Journal of Al-Qadisiyah for Computer Science and Mathematics Vol. 14(2) 2022 , pp Comp. 33–45

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Review on swarm intelligent techniques and their applications in different area

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ARTICLE INFO

Article history:
Received: 29 /04/2022
Revised : 18 /05/2022
Accepted : 31 /05/2022
Available online: dd /mm/year

Keywords:

Swarm Intelligent, Metaheuristics, Optimization, Genetic Algorithm, Ant Colony, Bee Colony, Whale optimization algorithm Salp Swarm, Particle Swarm Optimization, Tunicate Swarm, Bird swarm, Cat swarm optimization

ABSTRACT

Broadly, swarm intelligence (SI) algorithms are considered as nature-inspired techniques improved depending on the idea of communications between living entities such as birds' flocks, Ant Colony, and fish, which means deliberates the group behavior evolving through self-organizing of population individuals. SI has been stimulated via the surveillance of group behavior in its populations in nature because their behavior appears to have the ability to solve complex tasks and optimization problems. The fitness function which is based on SI has been improved to solve combinatorial and mathematical optimization problems by using these algorithms. This means, these techniques work based on the behaviors of individuals in their population so the observation, swam algorithms can be employed for solving the different problems in various applications such as in the medical systems or to enhance the performance of other application systems. In this paper, some swarm intelligent methodologies are reviewed and concerns with their applications in some areas are mentioned.

https://doi.org/10.29304/jqcm.2022.14.2.935

1. Introduction

Recently, metaheuristic methodologies have been utilized in different areas for solving the complex problems of real-life for example engineering, politics, economics, and management. These methodologies are classified into two classes depend on metaheuristic algorithm named single solution and population [1]. Essentially, Swarm intelligence (SI) is concerned with coordination and relies on the self-organization and control of a large groups of people in artificial and natural systems. These individuals have been defining their behavior in which swarm technique depend on it [2].

Fig. 1- Metaheuristic Algorithms Categories [1].

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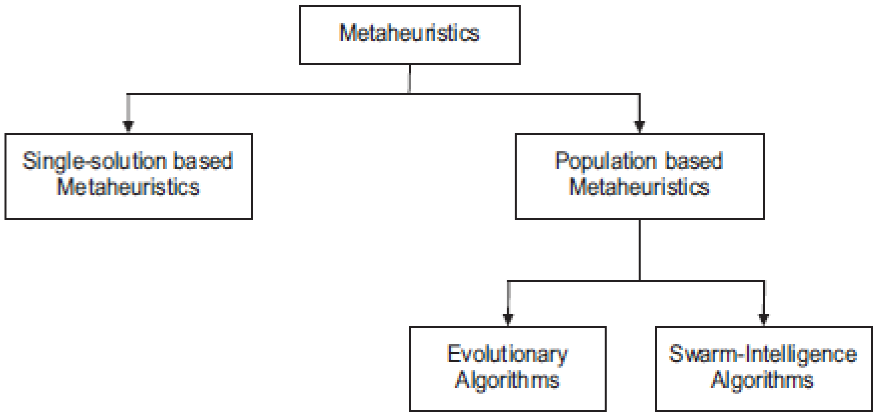

2. Swarm Intelligent

Swarm Intelligence is a type of meta-heuristic methodology whether it simulates a swarm's natural behavior [3]. In precisely, swarm intelligence technique is considered to be branch of optimization algorithms in which the simulation process and operation of modeling roughness, randomized, and stochastic aspects of received chemical, biological, or physical components at high levels of accuracy [4]. These algorithms reveal the required properties of interpretability, scalability, effectiveness, and strength. Term swarm has been referring to travel anywhere in great numbers [3]. In the following review on some swarm techniques and their applications.

2.1. Particle Swarm Optimization (PSO)

This algorithm was suggested by Kennedy and Eberhart in 1995. technique to model bird flocking (PSO). The PSO population is made up ofn particles that have two properties: speed (velocity) and position [5]. Because the simplicity of application of this algorithm in unsupervised, and compound problems, PSO considered as a well-known metaheuristic optimization algorithm. The PSO creates a swarm of particles that navigate around search space in quest of the ideal global greatest value. In detail, potential solution is considered a representation of each particle [6]. Search operation is implemented in global space for global optimal point by N PSO version the members of the group. New member direction is decided based on self and neighborhood member performance [7]. The following are equations 1 and 2 to update velocity and position respectively [2].

$$\mathrm{V(t+1)} = \mathrm{wy(t)} + \mathrm{c_1\, r_1}\, [\, {}^{\wedge}x(t) - x(1)] + c_2 r_2 [g(t) - x(t)] \qquad (1)$$

$$\mathrm{X(t+1)} = \mathrm{x(t)} + v(t+1) \qquad (2)$$

Here
x: refer to the location of a particle at time t
v: denotes particle velocity at time t
c1: mean the acceleration constant for the perceptive element
c2: is the acceleration constant used for the social part
r: which means stochastic random constant

2.2. Ant Colony (ACO)

M. Dorigo et al. are the first employing to solve a discrete optimization issue with Ant Colony Optimization (ACO). This algorithm is depending on ant's behavior for food foundation operation. Pheromone is deposit by ants during the way of walking and discover their route. Pheromone density deposition growths when ants go back with food to source [2]. When a food source is identified, food particles are moved, and once it flies back to its nest, a quicker route is taken, furthermore a quantity of pheromones is repeatedly deposited, which is regarded a way of telling the rest of the ants [4]. Figure 2 demonstrates the overall behavior tracked by the swarm-based methodology in terms of distance optimization [2].

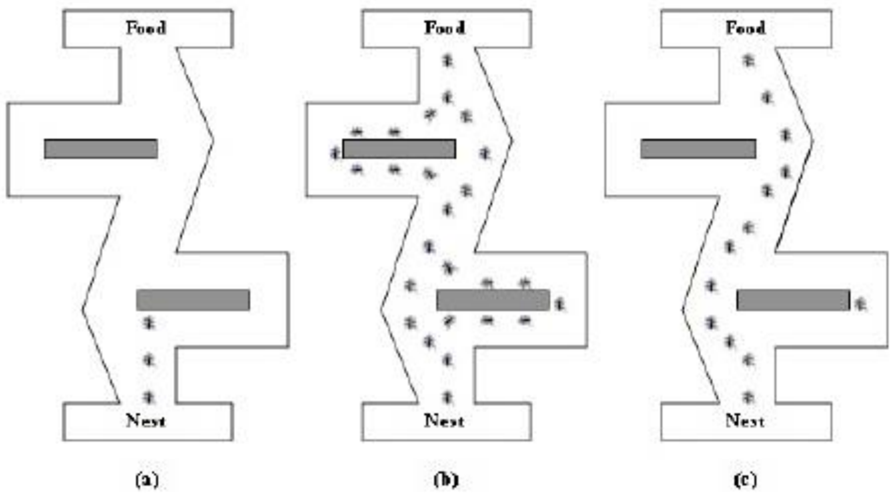

Fig.2- overall behavior tracked by the swarm-based methodology [2]

2.3. Artificial Bee Colony (ABC)

Karaboga first developed this method in 2005, based on honey bees' sophisticated seeking behavior. This algorithm is utilized for solving numerical and nonnumerical optimization problems from its producing [8]. ABC Based principle is a biological progression of honey bee's natural behavior for food-seeking. Mechanism of applying principle for detecting food sources or searching new ones uses many methods as waggle dance. Worker bees play three important responsibilities. Employed bees that are linked to specific food sources, onlooker bees, and scout bees that communicate information about food sources with onlooker bees [3].

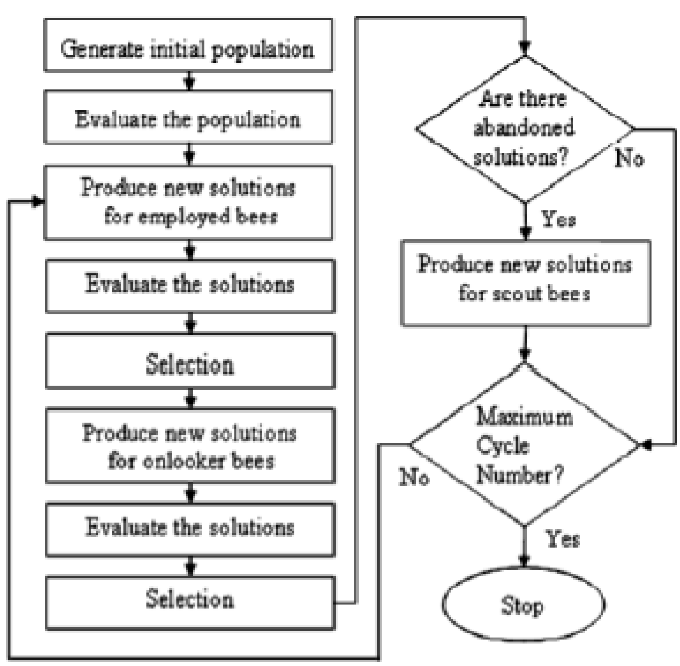

Fig.3- elementary steps of the ABC algorithm [3]

2.4. Genetic algorithm (GA)

GA is recognized algorithm amongst metaheuristic algorithm, make use of stimulation of biological evolution. The essential components of GA are representation of chromosome, selection of fitness, and biologically inspired operators. For more processing chromosomes are elected depend on its fitness value [1]. GA is adaptive so it is utilized for solving search and optimization problems. It depends on genetic processes of biological organisms. In GA, which is an evolutionary method used to solve problems of optimization based on the fittest principle, crossover and mutation are considered operators. GA used in various applications as traveling salesman problem [9].

The mathematical analysis of GA as in equation 3 [1]. GA dynamically modifications the search progression over the probabilities of crossover and mutation and got to the optimal solution [1].

$$R = (G + 2\sqrt{g}\,)/3G \qquad (3)$$

Where:
g: be present the number of generations.
G: refer to a number of evolutionary generations totally set by population.

2.5. Whale optimization algorithm (WOA)

Mirjalili et al. in (2016) produced an optimization algorithm relying on how whales behave named (WOA). Supreme exciting humpback whales' behavior mean with hunting way which known as bubble-net feeding [10]. Three operatives are contained in a whale approach for replicating humpback whales' victim search (Exploration Phase), encircling prey, and bubble-net feeding activity (Exploitation Phase) [11]. the global optimal of an assumed optimization issue based on WOA is identified by beginning the search procedure when a candidate solution set is assumed, the search guides update their locations in the direction of the best search agent until the end criterion is achieved.[12].

2.6. Salp Swarm Algorithm (SSA)

This algorithm based on Mirjalili et al 2017's arbitrary population-constructed algorithm. When seeking for food in waters, SSA resembles the swarming behavior of salps. Salps frequently form a swarm known as a salp chain in heavy waters [13]. Leader is the initial piece in the chain, as well as its behavior represents exploitation and exploration in the search method used by the optimization algorithm. As a result, the group path will be determined by the leader's search operation for food in their space, and its location will be updated in the direction of food source, which is regarded as the best solution [14]. The mathematical model for SSA is specified as in equations 4, 5, 6, and 7 [13].

$$z_n^1 = \begin{cases} p_n + r_1\big((u_n - l_n)r2 + l_n\big) & r_3 \geq 0 \\ p_n - r_1\big((u_n - l_n)r2 + l_n\big) & r_3 < 0 \end{cases} \qquad (4)$$

$$r_1 = 2e^{-}\left(-\frac{4a}{A}\right)^2 \qquad (5)$$

$$z_n^m = \frac{1}{2}ce^2 + v_0 e \qquad (6)$$

$$z_n^m = \frac{1}{2}(z_n^m + z_n^{m-1}) \qquad (7)$$

z_n^1 : Denotes the location of the leader in the nth dimension.
p_n : indicates food source location in the nth dimension.
u_n : means upper bound of nth dimension.

l_n : denotes to lower bound of the nth dimension
r1, r2, r3: refers to variables in random are consistently created in the interval of [0,1].
a: which means to the current iteration
A : indicates to the maximum number of iterations
z_n^m: Location of mith follower salp in the nth dimension.
e : indicates to time.
v_0 : that means the speed in initial.

2.7. Bird swarm algorithm

This algorithm considered as heuristic algorithm derivative based on bird foraging, vigilance and flight behavior in nature in which each one of bird provender food depending on its own experience or group experience [15]. This algorithm is molded on depending on five perfect rules: firstly, randomly bird behavior and it able to in foraging manner or keeping vigilance, secondly in foraging each one of bird quickly able to update individual and global best locations. Thirdly, during preserving vigilance, bird movement be toward swarm center. Fourth, commonly new places birds fly to them. Fifth, food has been searched actively [16]. The mathematical model of the algorithm is as equations 8, 9, 10, 11, 12, and 13 [15].

$$X_{i,j}^{t+1} = x_{i,j}^{t} + \left(p_{i,j} - x_{i,j}^{t}\right).C.rand(0,1) + \left(g_j - x_{x,j}^{t}\right).S.rand(0,1) \qquad (8)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + A1\left(mean_j - x_{i,j}^{t}\right).rand(0,1) + A2\left(p_{k,j} - x_{i,j}^{t}\right).rand(-1,1) \qquad (9)$$

$$A1 = a1.exp\left(-\frac{pFit_i}{sumFit+\varepsilon}.N\right) \qquad (10)$$

$$A2 = a2.exp\left[\left(\frac{p_{Fiti}-p_{Fiti}}{|p_{Fit}-p_{Fit}|+\varepsilon}.N\right)\frac{N.p_{Fitk}}{sumFit+\varepsilon}\right] \qquad (11)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + rand(0,1) \times x_{i,j}^{t} \qquad (12)$$

$$x_{i,j}^{t+1} = x_{i,j}^{t} + (x_{k,j}^{t} - x_{i,j}^{t}) \times FL \times randn(0,1) \qquad (13)$$

Where:

$x_{i,j}^{t}$: signifies the site of ith bird in the dimensionality of jth in the tth generation population.
c and s: denote learning coefficients.
gj : denotes the best earlier site common by the swarm.
p (i, j): mean the best earlier site of the bird.
k refers to a positive integer where $k(k \neq i)$
a1, a2 considered as two positive constants in [0,2].
sumFit: signifies the summation value of the swarm's best fitness
pFiti: represents the ith bird's best fitness value.
ε: the minimum constant in the computer, for preventing a zero-division error.
meanj : characterizes the component of the average location of the whole bird's swarm.

2.8. Tunicate Swarm Algorithm (TSA)

This algorithm considered as newest bio-inspired meta-heuristic algorithm. Two significant behaviors are based to make navigation and seeking for source food. One jet propulsion when somewhat propel in single direction and other swarm intelligence [17]. Mathematically first behavior modeling which known as jet propulsion encounter three Conditions: to avoid tunicates quarrels tunicates, modification the possible tunicate location, and near with potential tunicate. Alternatively best optimal solution is found by updating other explorers existence based on swarm behavior function [18]. Figure 3 illustrates the flowchart of this algorithm [17].

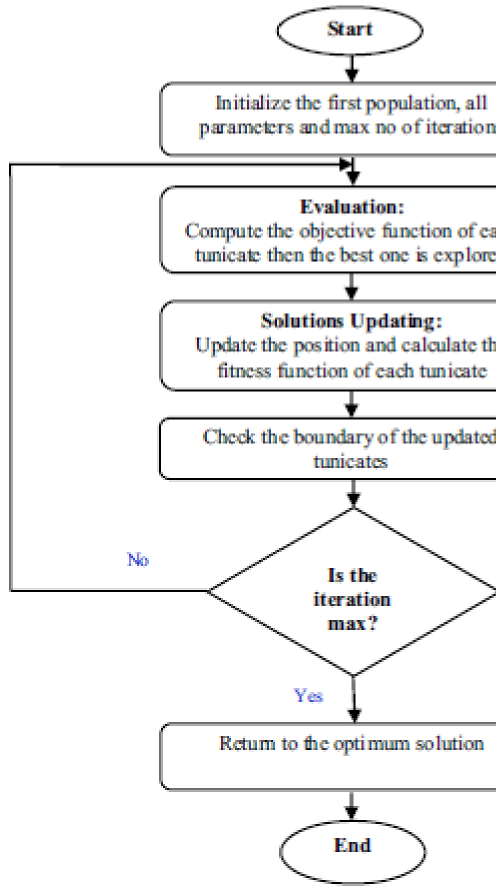

Fig. 3- Illustrates the Tunicate flowchart [17]

The comparisons between these swarm techniques are summaries in Table 1.

Table 1 - comparisons between these swarm techniques.

Technique	Description	Properties	utilization
(PSO)	model bird flocking (PSO), n particles population	based on 2 characteristics • velocity (speed), calculated as in Eq.1 • position and calculated as in Eq.2	in unsupervised, and compound problems, PSO considered as a well-known

			metaheuristic optimization algorithm
(ACO)	Model ant colony behavior to search food	Based on Pheromone which is deposit by ants to discover their route As explain in Figure 2	solve a discrete optimization issue
(ABC)	Model honey bees' sophisticated seeking behavior	Based on • Employed bees which associated to explicit food sources, • onlooker bees • scout bees which are link food sources information to onlooker bees as explain in Figure 3	for solving numerical and nonnumerical optimization problems
(GA)	simulation of biological evolution	Based on • Chromosome • selection of fitness biologically inspired operators	solving search and optimization problems
(WOA)	simulation of behavior of whales	Based on • Exploration Phase • encircling prey bubble-net feeding activity (Exploitation Phase)	optimization algorithm
(SSA)	look like the swarming behavior of Salps in water when search on food	• leader's search operation for food in their space • its location will be updated in the direction of food source as demonstrated in Eq. (4, 5,6 and 7)	optimization algorithm's search method
Bird swarm algorithm	heuristic algorithm derivative based on bird foraging, vigilance and flight behavior in nature	• randomly bird behavior and it able to in foraging manner or keeping vigilance, • in foraging each one of bird quickly able to update individual and global best locations. • during preserving vigilance, bird movement be toward swarm center. • commonly new places birds fly to them. • food has been searched actively as shown in Eq. (8, 9,10, 11, 12 and 13)	Search optimization
(TSA)	As newest bio-inspired meta-heuristic algorithm	Based on • jet propulsion when somewhat propel in single direction • swarm intelligence as showed in Figure 4	Search optimization

3. Some of an existing application on Swarm techniques in different areas

Many applications of SA have been reported from various fields. SA has been employed to solve real-world problems and optimization. A brief summary of the main applications of SA is shown below:

Chandirasekaran and Jayabarathi [19], designed a protocol based on Cat swarm optimization, or "CSO," is an evolutionary approach. This was run in real - time basis to reduce intra-cluster distances between heads and members of cluster and improve WSN energy distribution. They use sensor nodes placed in the field and aggregated into clusters in order to assess the WSN protocol's performance. The intensity of received signal, voltage of residual battery, and sensor node intra cluster distance are all investigated in the suggested approach. The battery energy level of the "LEACH" and "PSO" algorithms has been greatly raised when compared to"LEACH-C" and the approach of "PSO".

Eid [20], She proposed using a version of algorithm in binary for WOA to determine which feature subset is the most appropriate and improve classification accuracy “BWO”. Using nine benchmark datasets, the BWO was compared to three optimization-based feature selection algorithms: particle swarm, ant colony, together with a genetic algorithm. The findings demonstrate that the designed BWO can explore the space of feature for appropriate feature pairings and outperform existing methods on the most datasets in expressions of the classification accuracy average and rate of convergence speed. Asset allocation and constraint optimization are both possible with this method.

Almahdi and Yang [21] suggest with the Calmar ratio, a hybrid of RRL (recurrent reinforcement learning) and PSO. They demonstrate that a system with a target function based on the Calmar ratio has a much wider range of efficient frontiers than portfolios based on mean-variance and Sharpe ratio using S&P100 index stocks. The suggested method was compared to numerous “PSO” based long-only limited portfolios in order to construct an "RRL-PSO" portfolio rebalancing decision adaptive system with a stop-loss re - training technique. They further illustrate that the suggested model routinely exceeds the benchmark tests set, particularly if transacting at a high cost.

For handling portfolio optimization issues with cardinality limitations, Yang & et al [22] suggested "AI-BSA" stands for adaptive BSA with an uneven arbitrary flight. They demonstrate AI-local BSA's convergence under mild conditions and use numerical tests to demonstrate its usefulness. They also provide a thorough procedure for employing “AI-BSA” to tackle the cardinality-constrained portfolio optimization issue, as well as an example to comparing both of the PSO and the bird swarm techniques.

Evolutionary algorithms “EA” is utilized by Yaseen and et al [23] to formulated optimum operation guidelines for reservoir and dam water system. They developed "HB-SA," that combines "BA" and "PSOA" to create a hybrid optimization method. HB-SA is proven by reducing irrigated agriculture shortfalls in the dams of Golestan and Voshmgir in Iran, which are part of a multi-reservoir system. The findings showed that the "HB-SA" algorithm presented by the researchers can be effective and can produce the smallest irrigated agriculture losses over the time period of study and exceeds optimization methods that are currently available, as well as reducing the convergence procedure's computational time. To train neural networks, Bairathi and Gopalani [24] created "MLSSA" stands for " swarm algorithm using multiple leaders of salps ". MLSSA has been tested on thirteen datasets and put through its paces using a variety of mathematical optimization benchmark functions. The results demonstrate MLSSA's capacity to converge to the best solution.

For solving engineering design challenges, Abualigah and et al [25] suggested a hybrid "SSA" the Salp Swarm Algorithm combined with the "HC" the hill climbing methodology using several schemes of selection. There are two steps to the algorithm. I n the initial stage, the SSA with HC local search has been hybridized, named: HSSA, used to boost its exploitation capabilities. They used a selection scheme in the second stage to improve the exploring abilities of HSSA. They looked into six well-known selection methods. After that, select a proportionate scheme for selection since it yielded the most favorable results. The term "PHSSA" refers to a hybridized SSA that using a proportionate selection technique. The suggested method was put to the test utilizing a total of four engineering design issues, as well as thirty benchmark functions in a series of trials. The results of the benchmark functions show that "HSSA" was able to bypass the SSA's local search limits. PHSSA improved performance by striking the right balance between exploration and exploitation, while also preserving solution variety and preventing convergence too soon. It also achieved outcomes that were at least equivalent on engineering design issues, if not superior, to SSA.

For feature selection issues, Aljarah and et al [26] suggested an upgraded "ODSSA-lbest" is a multi-objective SSA method with two key elements, (1) a strategy that changes over time in a dynamic way together with (2) local best-fit solutions. The suggested "MODSSA-lbest" was compared to Multi-Objective Evolutionary Algorithms "MOEAs" on thirteen benchmark datasets. The research result reveal that the "MODSSA-lbest" method outperforms "MOEAs" algorithms by a wide margin. Kaur and coworkers [27] proposed TSA, or Tunicate Swarm Technique, is a bio-inspired metaheuristic optimization technique. They used sensitivity, convergence, and scalability analyses, as well as an ANOVA test, on seventy-four benchmark test issues, and compared it to numerous metaheuristic methodologies based on the derived optimal solutions. The suggested technique was also tested by applying six controlled plus one uncontrolled design issues of engineering to ensure toughness of it. In compared to other competitive algorithms, The findings demonstrate that "TSA" deliver superior optimum solution.

To solve high-dimensional functions, QIAO and YANG [28] suggested a method Kernel Fuzzy C-means as a based in additional to dolphin swarm algorithm. Kernel FCDSA (Fuzzy C-means dolphin swarm algorithm) was introduced in first phase to increase the dolphin swarm algorithm's global convergence capabilities. KFCDSA combination performance is then tested using five common high-dimensional functions in the second stage. Finally, the performance of various meta-heuristic algorithms is evaluated using some indicators. The results reveal that, based on five distinct evaluation indicators, the suggested algorithm's efficiency outperforms that of dolphin swarm method in addition to certain advanced algorithms based on metaheuristic. According to the results, incorporating Kernel Fuzzy C-means with DSA increases performance and delivers global optimal solutions for complex functions (high-dimensional).

Braik and et al. suggested an augmentation approach for the salp swarm algorithm "SSA" termed "ESSA" enhanced salp swarm algorithm [29]. To improve ESSA's convergence performance, they proposed three enhancements: (1) a new position updating procedure, (2) a new dominating parameter not utilized in SSA, in addition to (3) Using "ESSA" itself, a temporal convergence strategy for altering the dominating parameter of "ESSA". These "SSA" enhancements made possible by "ESSA" helps it solving a range of real-world optimization issues in order to prevent an early convergence and swiftly identify the global optimal solution. ESSA put numerous simple benchmark test routines to the test. ESSA's performance was put up against that of other meta-heuristic algorithms. To exemplify the usefulness of ESSA in addressing real-world problems and applications, five popular challenges of engineering design plus two industrial issues of real-world are employed. ESSA outperforms SSA as well as other meta-heuristic algorithms in terms of performance and convergence.

Zhang and et al. [30] proposed "CMSRSSSA", a "SSA" form of the strengthened salp swarm method using an ensemble mutation technique and a relaunch mechanism, to improve SSA's exploration and exploitation capacity and overcome the SSA's single search mechanism's limitation when it comes to solving difficulties involving continuous optimization. An "CMS" ensemble/composite mutation technique can increase SSA exploitation and exploration trends, also a tactic for restarting can help salps in escaping the local optimum. They measured the proposed "CMSRSSSA" functionality in handling difficulties of continuous optimization using "IEEE CEC2017" benchmark tasks, as well as Real-world benchmark challenges from the "IEEE CEC2011" dataset and issues of constrained optimization to analyze the CMSRSSSA quality in order to make practical recommendations. All contestants, along with the champions of the related IEEE CEC competition are beaten by the CMSRSSSA, according to experimental and statistical results.

As a type of method that uses Swarm intelligence to find solutions, Xia and et al [31] devised a barebones adaptive algorithm (salp swarm) plus quasi-oppositional training to adjust (QBSSA) for finding solution to SSA problem of stagnation. They presented an adaptive full featured method "QBSSA" that can aid in achieving both high solution quality and accurate convergence speed; The population can be steered out of local optimal trapping by using quasi-oppositional-based training to broaden the search field. The ability to deal with challenges that are multidimensional and multimodal is tested using "CEC 2017" benchmark test suit; Then, using "KELM" and "QBSSA," develop a "QBSSA–KELM" to overcome the difficulties in diagnosing medical diseases. In terms of solution accuracy and convergence speed, all the tests outcomes and their conclusions show that "QBSSA" outperforms and outperforms all other algorithms in comparison.

Yi (32), He constructs a model for estimating agricultural water requirement using the PSO, evaluates the drawbacks of the classical PSO, as well as making necessary enhancements to the algorithm for quantum particle swarms. They also analyze the implementation progression of PSO algorithms in the proposed system and create the functional structure of the agricultural water resource requirement forecasting system depending on predicted water resource requirement. They devised a simulation test to assess the impact of system forecasting on real-world data. Use the model you've built to look into the elements that influence water demand forecasting. The proposed model appears to be more effective in forecasting water resource demand based on the experimental results.

A summarization of Some existing application on Swarm techniques illustrated in table 2.

Table 2 – A summary of application on Swarm techniques.

Year, Author(s), reference	Techniques	Dataset	area	Real Time
(2017), Chandirasekaran and Jayabarathi [19]	(CSO)	conducted from (16) wireless sensor	application of control and monitoring in military, application of health care	☑
(2018), Eid [20],	(BWO)	(9) benchmarks from UCI (Australian, German Credit, Sonar, Zoo, NSL-KDD, Diabetic, Heart Disease, Segment, Liver Disorders)	Feature selection Problems	☒
(2019), Almahdi and Yang [21]	(RRL and PSO) with Calmar ratio	Constructed from the weekly closing prices of five years (1/1/2011 to 31/12/2015)	constrained portfolio problems	☒
(2019), Yang & et al [22]	(BSA)	fifteen benchmark functions as illustrated in [22]	constrained portfolio problems	☒
(2019), Yaseen and et al [23]	(HB-SA)	Built with the main features of the "Golestan and Voshmgir dams"over 5 years (2007 -2012)	Dam and reservoir water system operation guidelines	☒
(2019), Bairathi and Gopalani [24]	(MLSSA)	25 Mathematical benchmark functions selected from thirteen benchmarks (IEEE CEC-2015)	Solve problems of Optimization	☒
(2020), Abualigah and et al [25]	(SSA) hybridized with (HC)	30 functions from Popular benchmarks listed in [25]	solve problems of engineering design	☒
(2020), Aljarah and et al [26]	MODSSA	(13) benchmarks from UCI (Nci9, Colon, SonarEW, PenglungEW, Lymphography, WaveformEW, Zoo, HeartEW, Exactly, Exactly2, Glioma, Leukemia, SpectEW)	Feature selection Problems	☒
(2020), Kaur and coworkers [27]	(TSA)	test functions from benchmark (CEC-2015 and (CEC-2017)	solve problems of engineering design	☒
(2020), QIAO and YANG [28]	(KFCDSA)	Levy function with virus dimensions (75, 125, 175, 500, 1000)	Solve problems of high dimensional optimization function	☒
(2021), Braik and et al. [29]	(ESSA)	23 benchmark functions from (Dhiman and Kumar 2017, Mirjalili 2015)	Solve problems of Optimization	☒
Zhang and et al. [30]	(CMSRSSSA)	IEEE CEC2017 benchmark problems	Solve problems of continuous optimization	☒
(2022), Xia and et al [31]	(QBSSA)	CEC 2017 benchmark	solve problems of high dimensional and multimodal	☒

(2022), Yi (32)	(PSO)	Conducted from the monthly agricultural water demand predicted of past 6 years	Solve problem of agricultural water resources demand	☒

4. Conclusion and discussion

Different types of swarm intelligence techniques and its behavior, and innovative biologically stimulated meta-heuristic optimization algorithm are reviewed, so the observation from previous sections swam algorithm can be employed for solving different problem in various applications as see particle swarm algorithm used in Forecast of agricultural water resources demand, and also used in A constrained portfolio trading system and others, and it has its own efficiency in each application. Also as seen in using salp algorithm when the same algorithm is employed in different fields as explained when salp is used in Medical Diagnosis Systems, and also in enhancing the convergence performance, and utilized in feature selection and optimization problems. Each algorithm has its efficient performance in each application. In other hand for getting more suitable and accurate optimal solutions, some applications make use of hybrid two techniques swarm intelligent as illustrated in the previous reviewed section.

Acknowledgements

The authors thank the "Department of Computer Science", "College of Science", "Mustansiriyah University (www.uomustansiriyah.edu.iq) ", Baghdad-Iraq for supporting this present work.

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