A Review on Glowworm Swarm Optimization

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A Review on Glowworm Swarm Optimization

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ABSTRACT
This paper presents a review on glowworm swarm optimization (GSO) algorithm based methods. GSO is a current nature-inspired optimization algorithm that simulates the behavior of the lighting worms. GSO algorithm is suitable for a concurrent search of several solutions and dissimilar or equal objective function values. A number of reviews are provided that describe applications of GSO algorithms in different domains, such as clustering and various optimization problems.
Keywords **—** Clustering, Optimization, Swarm Intelligence, Glowworm Swarm Optimization.

I. INTRODUCTION

The behaviour of a solitary ant, bee, termite and wasp often is too simple, but their combined and social actions are of paramount consequence. The collective and social behaviour of living creatures are motivated the researchers to undertake the lessons of today what is known as Swarm Intelligence (SI). Historically, the phrase SI was coined by Beny and Wang in the context of cellular robotics [1]. A group of researchers in different parts of the world currently works almost at the same time to study the versatile behavior of different living creatures and in particular the social insects. The efforts to mimic such behaviors through computer imitation finally resulted into the fascinating field of SI. SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. Although there is normally no centralized control structure dictating how individual agents must behave, limited interactions between such agents often lead to the emergence of global behavior. A lot of biological creatures such as fish schools and bird flocks clearly display structural order, with the behavior of the organisms so integrated that even though they may change shape and direction, they appear to move as a single coherent entity [2]. The main properties of the collective behavior can be pointed out as follows and is summarized in Figure 1.

The **homogeneity** is every bird in flock has the same behavioral model. The flock moves without a leader, even though temporary leaders seem to appear. The **locality** is nearest flock-mates just influence the motion of each bird.

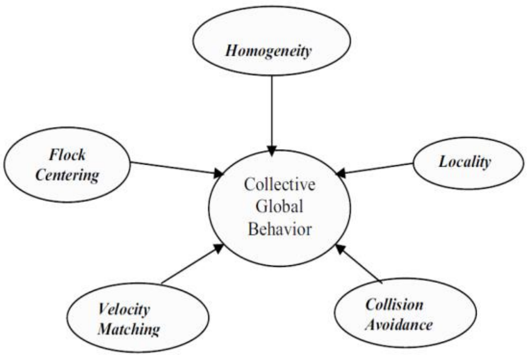

Fig. 1 Major character of collective behaviour

Vision is considered to be the most important senses for flock organization. The **collision avoidance** is used to avoid colliding with nearby flock mates. The **velocity matching** is attempted to match velocity with nearby flock mates. The **flock centring** is attempt to stay close to nearby flock mates Individuals attempt to maintain a minimum distance between themselves and others at all times. This rule is given the highest priority and corresponds to a frequently observed behavior of animals in nature [3]. If individuals are not performing an avoidance maneuver they tend to be attracted towards other individuals (to avoid being isolated) and to align themselves with neighbors [4], [5].

II. GLOWWORM SWARM OPTIMIZATION

The Glowworm Swarm Optimization (GSO) is a original swarm intelligence algorithm for optimization developed by Krishnanand and Ghose which imitate the flashing behaviour of glowworms [6]. Each glowworm carries a luminescence amount called luciferin, which is decided by the function value of glowworm's current location. All through the course of movement, glowworm identifies its neighbors based on local-decision area and selects a neighbor which has a luciferin value higher than its own using a probabilistic mechanism and moves on the way to it [7–12]. The GSO approach has been compared to the complete search algorithm, the honey bee mating optimization, the firefly algorithm, the Ant Bee Colony Optimization algorithm, and the Particle Swarm Optimization algorithm. The experiments were passed out using five level images and the experimental results showed that the proposed GSO approach efficiently identifies up to five thresholds that are very close to the optimal thresholds identified by the complete search method. Furthermore, compared to the new thresholding techniques, the computational time of GSO is competitive taking the second or third place behind the firefly algorithm and the artificial bee colony algorithm.

III. GSO ALGORITHM

GSO is one of the popular modern swarm intelligence method introduced by Krishnanand and Ghose [6]. GSO was first used for optimizing multimodal functions with equivalent or uneven plan function values. In GSO, glowworm swarm S, which consists of m glowworms, is distributed in the objective function search space. Each glowworm $g_j (j=1...m)$ is assigned a random position p_j inside the given function search space. Glowworm g_j carry its own luciferin level L_j, and has the vision range called local decision range rd_j. The luciferin level depends on the objective function value and glowworm position. The glowworm with a improved position is brighter than others, and therefore, has a higher luciferin level value and is very close to one of the optimal solutions. All glowworms seek the neighborhood set within their restricted decision range, and then move towards the brighter one within the neighborhood set. Finally, most of the glowworms gather to make compact groups in the function search space at multiple optimal locations of the objective function. At first, all the glowworms carry an equal luciferin level (L_0). The rd, radial sensor range r_s are initialized with the same value (r_0). After that, the iterative process consists of several luciferin updates and glowworm movements are executed to find the optimal solutions. Throughout the luciferin level update, the objective function is evaluated at the current glowworm position (p_j) and then the luciferin level for all glowworms is used to the new objective function values. The luciferin level L_j is updated using the following equation:

$$L_j(t) = (1-\rho)L_j(t-1) + \gamma F(p_j(t)) \qquad (1)$$

where $L_j(t-1)$ is the previous luciferin level for glowworm j; ρ is the luciferin decay constant $(\rho \in (0,1))$; γ is the luciferin enhancement fraction, and $F(p_j(t))$ represents the objective function value for glowworm j at current glowworm position (p_j); t is the current iteration. After that, each glowworm j explores its own neighbourhood region to extract the neighbors that have the highest luciferin level by applying the following rule:

$$z \in N_j(t) \quad iff \quad d_{jz} < rd_j(t) \quad and \quad L_z(t) > L_j(t) \qquad (2)$$

Where d is the distance and $\boldsymbol{z}$ is one of the closer glowworms to glowworm j, $N_j(t)$ is the neighbourhood set, d_{jz} is the Euclidean distance between glowworm j and glowworm z, $rd_j(t)$ is the local decision range for glowworm j, and $L_z(t)$ and $L_j(t)$ are the luciferin levels for glowworm z and j, respectively. After that, to select the best neighbor from the neighbourhood set, the probabilities for all neighbors are calculated using the following equation:

$$prob_{jz} = \frac{L_z(t) - L_j(t)}{\sum_{k \in N_j(t)} L_k(t) - L_j(t)} \qquad (3)$$

Where $\boldsymbol{z}$ is one of the neighborhood set $N_j(t)$ of glowworm j. After that, each glowworm selects the movement direction using the roulette wheel method whereby the glowworm with the higher probability has a higher chance to be selected from the neighborhood set. Then, the glowworm position (p_j) is adjusted based on the selected neighbor position (p_z) using the following equation:

$$p_j(t) = p_j(t-1) + s\frac{p_z(t) - p_j(t)}{Distance_{jz}} \qquad (4)$$

Constant, and d_{jz} is the Euclidean Distance between glowworms j and z. At the end of the GSO iteration, the local decision range rd_j is adjusted by the following equation:

$$rd_j(t) = \min\{rs, \max[0, rd_j(t-1) + \beta(nt - |N_j(t-1)|)]\} \qquad (5)$$

$rd_j(t-1)$ is the previous rd_j, r_s is the radial sensor range constant, β is a model constant, nt is a constant parameter used to restrict the neighborhood set size, and $|N_j(t)|$ is the actual neighborhood set size. In our proposed algorithm, we relaxed the local decision range update step and fixed the value of the rd_j to be the same value as the r_s

constant. However, the parameters nt and β are also relaxed. Fig.1 showed the flowchart of GSO algorithm in terms of computational procedure.

IV. GSO CLUSTERING ALGORITHM

The proposed GSO clustering algorithm is described as follows:

Input cluster data object;
Set maximum iteration number =*iter*_max;
Let *s* be the step size;
Let *r* be the local space radius;
Let l_i (0) be the initial luciferin;
Let $r_d^i(0)$ be the initial dynamic decision domain radius

Set *t* =1
While (*t* <= *iter_max*) do:
{
for *i* = 1 to *n* do

$$N_r(x_i(t)) = \{j: \|x_j(t) - x_i(t)\| < r\}$$

$$d(x_i(t)) = \frac{|N_r(x_i(t))|}{g}$$

$$J(x_i(t)) = -\ln\left(\frac{1}{g}\right) + \ln\left(d(x_i(t))\right)$$

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma J_t(t+1)$$

for each glowworm *i* do: % Movement-phase
{

$$N_i = \{j: d_{i,j}(t) < r_i^d(t) \ and \ l_i(t) < l_j(t)\}$$

where $\|\bar{x}\|$ is the norm of $\bar{x}$ for each glowworm $j \in N_i(t)$ do:

$$p_{ij}(t) = \frac{(l_j(t) - l_i(t))}{\sum_{k \in N(t)}(l_k(t) - l_i(t))}$$

j= select glowworm $(\vec{p})$ where $\vec{p}$ is the maximal element of *p*

$$x_i(t+1) = x_i(t) + s * \left(\frac{x_j(t) - x_i(t)}{\|x_j(t) - x_i(t)\|}\right)$$

$$r_i^d(t+1) = 255;$$

}

$$t \leftarrow t+1;$$

}

Algorithm symbolic description: $x_i(t)$ is the glowworm *i* in *t* iteration location; $l_i(t)$ is the luciferin of the glowworm *i* in *t* iteration; $N_i(t)$ is the neighborhood set of glowworm *i* in *t* iteration; $r_d^i(t)$ is the dynamic decision domain radius of glowworm *i* in *t* iteration;   is the upper bound of the $r_d^i(t)$; $p_{ij}(t)$ is the probability of glowworm *i* selects neighbor *j*.

V. LITERATURE SURVEY

Deng-xu et al., proposed a connected glowworm swarm enhancement to fathom the Multi-Constrained Multicast Routing (MQMR) issue utilizing an enhanced encoding strategy. With the fast improvement of Internet, more business demand the nature of administration of the system is Quality of Service (QoS) is required. This is the reason multi-compelled QoS multicast directing is proposed. Previously, there are numerous approaches to fathom the unconstrained QoS multicast steering issue by a few scientists, for example, dijkstra calculation, Steiner tree, and so on. Be that as it may, these conventional techniques are powerless to settle the multi-obliged QoS multicast steering issue.

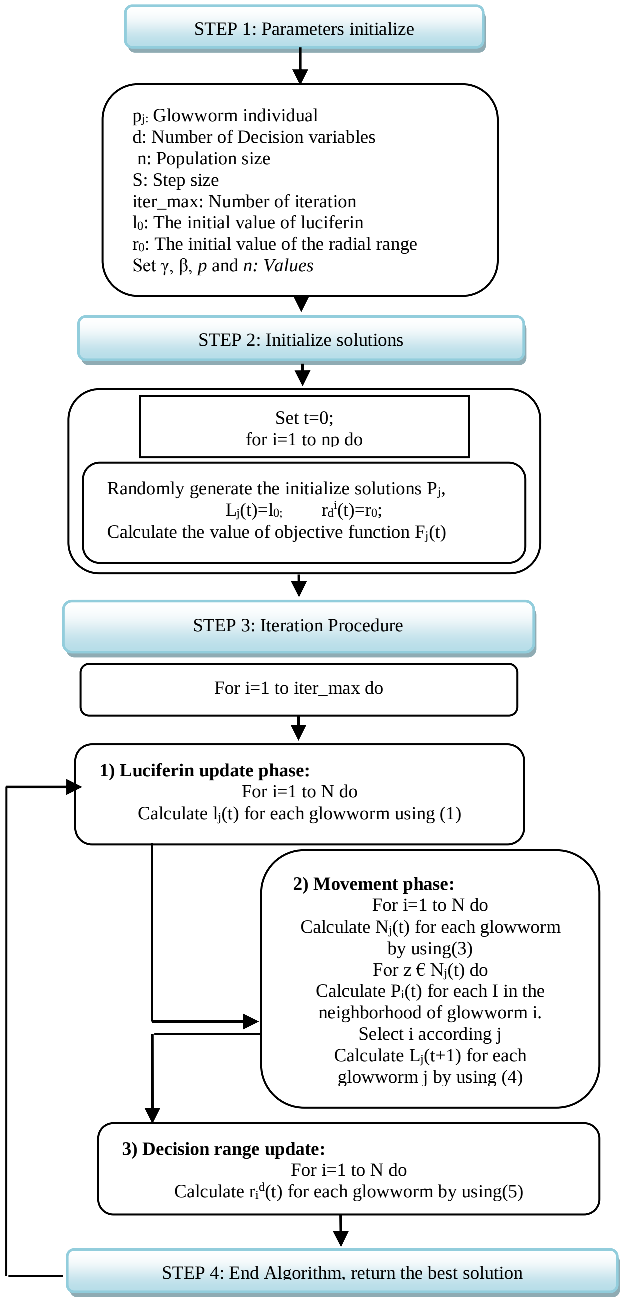

Fig.2 Flowchart of GSO

The recreation comes about substantiate that GSO beats ACO and GA execution for MQMR issue [13].

Zhang Yuli et al. propose a multi-robot collaboration methodology for scent sources limitation in view of an adjusted GSO calculation (M-GSO). The applications for utilizing independent robots to perform tuft following and smell source limitation are far reaching. A multi-robot collaboration methodology in view of changed glowworm swarm advancement system has been proposed to accomplish limitation for various smell sources. This system can guarantee robots to begin hunting down the following smell source after the disclosure of a scent source and guarantee that different robots would not re-find this scent source. Recreation comes about affirms that the proposed M-GSO can successfully empower the robot framework to inquiry and discover all the scent sources existed in the indoor environment rapidly and precisely [14].

J. Senthilnath et al utilized GSO bunching calculation for progressive part and converging of programmed multi-phantom satellite picture order. To make best utilization of land and its regular asset, there is a need decent genuine data of the land and its elements. The satellite picture is one of the sources which can catch the transient way of this information for land usage. Arrive cover mapping data can be utilized to review arrive utilization, with regards to city arranging and land-use. For a given satellite picture, if there is an absence of ground truth data then unsupervised procedure can be connected for naturally arranging a satellite picture into particular land cover areas. This paper epitomizes the utilization of GSO grouping calculation for various levelled part and converging of programmed multi-unearthly satellite picture arrangement. Multi-unearthly picture, for example, Landsite 7 topical mapped picture gained from southern area of India are utilized as contributions to the various levelled classifier display. The progressive method receives GSO and Mean Shift Clustering (MSC) for part the information set by fulfilling Bayesian Information Criterion (BIC) and k-implies calculation is utilized to combine the information set. The results of the paper authenticate that the, progressive classifier show GSO execution is unrivalled than the MSC unsupervised strategy [15].

Min li et al., recommended a technique to utilize the oil chromatographic disconnected information to accommodate the oil chromatographic on-line information utilizing GSO upgraded SVM. GSO has been utilized to streamline the SVM parameters, including mistake punishment consider, unfeeling parameter and part parameter. The oil chromatographic on-line observing of the transformer can immediately get a handle on the working status of the transformer, recognize and track potential blame, and give assurance to solid operation of the transformer. The test comes about demonstrate that the GSO streamlined can get littler fitting mistake, accomplish more steady and precise outcome, and more reasonable for field compromise of oil chromatographic on-line information when contrasted with execution of Neural Network prepared utilizing back engendering strategy[16].

Gao et al. Proposed a multilevel thresholding technique which was based on the optimization based algorithm (CQPSO). The quantum-behaved PSO employing the cooperative method (CQPSO) was proposed to save computation time and to overcome the profanity of dimensionality. This method maintains the fast convergence rate of PSO. OTSU method was used to evaluate the performance of proposed method and result showed the effectiveness in terms of less computational time of the traditional OTSU method [17].

Apurba et al., proposed a hue preserving color image enhancement technique which was based on PSO to find optimized solution for image enhancement. In proposed method the quality of the intensity image is improved by a parameterized transformation function which was similar quiet to propose. In addition gamut problem is also solved by rescaling method was then compared with other techniques like hue-preserving color image enhancement without gamut problem (HPCIE) and a genetic algorithm based approach to color image enhancement (GACIE). The proposed algorithm was very efficient and provided better results compared to other two methods [18].

Barrera and Coello [19] proposed a multimodal functions have many peaks (local maximum) with the equal or various objective values of GSO. They optimized the multimodal functions to set all maxima according to definite constraints. Spaces of high measurement increase the calculation of peaks and this cause the evaluation of each function to call for lengthier execution times in finding the greatest target peaks. Classify to solve multimodal functions, the swarm has to be able to divide itself into dissimilar groups for the sake of giving out extra local information for result more peaks, the amount of individuals has to be improved [20].

GSO is slow regarding union. Thus, *Zhou et al.*, [21] introduce an artificial GSO algorithm stuck on cloud model. This paper is discussed about the cloud based GSO for function optimization. In the meantime, a spontaneous version of GSO algorithm was introduced by *Tang et al*, [22]. This paper proposes the mutation usage in the optimal process in global solution. This version is known as the parallel hybrid mutation Glowworm Swarm Optimization.

Jayakumar and Venkatesh [23] was proposed a GSO algorithm identifying the finest solution for the problem of multiple-objective ecological economic dispatch. This paper proposes the usage of mutation in the exploration process of GSO. This will increase the range of the swarm and assist the swarm in discover the global optimum solutions. The mutation operation's change increases the population's range by the mutation of preferred solution.

Atheer and Nordin [24] in this paper proposes the usage of mutation in the exploration process of GSO, it will increase the range of the swarm and aid the swarm in discover the global best solutions. The mutation operation's modify increases the population's range by the mutation of preferred solution. The operation of mutation allows individuals solutions to be better. By way of mutation operation, some point of diffusion the solutions in space of search is retained.

This is to reduce the speed of meeting and to find new regions in search space. But, in some problems of optimization, some solutions turn into infeasible following the operation of mutation and migration. If such condition occurs, it is important that the solutions' possibility is verified via the addition of other method to attach the solutions. Further, in the iteration method, it does not get into account the suitability history of each individual, as well as GSO algorithm also has poor movement strength [25, 26].

Clustering with swarm-based algorithms is emerging as an alternative to more conventional clustering methods [27-30].

Yu Zeng et al, [31] combined heuristic strategy with GSO for the problem of rectangle layout optimization with equilibrium constraint. Layout optimization of satellite module concerns the best way to place a number of objects with different shapes, sizes and quality. Placement of objects cannot exceed the satellite round bottom and squeeze each other. With the direct use of heuristic algorithms to search, not only the search time is longer, the accuracy is also low standard. With the background of satellite module layout heuristic strategy can be combined with the glowworm swarm optimization for the problem of rectangle layout optimization with equilibrium constraint. On the basis of the heuristic strategy, glowworm swarm optimization algorithm is applied to search for the optimal placing order, and finally the optimal layout is obtained. Simulation's numerical results have shown that proposed approach is more effective than the existing algorithms like PSO and ACO algorithm with least maximum, minimum and average enveloping circle radius, least computational time and maximum space utilization.

Yang et al., [32] proposed a big data clustering method based on the Map Reduce framework. They used the ant colony approach to decompose the big data into several data partitions to be used in parallel clustering. This method used map reduces with the ACO algorithm lead to the automation of the semantic clustering to improve the data analysis. The proposed algorithm was developed and tested on data sets with large number of records and showed acceptable accuracy with good efficiency.

Ibrahim et al., [33] has presented GSO algorithm, for formulating the clustering problem as a multimodal optimization problem to extract the optimal cancroids based on glowworm's movement. Proposed GSO algorithm for clustering can discover the numbers of clusters without needing to provide the number in advance. Experimental results of GSO based clustering on several real datasets namely iris, Ecoli, glass, Balance, seed and two artificial data sets namely: mouse and vary density has proved to be efficient compared to well-known clustering methods that have been used in the literature such as K-Means clustering, average linkage agglomerative Hierarchical Clustering (HC), Furthest First (FF), and Learning Vector Quantization (LVQ).

Yongquan et al., [34] for clustering several benchmark images namely Lena, Mandrill and Peppers. Image classification is an image processing method of distinguishing between dissimilar categories of objects according to the different features contained in their image information. K-means works through several iterations, and updates every cluster center gradually until getting the best clustering results. However, there are two downsides for this algorithm. It depends on the initial condition, which may cause the algorithm to converge to suboptimal solutions and it falls into local optimum easily. To overcome this K-means image clustering algorithm based on glowworm swarm optimization (ICGSO) is proposed by combining GSO with K-means algorithm. Experimentation results have exposed that ICGSO algorithm performed very well when compared to the both K-means algorithm and fuzzy k-means clustering algorithm.

GSO algorithm has been applied for numerous complex optimization problems. *Qifang et al.*, [35] and *Horng* [36] used GSO algorithm based on Otsu's method and minimum cross entropy for multilevel threshold image segmentation and the experimental results show that the method has better performance for gray images. In order to improve the performance of the standard GSO algorithm and search the global optimal value efficiently and accurately, the improved glowworm swarm optimization (IGSO) is presented in this paper. Step size *s* is an important parameter in determining the convergence of GSO algorithm, so a new update method of step size is proposed. Furthermore the sensor range is extended to the whole search space and the random movement of the brightest glowworms of firefly algorithm is also introduced.

TABLE 1
An overview of GA, ACO, PSO and GSO and their behaviour

Subsequently the IGSO algorithm using different objective functions is used for multilevel color image thresholding problem, such as between-class variance and minimum cross entropy (MCE). The performance of IGSO algorithm for multilevel color image thresholding is measured in terms of the optimal threshold values, objective values, the peak signal

ITEMS	ALGORITHM			
	GA	ACO	PSO	GSO
YEAR	1975	1992	1995	2005
AUTHOR	John Holland	Marco Dorigo	James Kennedy & Russell Eberhart	K.N.Krishnanand and Debasish Ghose
OPTIMIZATION	Discrete Optimization	Meta heuristic Optimization	Stochastic Optimization	Meta heuristic Optimization
PARAMETERS	Reproduction, Crossover, Mutation.	Construct Ant Solutions, Daemon Actions (optional), Update Pheromones.	Current velocity, Personal Best, Neighbourhood Best.	Initialization, Updating Luciferin, Movement, Updating the Local- Decision Range.
PURPOSE	Find the best among others.	Find the shortest path.	Reach target with minimal duration.	Find the local finest solution.
ADVANTAGES	1) Efficient means of investigating large combinatorial problems and can solve them, 2) Many orders of magnitude faster than exhaustive 'brute force' searches.	1) Inherent parallelism. 2) Positive feedback accounts for rapid discovery of good solutions. 3) Efficient for Travelling Salesman Problem and similar problems. 4) Can be used in dynamic application (adapts to changes such as new distances, etc)	1) PSO can be applied into both scientific research and engineering use, 2) It has no overlapping and mutation calculation. 3) The search can be carried out by the speed of the particle. 4) PSO adopts the real number code, and it is decided directly by the solution.	1) GSO can deal with highly non- linear, multi-modal optimization problems naturally and efficiently. 2) GSO does not use velocities, and there is no problem as that associated with velocity in PSO. 3) The speed of convergence of GSO is very high in probability of finding the global optimized answer.
DISADVANTAGES	1) Computationally expensive 2) Some problems require many days or weeks to run. 3) However often still faster than force. 4) Blind, to direct a GA towards optimal solution area if know.	1) Theoretical analysis is difficult. 2) Sequences of random decisions (not independent). 3) Probability distribution changes by iteration. 4) Research is experimental rather than theoretical.	1) Tendency to a fast and premature convergence in mid optimum points. 2) The method cannot work out the problems of scattering and optimization. 3) Slow convergence in refined search step.	1) GSO is poor in high dimensional problems. 2) In GSO, the dynamic change of decision domains in the method of glowworms moving, the algorithm slows convention speed and has poor local search ability delayed in the iteration.
MEDICAL FIELD	Genetic Algorithm outperformed optimizes the artificial neural networks among others.	ACO also optimizes the artificial neural networks for applications in medical image processing.	1) Detection of Brain tumor using Image segmentation(MRI) 2) PSO used for optimize the artificial neural networks for applications in medical Image processing.	GSO will present new methods for future selection problems.

to noise ratio (PSNR), and structural similarity index (SSIM) and then compared with other swarm intelligence algorithms such as adaptive particle swarm optimization (APSO) [37] and self-adaptive differential evolution (SADE) algorithm [38]. The extensive review of GA, PSO, ACO and GSO is shown in Table 1.

VI. CONCLUSIONS

This paper describes the algorithm of GSO and attempts to review on GSO based on the several field like clustering, optimization problem, multicast routing problem (MQMR) problem and multi-robot based problems. The literature survey confirms that the outcomes of GSO are better when compared to the other optimization methods namely, PSO, ACO and GA.

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