Marek A. Galewski, Piotr Duba
Gdańsk University of Technology, Faculty of Mechanical Engineering
and Ship Technology

MARINE AND COSMIC INSPIRATIONS FOR AI ALGORITHMS

Abstract One of the important areas of Artificial Intelligence (AI) algorithms applications are optimisation problems. Authors of such algorithms have various inspirations. Probably the most commonplace is the nature. For example, Artificial Neural Networks were inspired by human brain and nervous system structure while Genetic Algorithm was inspired by the biological evolution process. Amongst AI algorithms used in optimisation, a particularly large and still broadening group are swarm intelligence algorithms. These algorithms are based mainly on observations of social and food searching behaviours of various species for example birds, ants, fish, bats, bees and many other. There are also other algorithms that implement physics laws, for example laws of gravity, or environmental phenomena like hydrologic cycle, water evaporation etc. Despite large number of swarm intelligence algorithms, there is not a single ultimate algorithm that solves all types of problems (single- and multi-objective, uni- and multi-modal, with and without boundaries, etc.). Thus, there is a permanent need for new algorithms with new, original inspirations, even though some of the algorithms of this class already gained wider recognition (for example Artificial Ant Algorithm and Particle Swarm Optimisation). In the paper, a short review is presented of selected interesting swarm intelligence optimisation algorithms that draw inspirations from marine nature and cosmic space. These are: Gravitational Search Algorithm, Artificial Fish Swarm Optimization, Krill Herd, Whale Optimization Algorithm and Salp Swarm Algorithm.

Keywords: Artificial Intelligence, Swarm Intelligence, optimisation algorithms, Gravitational Search Algorithm, Artificial Fish Swarm Optimization, Krill Herd, Whale Optimization Algorithm, Salp Swarm Algorithm

INTRODUCTION

Artificial Intelligence (AI) is a scientific area that currently sees an enormous growth. Various new algorithms and methods are developed and many of them have successful practical applications. Authors of new algorithms have diverging inspirations. Probably the most common one is the nature. For example, Artificial Neural Networks were inspired by the structure of human brain and nervous system while the classic Genetic Algorithm was inspired by the biological evolution process. One of the important areas of AI algorithms' applications is the solution to optimisation problems which can be encountered in practically all fields of science, technology and everyday life. Amongst AI algorithms used to solve optimization problems, especially large and still broadening group are swarm intelligence algorithms. They are nature-inspired, meta-heuristic algorithms which usually solve optimisation problems by mimicking biological or physical phenomena. They are based mainly on observations of behaviours of various species of animals, for example: birds[1], ants[2], grasshoppers[3], bees[4], bats[5], wolves[6], fish[7], dolphins[8] and many other, or implement physics laws or environmental phenomena like laws of gravity[9], motion of galaxies[10], lightning formation[11], hydrologic cycle[12], water evaporation[13], etc.

The general advantages of swarm optimisation are: simplicity, easy implementation and the lack of the objective function gradient information requirement. They are usually fast-converging and can bypass local optima. Despite large number of algorithms there is no single ultimate algorithm that solves all types of

1 J. Kennedy, R. Eberhart, Particle Swarm Optimization. Proceedings of IEEE International Conference on Neural Networks. 1995, pp. 1942–1948.

2 M. Dorigo, V. Maniezzo, A. Colorni, Ant System: Optimization by a Colony of Cooperating Agents, IEEE Transactions on Systems, Man, and Cybernetics–Part B, vol. 26, 1996, pp. 29–41.

3 S. Saremi, S. Mirjalili, A. Lewis, Grasshopper optimisation algorithm: Theory and application, Advances in Engeneering Software, vol. 105, 2017, pp. 30-47.

4 D. Karaboga, An idea based on honey bee swarm for numerical optimization, Eng. Faculty, Erciyes Univ., Kayseri, Turkey, Tech. Rep. TR06, 2005.

5 X. S. Yang, A New Metaheuristic Bat-Inspired Algorithm, in: Nature Inspired Cooperative Strategies for Optimization (NISCO 2010). Studies in Computational Intelligence. vol. 284, 2010, pp. 65–74

6 S. Mirjalili, S. M. Mirjalili, A. Lewis, Grey Wolf Optimizer, Advances in Engineering Software, Volume 69, 2014, pp. 46-61,

7 L.X. Li, Z.J. Shao, J.X. Qian, An Optimizing method based on autonomous animals: fish-swarm algorithm, Systems Engineering – Theory Practice, vol. 22, no.11, 2002, pp. 32-38

8 A. Kaveh, N. Farhoudi, A new optimization method: Dolphin echolocation, Advances in Engineering Software, vol. 59, 2013, pp. 53-70

9 E. Rashedi, H. Nezamabadi-Pour, S. Saryazdi, GSA: A Gravitational Search Algorithm, Information Sciences International Journal, vol. 179, 2009, pp. 2232–22487

10 V. Muthiah-Nakarajan, M.M. Noel, Galactic Swarm Optimization: A new global optimization metaheuristic inspired by galactic motion, Applied Soft Computing, vol. 38, 2016, pp. 771-787.

11 H. Shareef, A.A. Ibrahim, A.H. Mutlag, Lightning search algorithm, Applied Soft Computing, vol. 36, 2015, pp. 315-333.

12 H. Eskandar, A. Sadollah, A. Bahreininejad, M. Hamdi, Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems, Computers Structures, vol. 110–111, 2012, pp. 151-166

13 A. Kaveh, T. Bakhshpoori, Water evaporation optimization: a novel physically inspired optimization algorithm. Comput Struct, vol. 167, 2016, pp. 69–85.

problems (single- and multi-objective, uni- and multi-modal, with and without boundaries, etc.). Thus, there is a permanent need for more algorithms with new, original inspirations.

The paper presents general advantages of swarm intelligence algorithms and a short review of selected, interesting optimisation algorithms that draw inspirations from marine nature and the outer space. These are: Gravitational Search Algorithm, Artificial Fish Swarm Optimization, Krill Herd, Whale Optimization Algorithm and Salp Swarm Algorithm.

1. BASIC CHARACTERISTICS AND APPLICATIONS OF SWARM INTELLIGENCE

Swarm intelligence is defined as a collective behaviour of decentralised, self--organised systems, natural or artificial. The most important feature of these systems is that they are composed of many, usually identical individuals and there is no centralised controller or supervisor to the whole swarm. Each individual in the swarm follows quite simple rules and can perform elementary operations. One individual is not able to solve the problem but thanks to interactions with other individuals and the environment, the whole swarm is able to "intelligently" find the solution.

Swarm algorithms usually find optimal or close to optimal solutions in a relatively short time and with relatively small computational effort. They do not depend on gradient information of the objective function (as opposed to many classic optimisation algorithms) and show the ability to solve complex, non-linear, high dimensional problems. Some of them even allow for changing the objective or problem parameters during the search for a solution, which can be useful, for example, when performing tasks in a changing or non-stationary environment. Another advantage is the possibility to stop the search in any moment, however, although the result will obviously not be optimal in this case, it will likely be better than in the initial step. Although Swarm Intelligence algorithms are usually applied for optimisation problems in virtual, computational environment (for example in extrema search, design optimisation, production planning etc.) they may be also applied to control drones, robots, groups of various objects, group navigation, formation maintaining, etc. in the real world. Some examples are: swarms of boats tested by US Navy[14], trajectory planning of a wheeled robot[15], control of

14 J. Hsu, U.S. Navy's Drone Boat Swarm Practices Harbor Defense, IEEE Spectrum, 2016, https://spectrum.ieee.org/automaton/robotics/military-robots/navy-drone-boat-swarm-practices-harbor-defense, (Access: 20.02.2021)

15 X. Zhang, Y. Huang, Y. Rong, G. Li, H. Wang, C. Liu, Optimal Trajectory Planning for Wheeled Mobile Robots under Localization Uncertainty and Energy Efficiency Constraints, Sensors, vol. 21, 2021, 335

space satellite swarms[16], cooperation of simple robots[17] or moving target search using UAVs[18].

One of the advantages of using swarms in the real word is that they are constructed from simple, generally small, cheap units. This means that all the benefits of mass production could be achieved, allowing for reduction of manufacturing and maintenance cost. Additionally, swarm solutions scale easily and have intrinsic parallel processing capabilities. Adding more units to the swarm does not require the change of rules or control algorithms. The same applies to reduction (of course to some limit) of the number of units. When a swarm member is lost or destroyed for some reason, the rest of the swarm can still perform the task, although the efficiency of the swarm may obviously be reduced.

2. SELECTED ALGORITHMS

GRAVITATIONAL SEARCH ALGORITHM (GSA)[19]

The main principles of this algorithm are based on the Newtonian law of gravity: "*Any particle of matter in the universe attracts any other with a force varying directly as the product of the masses and inversely as the square of the distance between them*"[20]. In mathematical form this can be described as:

$$F = G\frac{M_1 M_2}{R^2} \tag{1}$$

where: F is the gravitational force, G is the gravitational constant, M_1 and M_2 are mass of the first and second particles respectively, and R is the distance between the two particles.

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16 A. Farrag, S. Othman, T. Mahmoud, A.Y. ELRaffiei, Satellite swarm survey and new conceptual design for Earth observation applications, The Egyptian Journal of Remote Sensing and Space Science, Vol. 24, 2021, pp. 47-54. Also: H. Hildmann, M. Almeidam E. Kovacs, F. Saffre, Termite algorithms to control collaborative swarms of satellites. In: Proceedings of the International Symposium on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS 2018), i-SAIRAS 2018, Madrid, Spain, 4–6 July 2018; European Space Agency: Paris, France, 2018

17 P. Levi, S. Kernbach, Symbiotic Multi-Robot Organisms, Reliability, Adaptability, Evolution, Springer-Verlag Berlin Heidelberg, 2010

18 M.D. Phung, Q.P. Ha, Motion-encoded particle swarm optimization for moving target search using UAVs, Applied Soft Computing, vol. 97, 2020, 106705.

19 E. Rashedi, H. Nezamabadi-Pour, S. Saryazdi, GSA: A Gravitational Search Algorithm, Information Sciences International Journal, vol. 179, 2009, pp. 2232–22487

20 Britannica, The Editors of Encyclopaedia, Newton's law of gravitation. Encyclopedia Britannica, https://www.britannica.com/science/Newtons-law-of-gravitation. (Accessed 21.02.2021.)

Additionally, according to the second Newton's law when a force *F*, is applied to a particle, its acceleration *a*, depends only on the force and its mass *M*:

$$a = \frac{F}{M} \tag{2}$$

A generalised case is shown below:

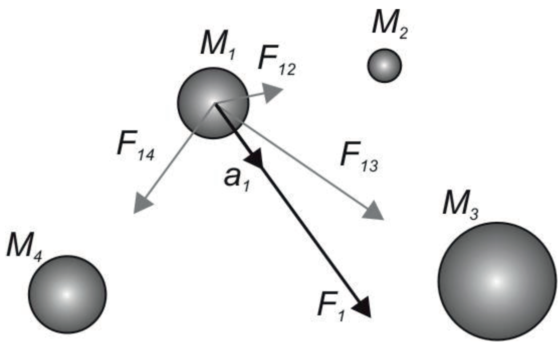

Figure 1. Forces acting on an object and its acceleration

In the GSA, possible solutions of the problem are represented as objects (search agents) and their performance is measured by their masses. All these objects attract each other, obeying the laws of gravity. Forces acting on objects cause movement of all objects in the search space. Heavier objects, which represent better solutions, move slower than lighter ones and attract lighter object stronger (with a force higher than lighter objects). Each mass (agent) is described by four parameters: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to the position of the potential solution of the problem, and its gravitational and inertial masses are determined using a fitness function that describes the problem being solved. The whole system of masses reassembles a small artificial universe with stars, planets and comets that travel through space, obeying two principal laws:

- Law of gravity – similar to Newton's law of gravity, however, instead of R^2, R is used in (1) as it appeared to give better algorithm performance.
- Law of motion – the current velocity of any mass is equal to the sum of the fraction of its previous velocity and the variation in the velocity. Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by mass of inertia, similar to (2).

Apart from above given laws, some additional rules and equations (especially for updating gravitational and inertial masses during search) are defined in the algorithm.

In the GSA, movement of each agent depends on its performance and the performance of other agents. A better solution is represented by an agent's greater gravitational mass which has a larger effect on other agents. As a result, the agents tend to move toward the best solution. On the other hand, the inertia mass is against the motion and reduces the movement of objects. Hence, as the agent approaches the solution, it gains mass, but it slows down and thus search the space more locally. This may be considered as an adaptive behaviour.

ARTIFICIAL FISH SWARM OPTIMIZATION (AFSO)[21]

The AFSO algorithm reproduces foraging, swarming and chasing behaviours of fish. One fish is a search agent that represents a location (X_i) of possible solution to the given problem. This artificial fish receives information about surrounding environmental through visual perception. While making a step, the fish seeks for food in a limited visual range (V_r) by checking the value of a fitness function $Y = f(X_v)$ (equivalent of food density in real life). If the Y value at the visual position Xv is better than in the current position X_i, it goes forward a step in this direction to the X_n position (figure 2). Otherwise, it continues random search around X_i. The search behaviour is also affected by the number of other fish in visual range. If this number is below a threshold, which means that visual scope is not crowded, the fish moves toward the centre of the local swarm (formed from fish visible in the visual range) if the Y value is better there, or towards the fish representing the best solution (neighbouring fish with the best Y), depending on which is better; or it moves randomly if above criteria are not met. If the number of fish in visual range is too high (neighbourhood is crowded), the fish also performs a random search step.

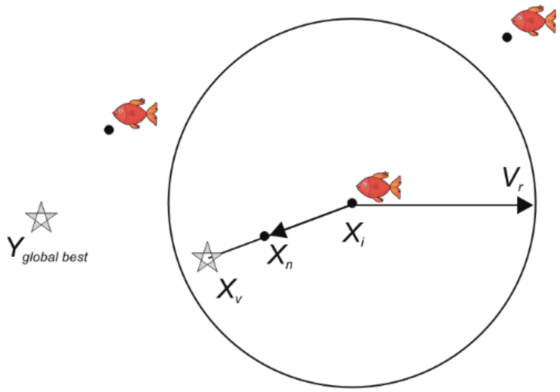

Figure 2. Artificial fish and its environment

[21] L.X. Li, Z.J. Shao, J.X. Qian, An Optimizing method based on autonomous animals: fish-swarm algorithm, Systems Engineering – Theory Practice, vol. 22, no.11, 2002, pp. 32-38. Also: M. Neshat, A. Adeli, G. Sepidnam, M. Sargolzaei, A. Najaran Toosi, A review of artificial fish swarm optimization methods and applications, Int. Journal on Smart Sensing and Intelligent Systems, vol. 5, 2012, pp. 107-148

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After its initial publication, the AFSO algorithm quickly gained recognition and various applications. Many improved versions have been proposed as well[22]. The algorithm has high convergence speed, is flexible and has good error tolerance.

KRILL HERD (KH)[23]

This algorithm takes its origin in observations of arctic krill and the way it forms large swarms. The three main actions are represented in the algorithm: movement induced by other krill individuals, foraging and random diffusion. The first one defines the direction of krill individuals (search agents) motion and consist of the effects of local swarm density (local effect), a target swarm density (target effect) and a repulsive swarm density (repulsive effect). The effect of the neighbours acts as an attractive/repulsive tendency between the individuals for a local search. Neighbours and its number can be identified in various ways. The simple way is to use "sensing distance" around the krill individual (figure 3).

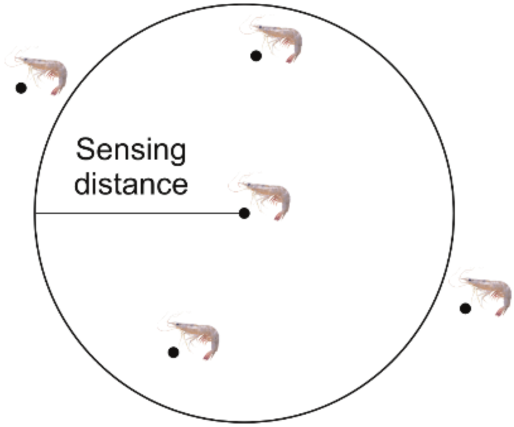

Figure 3. Neighbours identification in Krill Herd Algorithm

The foraging motion is calculated according to the food location and the motion calculated in the previous movement step. The food location is estimated according to fitness function values of the krill individuals, for example using the "centre of mass" idea. The third element of krill movement is physical diffusion which is a random process. However, as the algorithm progresses, the influence of this random element is gradually reduced. All of these actions work in parallel. Individuals that have better fitness values attract other krill while individuals with

[22] Ibid.

[23] A. H. Gandomi, A. H. Alavi, Krill herd: A new bio-inspired optimization algorithm, Communications in Nonlinear Science and Numerical Simulation, vol. 17, issue 12, 2012, pp. 4831-4845

worse values – have repulsive effect. Additionally, the KH algorithm can be improved by adding the mechanism of crossover and mutation known from genetic algorithms.

The KH is a sophisticated and efficient algorithm. An interesting fact is that values of various hyperparameters were set by KH authors according to the results of studies on the real arctic krill behaviours. Another distinctive property of the algorithm is that the global best result is estimated as the centre of food determined according to the fitnesses of all of krill individuals. Usually, in other algorithms, the best solution is simply the best result obtained by one of the search agents.

WHALE OPTIMIZATION ALGORITHM (WOA)[24]

Whale Optimization Algorithm, as its name suggests, was inspired by humpback whales hunting technique called „bubble-net method". During the hunt, whales approach swarms of krill or small fish in a spiral path, starting a dozen of meters under the water surface and then gradually approaching the surface. When circling, humpbacks create air bubbles which force prey to concentrate in the middle of the circle (figure 4).

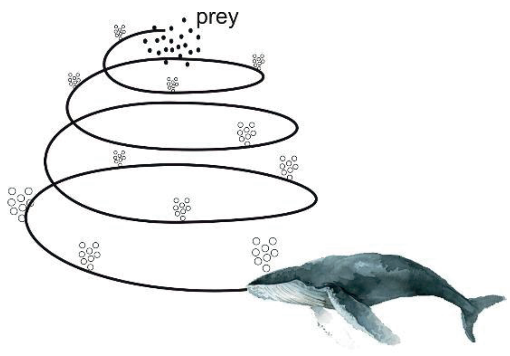

Figure 4. Bubble-net spiral attack behaviour of humpbacks.

Those strategies of encircling and bubble-net attacking are represented in WOA. Additionally, random search for food is implemented. The following equations describe the encircling strategy, and the agent's moves are performed around the current best result:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)\right| \tag{3}$$

[24] S. Mirjalili, A. Lewis, The Whale Optimization Algorithm, Advances in Engineering Software, vol. 95, 2016, pp. 51-67

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \tag{4}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{5}$$

$$\vec{C} = 2\vec{r} \tag{6}$$

where: t indicates current iteration number, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}$ is the agent's position vector, $\vec{X}^*$ is the position vector of current best solution, $\vec{a}$ is coefficient linearly decreased from 2 to 0 along the course of the algorithm, $\vec{r}$ is a random factor with uniform distribution in the range <0,1>.

However, if the value of $|A| \geq 1$, current best result $\vec{X}^*$ is replaced in (3) and (4) by the position of randomly selected, other agent $\vec{X}_{rand}$. This favours the exploitation of search space as in the initial phase of the algorithm it is likely that the circle will be broadened. As the algorithm progresses, the broadening of the circle is less likely to happen than shrinking. At the same time, the spiral deterministic move can be performed by the search agent. This is described by the equation:

$$\vec{X}(t+1) = \left|\vec{X}^*(t) - \vec{X}(t)\right| \cdot e^{bl} \cdot cos(2\pi l) + \vec{X}^*(t) \tag{7}$$

where: b is a constant defining the shape of the logarithmic spiral and l is a random factor with uniform distribution in the range <0,1>.

The decision of selecting encircling or spiral move is chosen randomly.

Despite being a relatively new algorithm, WOA already found many practical applications in various engineering fields and multidisciplinary problems[25]. This is probably mainly due to its relative simplicity, fast convergence and providing a good balance between exploration and exploitation.

SALP SWARM ALGORITHM (SSA)[26]

Another inspiration for swarm intelligence algorithm came from salps. Salps are barrel-shaped, gelatinous organisms that move by pumping water through their bodies which is an example of natural jet propulsion. They are common in oceans around the world. Salps may live alone but often form long, stringy colonies. The SSA is a very simple yet effective algorithm. It reflects two social

[25] N. Rana, MSA. Latiff, SM Abdulhamid, H Chiroma, Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments. Neural Computing and Applications, vol. 32, 2020, pp. 16245–16277.

[26] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, S. M. Mirjalili, Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems, Advances in Engineering Software, vol. 114, 2017, pp. 163-191

behaviours of salps: food chasing and swarming in chain-like forms. In the algorithm, a salp represents a search agent. During initialisation, agents are randomly placed in the search space. One of them is selected as chain leader moving towards the food, as in the best solution found so far (eq. 8).

$$x_l^1 = \begin{cases} F_{currentbest} + c_1((ub - lb)c_2 + lb) \; for \; c_3 \geq 0.5 \\ F_{currentbest} - c_1((ub - lb)c_2 + lb) \; for \; c_3 < 0.5 \end{cases} \tag{8}$$

where ub is the upper bound and lb is the lower bound of the search space.

This move is distorted by c_1, c_2 and c_3 coefficients. Coefficients c_2 and c_3 are random values with uniform distribution in the range <0,1>. The c_1 factor is calculated in each iteration as:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{9}$$

where l is the current iteration number and L is the maximum number of iterations.

At the beginning, the value of c_1 is close to 2 and it dominates the leader moves but as the algorithm progresses, it is quickly reduced and the leader moves around current best solution in gradually smaller and smaller steps. The coefficient c_1 is the key parameter in SSA, because it balances exploration and exploitation.

Apart from the leader, all other salps move towards the proceeding salp (for example, the one with the lower index on the agents list):

$$x_l^i = \frac{1}{2}\left(x_l^i + x_l^{i-1}\right) \; for \; l \geq 2 \tag{10}$$

This mimics the forming of the salp chain, which follows the leader and gradually shrinks around current best solution that helps find an even better solution if it is located nearby (figure 5).

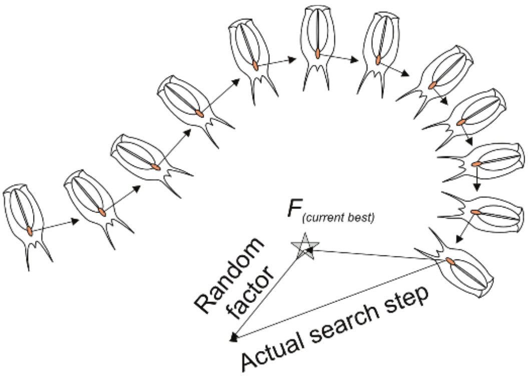

Figure 5. Salp swarm – chain forming and food chasing schematic

The SSA shows good performance in optimisation tasks also in case when optimum solution changes its location during search. A practical advantage of SSA is a small number of algorithm's hyperparameters. Additionally, those hyperparameters' values are predefined by SSA authors and there is usually no need to search for a set of these values that suits best to the particular application of SSA. Additionally, modified version of the SSA for multiobjective problems is available as well.

Although SSA was developed recently, thanks to its simplicity and desired properties it quickly gains recognition and practical applications, currently mostly in, but not limited to, energy industry and power distribution optimisation, for example: prediction of pressure burst in pipelines[27], optimization of wind turbine location[28], technical, economic and environmental optimisation of operation of power systems [29] and prediction of wind power[30].

3. SUMMARY

Selected Swarm Intelligence algorithms, that draw inspiration form marine nature or the outer space, have been briefly presented above. These are of course only some examples of a large and still growing group of swarm algorithms. Different algorithms have different efficiency for a different classes of problems and there is no one, ultimate algorithm to solve them all. Thus, there is the permanent need for new algorithms with fresh, original inspirations as well as for modifications of already developed ones. The main areas where the performance of the algorithms may be improved are: better local optima avoidance, faster convergence, reduction of the number of hyperparameters and reduction of computational complexity. Apart from basic versions of the above mentioned algorithms, there are also many modifications and hybridisation with other algorithms proposed (especially with Genetic Algorithms), examples of which are

27 H. Lu, T. Iseley, J. Matthews, W. Liao, M. Azimi, An ensemble model based on relevance vector machine and multi-objective salp swarm algorithm for predicting burst pressure of corroded pipelines. Journal of Petroleum Science and Engineering, vol 203, 2021.

28 S. Settoul, M. Zellagui, R. Chenni, A New Optimization Algorithm for Optimal Wind Turbine Location Problem in Constantine City Electric Distribution Network Based Active Power Loss Reduction, Journal of Optimization in Industrial Engineering, vol. 14, 2021, pp. 13-22.

29 R.A. El Sehiemy, F. Selim, B. Bentouati, M.A. Abido, A novel multi-objective hybrid particle swarm and salp optimization algorithm for technical-economical-environmental operation in power systems", Energy, vol. 193, 2020.

30 L. Tan, J. Han, H. Zhang, Ultra-Short-Term Wind Power Prediction by Salp Swarm Algorithm-Based Optimizing Extreme Learning Machine, IEEE Access, vol. 8, 2020, pp. 44470-44484.

presented by Gandelli et al [31] and by Nawiis et al.[32], whose works are worth mentioning here, but they fall outside the scope of the present article.

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