2019 Scientific Conference on Network, Power Systems and Computing (NPSC 2019)

A review of glowworm swarm optimization algorithm

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***Abstract*—This paper reviews glowworm swarm optimization algorithm (GSO), which is a meta-heuristic swarm intelligence algorithm. The GSO algorithm is applied for solving optimization problems. Shortcoming of the GSO algorithm has been identified with the introduction and discussion of the improvement taken place in recent years. Adaptive step size and new movement rules have been widely used in the improvement of GSO algorithm. The application of GSO including clustering techniques is also presented. Very promising GSO clustering versions use MapReduce framework to improve the computational efficiency when the clustered data set is large and thereby reducing the time complexity.**

Keywords—Glowworm swarm optimization, Optimization, Swarm intelligence, Clustering

I. INTRODUCTION

Swarm Intelligence (SI) originates from the study of the group behavior of social insects represented by ants and bees. Like the group phenomenon we see in nature, SI is the individual in the group that uses local information to perform a series of actions, then propagated by neighbors between individuals [1]. Meta-heuristic algorithms deriving from biological SI has the core of using biological information, including Ant Colony (ACO) [2] algorithm,

Artificial Bee Colony (ABC) [3] algorithm, Artificial Fish-swarm (AF) [4] algorithm, Particle Swarm Optimization (PSO) [5], Glowworm Swarm Optimization (GSO) [6] algorithm and so on. Many modern and complex problem can be solved by using a group of biological meta-heuristic algorithms. Heuristic search is to evaluate each location in the target space, find the best location, and then search from that location until the goal is reached. This type 10 of search can avoid searching for unnecessary paths and improve optimization efficiency.

Having its own local dynamic decision range and unique luciferin update behavior and relying on local information to search for the global optimal solution, GSO is a newer SI algorithm with some problems to solve and improve. GSO has obvious advantages in solving the local optimal problem by comparing with other nature-inspired techniques [7]. However, when solving global optimization problems, GSO has the problems of slow convergence 15 and low accuracy in the later stage, especially when optimizing complex functions.

The remainder of this paper is organized as follows: Section 2 presents GSO basis and followed by the introduction of GSO working principle in the context of the phases that constitute each cycle of the algorithm. In Section 3, the shortcomings of GSO was analyzed with improvement suggested. The applications of GSO on clustering algorithm and further development are shown in Section 4 and 5, respectively.

II. GLOWWORM SWARM OPTIMIZATION

GSO stems from the study of the behavior of glowworms in nature. Glowworms with higher levels of luciferin attract the companions within the field of view (local-decision range) to move toward them. The direction in which the glowworms move each time depends on the location of their neighbors. The brightness of the glowworm is related to the fitness value of the objective function. The higher the level of luciferin carried by glowworms, the brighter the glowworms, the better the location of the glowworms, that is, the corresponding objective function value is optimal. GSO is a more effective way to identify multiple peaks comparing with most of earlier approaches dealing with multimodal function optimization.

GSO introduced by Krishnanand and Ghose in 2005 is an original SI algorithm for optimization. As an optimization algorithm, GSO has shown the ability to perform disaster response including the discovery of nuclear leaks, hazardous chemical spills, and sources of fire in forest fires [8–14].GSO algorithm can be used to find multiple local maxima or minima of multimodal functions with the ability to capture all extreme points of a multimodal function simultaneously. GSO begins by placing n glowworms in the search space of dimension d randomly consisting of the following steps: initialization, luciferin update, finding neighbors, movement, location update and neighborhood range update (Figure. 1).

Initially, each glowworm is assigned an equal luciferin value and a threshold decision radius. At the first iteration of the GSO algorithm, glowworms begin to update luciferin, the luciferin level of each glowworm increases according to the objective function value of its position and decays over time. After that, each glowworm begins to find its neighbors in the local-decision range whose luciferin value higher than its own and selects one of its companions within its neighborhood as the target of its own movement, thereby updating the location. All glowworms then dynamically adjust their local-decision range making to find more companions. After multiple iterations of the algorithm, most of the glowworms will eventually gather in several optimal locations.

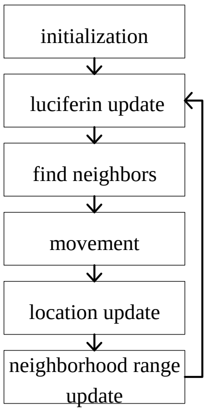

Figure. 1. The general phases of the GSO algorithm.

III. Improvement Of The Gso Algorithm

Through the analysis of the GSO algorithm in Section 2, it is considered that the algorithm may have the following shortcomings: *(1)* The GSO algorithm must require excellent individuals within the sensor range to provide information to them, otherwise the individual will stop searching, the high dependence on the excellent individuals slows down the convergence speed. *(2)* When the individual is approaching the peak, if the step size is greater than the distance, the individual can oscillate near the peak. *(3)* In the absence of neighbors, the agents may not move at all, which will reduce the final optimization accuracy of GSO.

In response to the problems of the GSO algorithm, researchers proposed modifications of GSO as shown in Table 1, which are mainly focused on either modifying GSO for global optimization problems or improving the convergence speed and the accuracy of basic GSO. The table consists of three main sections: Modified (adjustment to the basic GSO algorithm), Hybrid (fusion of the GSO algorithm with other algorithms) and Others (other improvements of the GSO algorithm).

A. Adjustment to the basic GSO algorithm

He et al. [15] proposed ansection:6 algorithm of small-scale and multi-population glowworm groups (MPGSO). The principle of MPGSO is dividing the domain of the objective function into k parts, and then the *k* populations find their extreme points individually. The experimental results show that comparing with GSO, MPGSO significantly reduce calculation time and improve the calculation accuracy.

TABLE I. Publications Of Improved Gso Algorithms

GSO variant	**Topic**	**References**
Modified	Initialization	[15, 16]
Modified	Step size	[17–23]
Modified	Sense range	[24]
Modified	Movement	[16, 17, 24–26]
Modified	Location update	[24, 26]
Hybrid	Complex method+GSO	[27]
Hybrid	Chaotic+GSO	[28]
Hybrid	ABC+PSO+GSO	[29]
Hybrid	BFGS+GSO	[30]
Hybrid	AF+GSO	[31]
Others	Discrete	[32, 33]
Others	Layering	[34]
Others	Sub-population	[35]

He et al. [16] proposed another method for initializing glowworms based on chaos theory, and a new movement strategy is also proposed. When the number of iterations of the algorithm is greater than 10, the average position of all glowworms is used to replace the position of a portion of glowworms with poor fitness function values, enabling 65 glowworms to quickly search for the optimal value. The author also proposed a new search method based on self-adaptive step size and global information [17]. A method of adjusting the step size by iterative nonlinear adaption is proposed to solve the problem when the glowworm approaches the best solution and the fixed step size is larger than the distance between the glowworm and the optimal solution, the glowworm crosses the peak. In the movement phase, random function and optimal fitness function value *gbest* are added to improve the convergence speed of GSO allowing a quick and accurate convergence to the global optimal solution.

Ouyang et al. [18] proposed the Self-Adaptive Step Glowworm Swarm Optimization (ASGSO) solving the problems that GSO cannot acquire solutions exactly and converge slowly in the later period for solving the multimodal function. ASGSO combines with the luciferin-factor to adaptively adjust the step showing good experimental results show for quick and precise global optimization. Later, many scholars [19–23] have proposed to improve the convergence speed and optimization precision of the algorithm in the late iteration by replacing the fixed step size in GSO with adaptive step size. Glowworms in the GSO algorithm do not move without neighbors, which cause the unbalanced loads problem in the case of parallel processing. Oramus [24] proposed three improved strategies for traditional GSO. The author believed that the improved GSO algorithm should use small groups more efficiently with fewer iterations, i.e. it should consume less memory and CPU. The first adjustment strategy is to try to jump to a new location if the agent glowworm has no neighbors. The new location is randomly generated based on the previous location, and the jump is accepted only if the current solution does not deteriorate, otherwise the location of the agent glowworm remains. The second adjustment strategy is that when the number of glowworms in the neighborhood set with a radius equal to the sense range is less than the neighborhood threshold, the sense range will be extended by 5%.

The author explained that this improved strategy helps to weaken the impact of the random motion introduced in the first strategy and helps the agent to use information obtained from other agents. The third adjustment strategy is to assign a master to each group to determine the movement of slaves in the group. The author used five test functions to compare the standard GSO algorithm with three adjusted strategies. Experiments show that the simple adjustments of the standard GSO can significantly improve the performance.

Zhou et al. [25] proposed a leader GSO (LGSO) algorithm to improve the global optimization ability of GSO. GSO has bad optimization ability at the high dimension. In the LGSO algorithm, after the algorithm determines the local-decision range of each glowworm, select the glowworm at the best location of the current iteration as the leader, then all the glowworms move to the position of this leader, thus making the glowworms have better global optimization capabilities and good performance in high-dimensional space. Liu et al. [26] proposed an adjusted movement rule to improve the global search accuracy of the GSO algorithm. By adding a random number to the position with the highest value of the glowworm fitness function to form the position of the next moment, the no neighbor problem can be solved. Experiments were conducted with eight benchmark functions, and the improved location update strategy improved the accuracy of the GSO algorithm for searching the global optimal solution.

B. Fusion of the GSO algorithm with other algorithms

Zhao et al. [27] proposed the complex method guidance the GSO algorithm (CGSO) to solve the shortcomings of the GSO algorithm with poor optimization results in high-dimensional space. By introducing the complex method to guide the glowworm swarm's search, CGSO algorithm continuously makes the worst glowworm swarm become the better glowworm swarm, so that the glowworms gathered to the position of the better glowworm, finally successful search for the optimal solution. The experiment shows that the improved GSO algorithm not only resolves the shortcoming of the GSO algorithm in high-dimensional space, also effectively avoid falling into local optimum and improve search accuracy. Huang and Zhou [28] proposed a new GSO algorithm based chaotic (CGSO), which combines chaotic search strategies with the GSO algorithm to initialize the first iterative solutions. The CGSO algorithm avoids the problem that GSO is easy to fall into the local optimal solution, resulting in high-quality initial solutions and improved the convergence speed and precision.

Wu et al. [29] proposed two rules about the movement of glowworms for continuous optimization problems to improves the accuracy and convergence efficiency of GSO. The new movement formulas which are inspired by ABC and PSO and the greedy acceptance criteria for the location update phase are proposed in this paper. Authors compared this improved GSO algorithm with basic GSO and with other SI algorithms to show the ability of improved GSO algorithm to solve global optimization problems. Ouyang et al. [30] proposed a hybrid algorithm BFGS-GSO. Broydenndash; Fletcherndash; Goldfarbndash; Shanno (BFGS) is a classical gradient algorithm and GSO for optimization problems. Eight standard test functions were used to show that BFGS-GSO has better global optimization ability than traditional GSO algorithm.

Zhou et al. [31] proposed a hybrid AF and GSO algorithm (HGSO) which adds predatory and evolution behavior of fishes into GSO to solve global optimization problems. In addition, the author applied the local optimization feature of the simulated annealing algorithm to solve the problem of premature convergence of GSO. The experiments on standard test functions verify that the HGSO algorithm improved the convergence ability and computational accuracy of GSO.

C. Other improvements

Zhou et al. [32] proposed a discrete GSO (DGSO) algorithm to improve the local search ability of GSO and accelerate the convergence speed. A new distance formula and encoding formula for the location update phase of DGSO are given. In addition, in order to increase the diversity of the solution and accelerate the convergence of the algorithm, the author introduced a simple 2-Opt operator as a local optimization method in DGSO to improve the optimal solution obtained by each evolution. The experimental results show that DGSO has less computation and evolution time than GSO in finding the global optimal solution. Li et al. [33] proposed a binary form of GSO, which is also a discrete GSO algorithm. In this new GSO algorithm, the Euclidean distance in the location update phase of the classic GSO was replaced by Hamming distance.

He et al. [34] proposed a new GSO algorithm with a two-layer hierarchical structure (HGSO). For top swarm, the operation of selection and crossover is incorporated to enhance the diversity of glowworms and adaptive step size update strategy is proposed. The experimental results show that the computing time is greatly reduced in solving multimodal functions. Zhou et al. [35] proposed to introduce the concept of the tribe in GSO (TGSO) to improve the problem that traditional GSO algorithm is easy to fall into local optimal solution and low accuracy in later optimization. The0 TGSO algorithm treats each evenly distributed sub-population as a tribe. Each tribe constitutes the first level and evolves independently according to the classic GSO. The obtained optimal individual forms the second level, and then uses the most tribe. The excellent solution carries out the communication between the tribes to obtain the global optimal solution.

IV. GSO CLUSTERING ALGORITHM

Clustering analysis plays an important role in knowledge discovery and data mining [36]. It adopts the unsupervised learning method, and the results of clustering are similar within the class and are different between classes. Aiming at some shortcomings of traditional clustering algorithms, some techniques for clustering using natural heuristic algorithms have emerged [36–38]. The GSO algorithm has been applied well in clustering analysis with its excellent performance.

A. CGSO

Kao et al. [39] proposed a new clustering algorithm (CGSO) that use GSO to search the best set of clustering centers in a real number space. Experiments show that the CGSO algorithm has strong advantages compared to other biological SI based algorithms. The main aim of CGSO is to search for optimal *K* cluster centers to minimize the distance between points x_i and other cluster centers m_i. That is, the data clustering problem is transformed into a minimization problem:

$$MinF(x,m) = XX_{KX_j} - KN_i m_i k \quad (1)$$

$$\|x_j - m_i\| = \sqrt{\sum_{p=1}^{P}(x_{jp} - m_{ip})^2} \quad (2)$$

where, K represents the number of clusters, N_i represents the number of data point belonging to the i^{th} cluster, x_j is the j^{th} data point, m_i is the i^{th} cluster center, and P represents the number of data attributes. In order to make each data point as close as possible to the nearest data clustering center, the author designed the following fitness function:

$$J(X_j) = mink_{X_j} - m_i k, i = 1,2, \dots, K \quad (3)$$

where, $X_j, j = 1,2, \dots, N$, m_i is the center of cluster i. $J(x_j)$ represents the fitness of glowworm x_j position, which is the objective function. The experimental results show that the solution quality of the CGSO algorithm on data sets Thyroid, Iris and Wine is better than those of K-means [40] and ACO clustering algorithm proposed by Schelokar, SACO (2004) [41]. CGSO get a better objective value compared with SACO and K-means on these three data sets used in experiments. K-means always requires a very short time to complete computation but provides worse objective function values. CGSO found the optimal objective value with shorter time compared with SACO for all three data sets.

B. GSOCA and GSOCA+K-means

Huang and Zhou [42] proposed two clustering approaches base on the GSO algorithm in 2011. The first algorithm is using GSO to realize self-organization data clustering (GSOCA). To achieve intra-class similar clustering results and different classes separated, the authors use the local space relative density to reflect the local data similarity. $X(x_1,x_2,\cdots,x_m)$ is a cluster data object of glowworm i in m-dimensional search space, and the local space relative density is calculated as below:

$$d(X) = \frac{|N(X,r)|}{num-g} \quad (4)$$

where, $|N(X,r)|$ represents the neighborhood set containing in local search space within distance of X, and num_g represents the number of data object.The attraction of $X(x_1,x_2,\cdot\cdot\cdot,x_m)$ is computed by the equation:

$$J(X) = -ln(\frac{1}{num-g}) + ln(d(X)) \quad (5)$$

Here the meaning of $J(X)$ in the GSOCA algorithm is similar to the fitness function in the GSO algorithm. The rest of GSOCA remains the same as basic GSO in Section 3. Obviously, the highlight of the CGSO algorithm is the ability to implement self-organization clustering without the need to initialize the number of cluster centers. The second algorithm is a hybrid GSOCA and k-means. The general idea of this hybrid algorithm is to first perform GSOCA and terminate the GSOCA algorithm when the algorithm iteration reaches the threshold. Then authors inherit the result of the GSOCA algorithm as the initial seed of the K-means algorithm, and finally enters the K-means algorithm process until the algorithm stops. In the test, the authors showed that the hybrid algorithm of GSOCA and K-means outperformed PSO, basic K-means, and two other clustering algorithms New1 and New2 [43] in Artificial data 2 and Iris data sets.

C. CGSO, MRCGSO, and CGSOm

Aljarah and Ludwig [44] proposed a novel clustering algorithm based on GSO in 2013 named CGSO. It is a partitioning-based clustering. Not like the traditional clustering algorithms, this CGSO algorithm does not require prior-knowledge about clusters number. CGSO considers the advantages of GSO multimodal search capability to locate the optimal center, each center represents a class of local the optimal solution, and all local optimal solutions together constitute the global optimal solution of the clustering problem. Compared with the main flow of the basic GSO algorithm mentioned in 2, the CGSO algorithm replaces the location update phase in GSO with the construction of the candidates center. In addition, three different fitness functions 6 7 8 were proposed to add flexibility and robustness to the CGSO algorithm.

$$F1(g_j) = \frac{1/n \times |cr_j|}{SSE \times \frac{intraD_j}{max_j(intraD_j)}} \quad (6)$$

$$F2(g_j) = \frac{InterDist \times 1/n \times |cr_j|}{\frac{intraD_j}{max_j(intraD_j)}} \quad (7)$$

$$F3(g_j) = \frac{InterDist \times 1/n \times |cr_j|}{SSE \times \frac{intraD_j}{max_j(intraD_j)}} \quad (8)$$

where, *SSE* represents the Sum Squared Error, *crj* is the coverage set, *intraD* and *inteDist* are the intra-class distance and the inter-class distance, respectively. The experiment was completed under multiple real and artificial data sets. The results show that CGSO has great advantages compared to other clustering algorithms in [40, 45–47]. The CGSO [44] clustering algorithm is very suitable for solving data clustering problems, but it requires a long calculation time when dealing with large-scale data sets. In 2014, Aljarah and Ludwig [48, 49] applied the MapReduce computing framework to the GSO algorithm to solve computational efficiency problems. MapReduce is a parallel computing framework developed by Google for processing a large amount of off-line data [50]. It is a scalable solution of GSO clustering (MRCGSO) using MapReduce. They use GSO to conduct multiple searches to find the best centroid of the target space, using MapReduce in order to enhance the scalability and efficiency of CGSO. Experiments show that MRCGSO can be well extended with the change of data set to improve the computational efficiency of the algorithm while ensuring the clustering quality and make the calculation achieve near linear acceleration.

Isimeto et al. [51] proposed an enhanced clustering algorithm based on GSO (CGSOm) in 2017. CGSOm is an extension of the CGSO [44] algorithm that adjusts the glowworm's initialization mode and the fixed sense range r_s and introduces an error function for evaluation in each iteration of the algorithm. The initial position of the glowworm in the CGSOm algorithm is generated based on the location of the selected data points. This improvement allows all glowworms to cover at least one data. Experiments show that for most common data sets, compared with all clustering algorithms used in [44], the CGSOm algorithm has better entropy and purity values, that is, the best clustering effect. In addition, Peng et al. [52] proposed a new fitness function based on the CGSO clustering algorithm to solve the problem of missed opportunity risk assessment. The proposed new fitness function measures the improvement of the Intra-Distance on the one hand and SSE on the other hand. The author stated that by summing the two terms, the total improvement brought in by the glowworm is obtained.

D. Other GSO clustering algorithms

Cheng and Bao [53] proposed a fuzzy clustering algorithm based on GSO (GSO-KFCM). The authors were inspired by the SVM kernel function and introduced it into the fuzzy mean clustering (FCM) algorithm to improve the efficiency. The objective function of FCM adopts Euclidean distance and has insufficient processing power for nonlinear problems. The SVM kernel function is used to map the data to high-dimensional space for clustering [54], and the nonlinear mapping is used to partition, extract and amplify useful features. However, the clustering results of the KFCM algorithm are easily affected by the initial clustering center and are easily trapped in the local minimum solution, and the GSO algorithm has a good ability to search. Therefore, the author proposed to use the GSO algorithm to obtain optimal solutions as initial clustering centers of KFCM, and then use KFCM to optimize clustering centers. The authors experimented on the proposed algorithm on three data sets. Experiments show that GSO-KFCM has a better classification accuracy and the shortest running time.

Pushpalatha and Ananthanarayana [55] proposed to apply GSO to a clustering algorithm (GSOMDC) that divides multimedia documents with similar information into one cluster and group these documents into topics. Different from other GSO clustering algorithms, the GSOMDC algorithm is very beneficial for clustering multimodal data, and a new strategy is adopted in the glowworm selection neighbor phase. In the new neighbor selection rule, the neighboring glowworm's luciferin level is not only greater than the luciferin level of the agent glowworm but also less than three times the luciferin level of the agent glowworm. The GSOMDC algorithm uses the dataset MD of N unified multimedia documents as input and outputs clusters of multimedia documents. Experiments show that GSOMDC has high precision in clustering multimedia documents.

Senthilnath et al. [56] proposed a hierarchical clustering algorithm based on GSO. This clustering algorithm divides the larger cluster into small clusters according to the nearest centroid. The data sets are split using GSO, Niche Particle Swarm Optimization (NPSO) and Mean Shift Clustering (MSC) methods respectively. A large number of complex data sets are then divided into a certain number of clusters by satisfying Bayesian Information Criteria (BIC), which is usually used for model selection [57]. In the merging method, K-means is used to merge data points according to the searched clusters. The experimental results show that the hierarchical clustering algorithm based on GSO has better accuracy and robustness. Tapas et al. [58] proposed a clustering technique with an improved GSO algorithm that combines the generalized opposition-based learning [59] (GOBL) to form GOBL-GSO, which enables the algorithm to obtain a better solution in the search process. The authors used GOBL-GSO to detect lesions in brain MR images and used the dynamic search space to calculate the generalized opposite solution in GOBL-GSO algorithm. Experiments have found that higher diversity helps GOBL-GSO explore the search space and produce better solutions. The experimental results show that GOBL-GSO is more robust and effective in the segmentation of brain MR and can better detect brain lesion.

Burugari and Periasamy [60] proposed a hybridized Pareto-glowworm swarm optimization clustering algorithm to improve network lifetime. The authors used hybrid Pareto-GSO to select optimal clusters. This algorithm selects cluster nodes according to the level of luciferin carried by glowworms. The glowworm with the highest luciferin level will be selected as the cluster head of the cluster and then clustered. Li et al. [61] proposed a clustering method of improved GSO algorithm based on the good-point set (GSOK GP). The main idea of GSOK_GP is to first initialize the glowworm swarm based on the good-point set, and then perform the subsequent steps of the GSO algorithm to meet the termination condition. Finally, k optimized extreme points are selected as initial clustering centers of K-means clustering, K-means is executed to output clustering results. GSOK GP optimizes the GSO initialization phase based on good-point set, thereby avoiding the problem that randomly distributed glowworms cannot cover all the conditions in the solution space. On the other hand, GSOK GP uses GSO to select the optimal cluster initial centers of K-means, which improves the clustering efficiency. The experimental results show that GSOK GP has better clustering effect and stability.

V. CONCLUSION

This paper describes in detail the GSO algorithm and reviews the improvements of this algorithm from many angles in view of the fact that GSO is easy to fall into local optimal defects. These improved GSO algorithms improve the convergence speed and accuracy of the algorithm and greatly reduce the running time. The applications of GSO in clustering like CGSO, GSOCA, GSOCA+K-means, the new CGSO, MGCGSO, CGSOm, and other GSO clustering algorithms were introduced. In the research work, we also considered some issues worthy of further study:

(1) At present, there is no mathematically theoretical basis for setting the parameter values of the GSO algorithm. Krishnanand and Ghose have experimentally analyzed the influence of some initialization parameters on the performance of GSO [62]. Future work involves a comprehensive analysis of the effects of various parameters on the performance of the GSO algorithm. The main purpose is to provide theoretical analysis for the conclusions drawn from the experiments. *(2)* As the number of data increases, the difficulty of data processing and analysis raise. Exploring the application of GSO algorithm on large-scale datasets will also be the key direction. *(3)* The application of GSO in data processing is limited to off-line data and is rarely used in real-time data stream analysis. Therefore, the application of GSO in processing data streams will be our future work. At present, most of the applications for the GSO algorithm are done by simulation, practical implementation of the algorithm needs to be investigated.

ACKNOWLEDGMENT

This work was supported in part by National Key R&D Program of China under Grant 2016YFB1200602-26, in part by National Key R&D Program of China under Grant 2016YFB1200601-B24.

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