 85 graduate students in computer science at the Ph.D. and masters levels.
She is past President of NAFIPS (North American Fuzzy Information Processing Society) 2019-2020. Prof. Melin is the founding Chair of the Mexican Chapter of the IEEE Computational Intelligence Society. She is member of the IEEE Neural Network Technical Committee (2007 to present), the IEEE Fuzzy System Technical Committee (2014 to present) and is Chair of the Task Force on Hybrid Intelligent Systems (2007 to present) and she is currently Associate Editor of the Information Sciences Journal, IEEE Transactions on Fuzzy Systems and Journal of Complex and Intelligent Systems. She is member of NAFIPS, IFSA, and IEEE. She belongs to the Mexican Research System with level III (highest level). Her research interests are in Modular Neural Networks, Type-2 Fuzzy Logic, Pattern Recognition, Fuzzy Control, Neuro-Fuzzy and Genetic-Fuzzy hybrid approaches. She has served as Guest Editor of several Special Issues in the past, in journals like: Applied Soft Computing, Intelligent Systems, Information Sciences, Non-Linear Studies, Engineering Applications of Artificial Intelligence, Fuzzy Sets and Systems.