Optimizing Garbage and Recycling Collection problem using Glowworm Swarm Optimization

A Dissertation submitted

By

Er. Anita Sharma

To

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In partial fulfilment of the Requirement for the

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In

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Under the guidance of

Mrs. Monica Sood

(Assistant Professor, Lovely Professional University)

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PAC APPROVAL

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DISSERTATION TOPIC APPROVAL PERFORMA

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PROPOSED TOPICS

1. Algos of Swarm Intelligence like Bat Algorithm Glowworm Optimization
2. Techniques like PSO, BBO etc
3. Genetic Algorithms in Swarm Intelligence

Monica Sood

Signature of Supervisor

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*Supervisor should finally encircle one topic out of three proposed topics and put up for approval before Project Approval Committee (PAC)

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ABSTRACT

Swarm intelligence, an optimizing technique is inspired from biological processes. Many computational algorithms inspired by nature, such as swarm intelligence, has been successfully applied to a number of optimization problems. GSO is a technique derived from swarm intelligence and is inspired by a collective behavior of animals. In GSO glowworms work as agents and has a luciferin count by which they attract other glowworms and then find a best possible solution to a problem. Agents in GSO carry the information and find the best possible way to reach the target. This work focuses on the application of Glowworm swarm optimization (GSO) to a problem of garbage and recycling collection using a swarm of robots. The basic idea is to train numerous robots to behave and interact with each other, attempting to simulate the way a group of animals behave like a single cognitive entity. They carry information with the help of agents and an optimal path is found. Also agents are simulated in such away that they collect the items and then deposit the same in the desired stations.

ACKNOWLEDGEMENT

I would like to take this opportunity to express my deep sense of gratitude to all who helped me directly or indirectly during thesis work. I also would like to thank my supervisor **Mrs. Monica Sood** for being great mentor and best adviser I could ever have. Her advice, encouragement and critics are sources of innovative ideas, inspiration and cause behind the successful completion of this dissertation. I am highly obliged to all faculty members of computer science and engineering department for their support and encouragement. I would like to express my sincere appreciation and gratitude towards my friends for their encouragement, consistent support and invaluable suggestions at the time I needed the most. I am grateful to my family for their love, support and prayers. I would like to thank to the **Project Approval Committee members** for their valuable comments and discussions. I would also like to thank to **Lovely Professional University** for the support on academic studies and letting me involve in this study.

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DECLARATION

I, ANITA SHARMA hereby declare that the dissertation-II entitled "**Optimizing Garbage and Recycling Collection problem using Glowworm Swarm Optimization"**, submitted for the M.Tech (Information Technology) degree is entirely my original work and all ideas and references have been duly acknowledged. It does not contain any work for the award of any other degree or diploma.

Date:

Investigator: Anita Sharma

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CERTIFICATE

This is to certify that **ANITA SHARMA** has completed M. Tech dissertation II titled **"Optimizing Garbage and Recycling Collection problem using Glowworm Swarm Optimization"** under my guidance and supervision. To the best of my knowledge, the present work is the result of her original investigation and study. No part of the dissertation report has ever been submitted for any other degree or diploma. The dissertation report is fit for the submission and the partial fulfillment of the conditions for the award of M.Tech Computer Science and Engineering.

Date:

Signature of Guide

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Chapter 1
INTRODUCTION

Computational Intelligence [1] is a sub branch of artificial intelligence which is a combination of learning, adaption, evolution, association and fuzzy linguistic to make some intelligent programs. It enables intelligent behaviors in complex and changing environments by studying the adaptive mechanisms. From the time when abacus was developed humans have been looking for the simplest and the fastest way of computing with different complexities and different machines. Eventually electronics replaced the mechanical machines, which gave a boost to the digital calculations. There were still some problems in the past that could not be solved by sequential processes and then some researchers thought whether machines can be made which think like us. Every person now almost has a computer for work, play and communication. Now as computers have become sophisticated, scientists have become more interested in the possibility of creating autonomous machines, so as to help to solve complex problems faster and effectively. Biology after this influence computing science the early days of computer science.

Also computers have a huge amount of cost to be spent on hardware and software increasing the efficiency and productivity.bt this chip manufacturing chips becomes expensive. The computing systems inspired by the biological systems are an attractive alternative. Many types of bio inspired techniques are there such as artificial intelligence, swarm intelligence, genetic algorithms, hybrid systems etc.CI is used to solve the problems which are not solved by other means.

CI has many paradigms by which it solves complex problems. CI solves problems with the help of these paradigms. Sometimes only one of them is used to solve a problem and other hybrid approaches can also be used in order to get more optimized and accurate results. Intelligent systems one of the aspect of artificial intelligence focuses on the development of some latest research into the real and practical, fielded applications whereas CI is a collective effort in emerging computational paradigms. Each of these paradigms have their origin from Computational Intelligence (CI). Five of them are shown in figure 1.1.

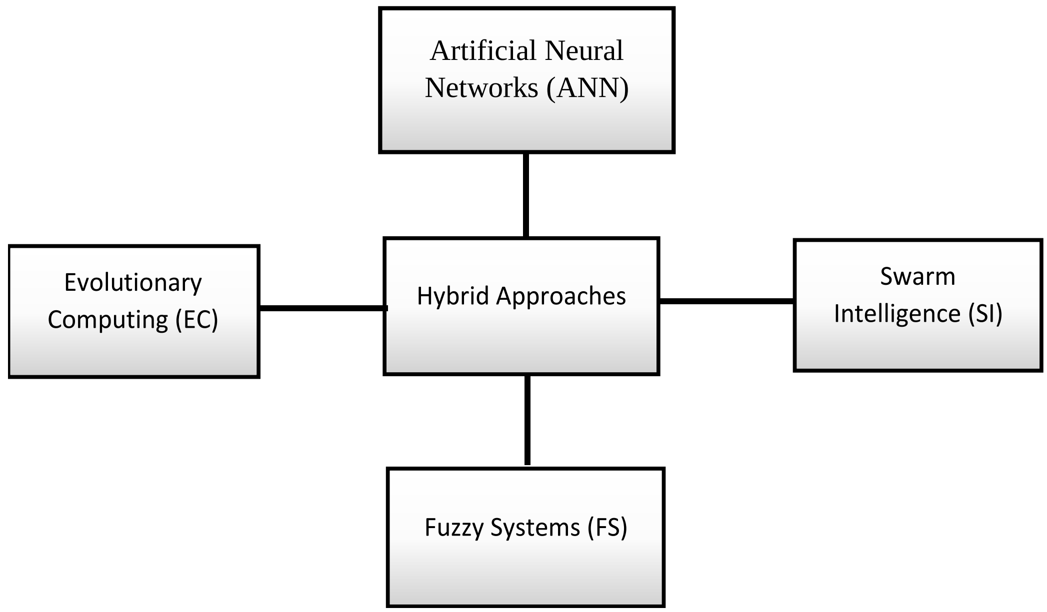


Figure 1.1 CI Paradigms

NN models neural system, evolution models natural evolution. AIS models human immune system and FS phenomenon of how organisms interact with environment comes from the Out of these paradigms we deal with swarm intelligence which deals with the study of swarms.

1.1 Swarm Intelligence

Swarm Intelligence (SI) is the branch of computer science that designs computational methods for solving problems which is inspired by a cooperative behavior of individuals as such, a group of bees with a queen bee migrate to form a new colony, group of glowworms searching for high luciferin and this swarm intelligence also presents the methods for solving optimization problems. Swarm means group of individuals or agents communicating with each other. Swarm intelligence is the problem solving approach which is emerged from the problem solving behavior and the computational swarm intelligence is the algorithmic approach to accomplish that behavior. It may be natural and artificial system in which large number of individuals interacts with one another and with the environment. This depicts the natural behavior seen in some of the insect colonies i.e. ant colonies. Every particle in swarm is a simple agent moving through a search space which is multi- dimensional sampling an objective function at various positions. In a search space the best solution can be represented with a point. Some potential solutions are plotted on the graph and seeded with some initial values.

The particle’s performance is evaluated with a predefined fitness function having the characteristics of the optimized problem. With time the particles will accelerate towards those with best possible fit values.

1.1.1 Turning to swarm intelligence

The collective behavior of swarms has now become an exciting phenomeneon in the field of artificial intelligence. The human mind is very complex to understand and with limitations to what extent they have the observing power and also some limits to how it can be used as a model of computational intelligence. Solution to all these problems lies in observable collective behavior which is simulated and is to be found in swarms of living creatures in this world rather than humans. When in groups they behave in very effective and clever manner.

This research has two main branches of study. The first deals with the study of ants like how they manage to find the shortest path to find their food, without seeing each other, no voice, no language, just by using pheromones that they release while walking. The other is the collective behavior which focuses on the smart behavior of groups or swarms of bees, schools of fish, groups of glowworms etc.

1.1.2 Developments in Swarm Intelligence

Since 1980’s Work on robots has been going, inspired by social creatures like the bees ants, glowworms etc., they all work as one and becomes more sophisticated. It also has an advantage that if a single robot stops functioning then others still are in functioning. Each robot communicates with the robot which is at optimized path from its location. This produces an emergent behavior known as swarm intelligence.

This collective behavior of the individuals or insects shows their intelligence, how they communicate and interact with other individuals. There are many systems which exhibit swarm intelligence:

- Insect colonies: bees, glowworms etc.
- The brain: interactions of simple neurons.
- The cells : protein interactions

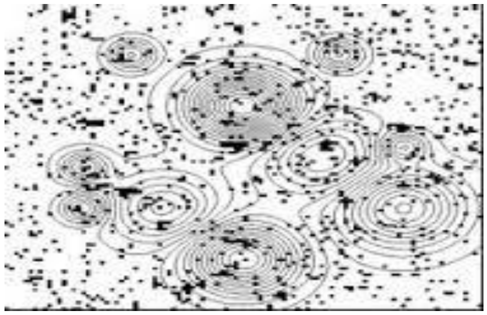


Figure 1.2 Swarm interaction

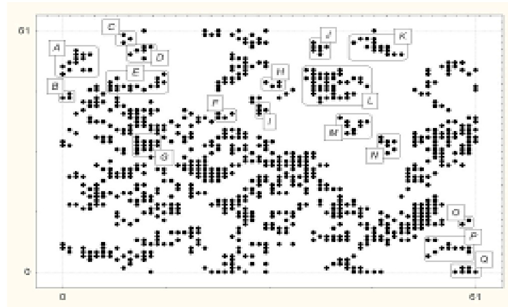


Figure 1.3 Swarm in groups

Within the swarms the structures are relatively quite simple but collectively their behaviors are complex. The behavior of swarm is said to be emergent as it does arise from a rationale choice or from any finalized analysis. The complex behaviors cannot be predicted or deduced from simple behaviors of the individuals. Every agent in the system is not aware of what is happening globally and also does not have any global perspective. The individuals do not know they are doing anything intelligent. This is known as emergence.

1.2 Classification of SI Systems

- **Natural v/s Artificial**: Natural system are those that are existing naturally i.e. bee colony, Ant colony. Whereas artificial system are those that are manmade i.e. behavior of robots.
- **Scientific v/s Engineering**: Scientific category represents the coordinating behavior of Individuals, how the system act as a whole and also the individual-individual interaction and individual-environment interaction takes place. Engineering group follows the scientific group and design the system to solve the problems practically.

1.3 Principles of Swarm Intelligence:

Two principles in swarm intelligence are:

- **Self-organizing (intelligence)**

a) Local to global: mostly in swarms the interactions are local still some have global.

b) Order to disorder: a system may start in a disordered state but after some time it is in ordered state.

- **Stigmergy (stimulation by work):** The work can be continued by any agent. Same, simple rules can create different designs according to the environment.

i. **Positive feedback** – strengthen good solutions present in the system.

ii. **Negative feedback** – takes off poor or old solutions.

iii **Amplification of fluctuations:** randomness enables discovery of new solutions.

iv **Multiple interactions**: a minimal density of mutually tolerant individuals is required to generate a self-organized structure.

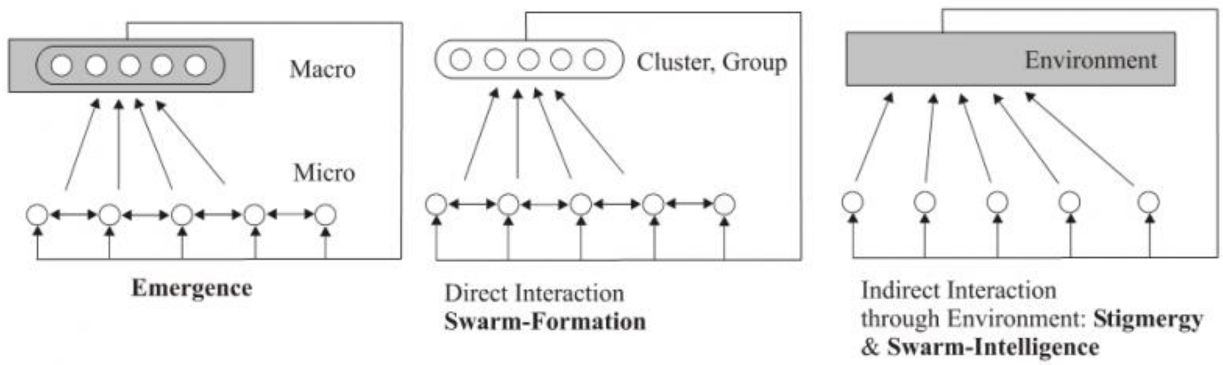


Figure 1.4 Swarm principles

1.4 Characteristics of Swarm intelligence

- Large number of individuals are there in a group.
- All the agents or individuals are identical.
- Interaction between the individuals is by simple behavioral rules they possess as in case of bird flocking birds move following the rules of collision avoidance and velocity matching. And exchange the information with the environment.
- The group behavior observed is self-organized there is no one coordinator among the individuals mean distributive, no central control or database.
- Ability to change the environment.
- Perception of environment, sensing.
- The algorithms in swarm intelligence are flexible.
- Agents show complex problem solving skills arising from their interactions between them.

1.5. Benefits of Swarm Systems

- **Adaptable**–It is possible to develop systems the adjust to predetermined stimulus but if we need to construct a system which needs to adjust in a different stimulus or to change beyond a narrow range ,this requires a swarm .these systems can adapt to various situations and coordinate with each other to form an efficient system.
- **Evolvable** – these systems can shift the location of adaption over time from one part of the system to the other i.e from one body to other or from body to genes then it must be swarm based.
- **Boundless** – the systems are boundless as in this positive feedback can lead to increasing order. In this by extending the structures beyond the bound of its initial stage a new advanced structure can be formed .information leads to new information, order creates more order
- **Novelty** – swarm systems are novel due to some reasons: they are sensitive to initial conditions. They can have many possibilities with the combinations of many interlinked agents.

Swarms possess robustness i.e they can cope with the loss of individuals. This is done with the help of the redundancy and absence of a leader. Also they can perform in different group sizes. Any new addition or any new removal does not affect much. Scalability is promoted by sensing and communication in social animals. Flexibility is also promoted in them by the concept of redundancy, simplicity of behavior and mechanisms. Some of the other advantages of swarm intelligence are multipath routing, low complexity, scalability, distributed algorithm, flexibility, and inherent parallelism. Theses can also be used in mobile ad-hoc networks. With these features swarm intelligence has the ability to be used in real time applications, in robotics, sensors etc.

In swarm intelligence many paradigms are used to solve complex problems. Some of them are ant colony optimization, particle swarm optimization and many more. Glowworm optimization is one of the swarm intelligence optimization algorithm based on the behavior of glowworms which is recent inspired by the emergent behavior that finds solution to the optimizing problems defined on multimodal functions. Glowworm swarm optimization is a new swarm intelligence method given by K.N Krishnanand and D.Ghose in 2005. This was inspired from the phenomenon that glowworm attracts mates. Glowworm swarm optimization is developed on the behavior of glowworms i.e insects which are capable of modifying their light emission with their positions and use their luminescence glow for various purposes.

1.6 Swarm Robotics

Swarm robotics, the study of robotic systems consist of a large group of relatively simple and simple robots that interact and work cooperatively with each other in order to solve problems which are outside their own capability. This exhibits interesting features like high degrees of parallelism, duplicity and robustness. These robots are highly adaptive to the changes in environment, solutions are scalable to the problem and swarm size.

1.6.1 Criteria for Swarm Robotics

Large number: Units in large numbers are required so as to have a co-operative behavior. Homogeneous groups are required to make swarm robotics consisting of large number of units. The heterogeneous robots are not considered under swarm robotics.

Limited Capabilities: robots are relatively inefficient of performing a task of its own.

Scalability and robustness: a swarm robot system should be robust and scalable. Even if some units are removed this shouldn't cause any catastrophic failure. Also adding new units performance of the system will be improved.

Distributed Co-ordination: Swarm robotics should have local and limited sensing range also communication capabilities. Co-ordination is distributed among the robots. Autonomy will be influenced using the global channel for co-ordination.

All these criteria are to be used for measuring the extent to which the term swarm robotic might be applied to the systems. The advantages and benefits of swarm robotic systems make them more and more appealing than the classical ones some of the tasks are such that they cannot be done only by one robot, here comes the need of swarm robotics i.e. number of robots are required to cooperate and communicate with each other to reach an optimal solution. Also the speed is increased using many robots, even when the cooperation is not present. Swarms provides high fault tolerance capability, enhanced task performance and also cost factor s decreased. A single robot sometimes is not able to do some tasks. Swarm robotics shows the set of primitive individual behaviors enhanced with communication will produce a large set of complex swarm behavior. The swarm robots can be used for collective transport, also to reach the points that can't be reached by a single unit.

1.6.2 Swarm Robotics applications

Forging: This scenario has many applications and deals with skills from group of robots, covers the important issue of collective behavior

Dangerous tasks: swarm robotics can be created by an individual making the system suitable for dangerous tasks.

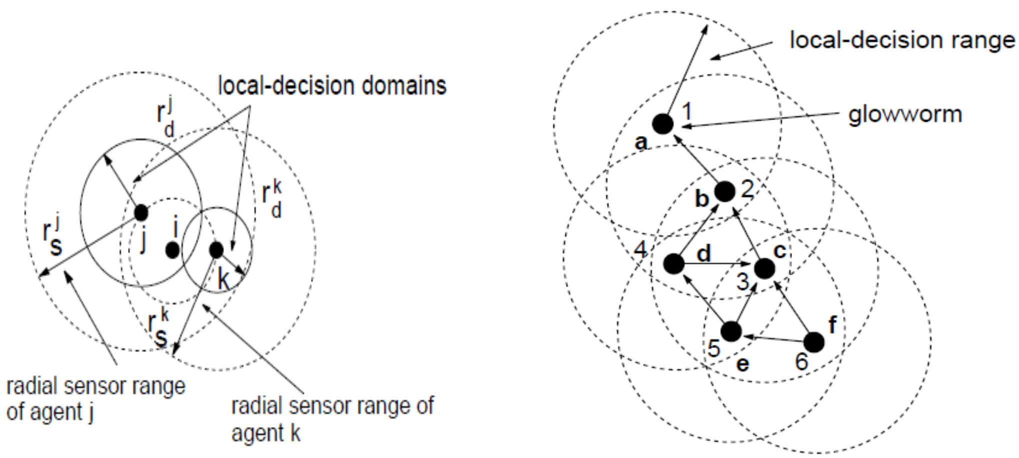
Exploration and mapping: all the engineering structures are inspected using a swarm of robots. Robots have limited sensing capability but collective perception of swarm can be used to create global knowledge.

The main objective of swarm robots to be designed is the hardware implementation, test and use of self-organizing, self-assembling, metamorphic robotic systems called swarm-bots, and are composed of a swarm of many assembled s-bots. These are just like swarms, inspired by collective behavior of social insect's colonies, simple robots known as s-bots are capable of autonomously carrying out individual and collective behavior by exploiting all the local interactions between the s-bots and also among them.

1.7 Glowworm Swarm Optimization

In glowworm algorithm the agent's i.e. any physical entities are considered to be randomly distributed in a work area. The agent in GSO carries some luminescence quantity along with them known as luciferin. Glowworms are considered as agents which emits light, the intensity of this is proportional to the associated luciferin value and also has a variable decision range, which is bounded by a circular range.

Every Glowworm identifies other glowworms within its local decision domain and depends on these to make the decisions. The algorithm obtained is highly decentralized and leads to the requirements of collective robotic systems. Glowworms split into subgroups with these movements and they exhibit a simultaneous taxis behavior towards the best locations which leads to the detection of multiple optima of the given objective function. The glowworm looks for the brighter glow in its neighbor set, in the local decision range and gets attracted towards this traverse and the direction of flight varies each time along with the choice of the neighbor. Also the local decision range is influenced by the quantity of neighbor. When the density of neighbors will be low then the glowworm will enlarge its radius and look for more neighbors else the policy making radius decreases. In the end the majority of the glowworms gather at the multiple optima of the given objective function. The GSO does well in searching for optimal clustering in parallel, global searching. Therefore it avoids the influence of initial position.



(a) **(b)**

Figure 1.5.(a) rkd< d(i,k) = d(i,j) <rjd<rks<rja. Agent i is in the sensor range of j and k (equidistant to both), having different [2] decision-domains. Hence, only j uses the information of i.Figure 5(b) rkd< d(i,k) = d(i,j) <rjd<rks<rja. Agent i is in the sensor range of j and k (equidistant to both), having different [2] decision-domains. Hence, only j uses the information of i.

The brighter the glow is the better the position of a glowworm which in turn means a good target value. Concurrent search for several solutions can be done with GSO having equal or dissimilar objectives. For this swarm must have ability to break into disjoint sets. Only one optimal is found with others (local or global). In GSO the movements of glowworm are deterministic and they exchange information locally. The agents carry luciferin which is a luminescence quantity along with them. In GSO swarm of agents known as glowworms emit light and this intensity of luminescence is directly proportional to the associated luciferin. Each agent in GSO uses the luciferin for communicating the function profile information at its present location to its neighbors. These glowworms are dependent on local decision domain which varies accordingly and is bounded by circular sensor range to determine their movements. Every glowworm finds a neighbor that has a luciferin count higher than its own value and then moves towards it.

1.7.1 Algorithm Description

The GSO algorithm's initial step is just to place the glowworms randomly in a workspace so as to make them dispersed properly. Every state of a glowworm i at time t can be described with some set of variables: a position in the search space, a luciferin level and a neighborhood range. GSO explains and presents how these variables change their values accordingly with time. Initially these glowworms contain an equal amount of luciferin. Every iteration consist of some definite stages, a luciferin-update followed by a movement phase based on transition rule.

Luciferin-update phase

The luciferin update is dependent on the functional value at the position of glowworm, though all the glowworms start with the same luciferin value initially, these values change according to the functional values at their present position. In this phase a glowworm adds some quantity of luciferin value to its previous luciferin level, quantity proportional to the sensed profile like temperature, radiation, Wi-Fi strength at that point. In the case of a function optimization problem this value will be of the objective function at that particular point. Luciferin also decays with time so small fraction of this value is subtracted from it. The luciferin update rule is given by:

$$li(t) = (1 - \rho)li(t - 1) + \gamma J(xi(t)) \qquad (1.1)$$

where, ρ is the luciferin decay constant ($0 < \rho < 1$)and γ is the luciferin enhancement constant and Jj(t)represents the value of the objective function at agent j's location at time *t*.

Movement –phase

During this phase, each glowworm using a probabilistic mechanism decides to move towards the brightest neighbor i.e that has the higher luciferin value than its own. These glowworms are attracted by the brighter neighbor than them. The glowworm j's neighbor need to meet some requirements:

- The glowworm should be within the decision domain of glowworm j,
- The luciferin value larger than the glowworm.

Glowworm i moves toward a neighbor j which comes from Ni((t) with some probability is $p_{ij}(t)$. Probability is calculated by:

$$p_{ij}(t) = \frac{l_j(t)\text{-}li(t)}{\sum_{k\in Ni(T)k} l(t)\text{-}_i l(t)} \qquad (1.2)$$

After moving, glowworm i's location is updated, the update formula is

$$x_i(t+1) = \frac{xi(t)+st*\{x_j(t)-x_i(t)\}}{x_j(t)-x_i(t)} \qquad (1.3)$$

where st is the step size.

Local decision range update rule

With the glowworm's position update, its neighborhood range is also updated. The neighborhood range will be increased if the neighborhood range covers low density of glowworms. In this phase the neighborhood range is updated to limit the communication range in a group of agents. In GSO the radial sensor plays a very vital part as the glowworms depend only on local information to decide about their movements i.e the maximum number of peaks captured will depend upon the radial sensor range as these peaks are strong function of sensor range. As an instance the entire workspace has a sensor range, all the local optima are ignored as all the agents move to global optimum point .since it is an assumption that prior information about the objective function is not available so a varied sensor range must be there i.e it can be Wi-Fi strength also.

The formula for neighborhood range update is

$$r_i^d(t+1) = \min\{r_s, \max\{0, r_i^d(t)+b\,(n_t-|N_i(t)|)\}\} \qquad (1.4)$$

where and n_t is a parameter used to control the number of neighbors b is a constant parameter. The quantities ρ, γ, s_t, β, n_t are algorithm parameters for which we can get them using the experimental method and evolutionary learning.

1.7.2 Algorithm

Function optimization using GSO algorithm usually requires the following seven steps:

Step 1. Initialize the parameters.

Step 2. Placing a population of n glowworms randomly in the search space of the object function.

Step 3. Using the formula (1.1) put the J(xi(t)) into the li(t). li(t) represents the luciferin level associated with glowworm i at time t. J(xi(t)) represents the value of the objective function at glowworm i's location at time t.

Step 4. Each glowworm selects a neighbor that has a luciferin count higher than its own within a variable neighborhood range $r_i^d(t)(0 < r_i^d \leq r_s)$ to make up the $N_i(t)$. $N_i(t)$ is the set of neighbors of glowworm i at time t. $r_i^d(t)$ represents the variable neighborhood range associated with glowworm i at time t.

Steps 5. Using the formula (1.2) calculate the probability that each glowworm i moves toward a neighbor j.

Step 6. Glowworm is using the roulette method selects a neighbor j and move toward it, then using the formula (1.3) update the location of the glowworm i.

*Step 7***.** Using the formula (1.4) update the value of the variable neighborhood range.

These steps are repeated till it reaches the maximum iterations. All the glowworms need to be covered and their positions need to be updated according to their luciferin value. Every time the search radius is revised and then the glowworms look for other glowworms having higher luciferin count. The glowworms by doing this make their way to reach the target in the best possible way. By this way the search from local becomes global and the best glowworm acts as the leader and others follow it. The algorithm is used to find the local best among the all and with number of iterations all the local best are found. All the local best are used to find the global best. For the GRC application we need to find the local best and then will use that. The glowworm with brightest luciferin count will attract other glowworms and will do the task efficiently. The flowchart is shown with all the steps carried out in this process of optimization.

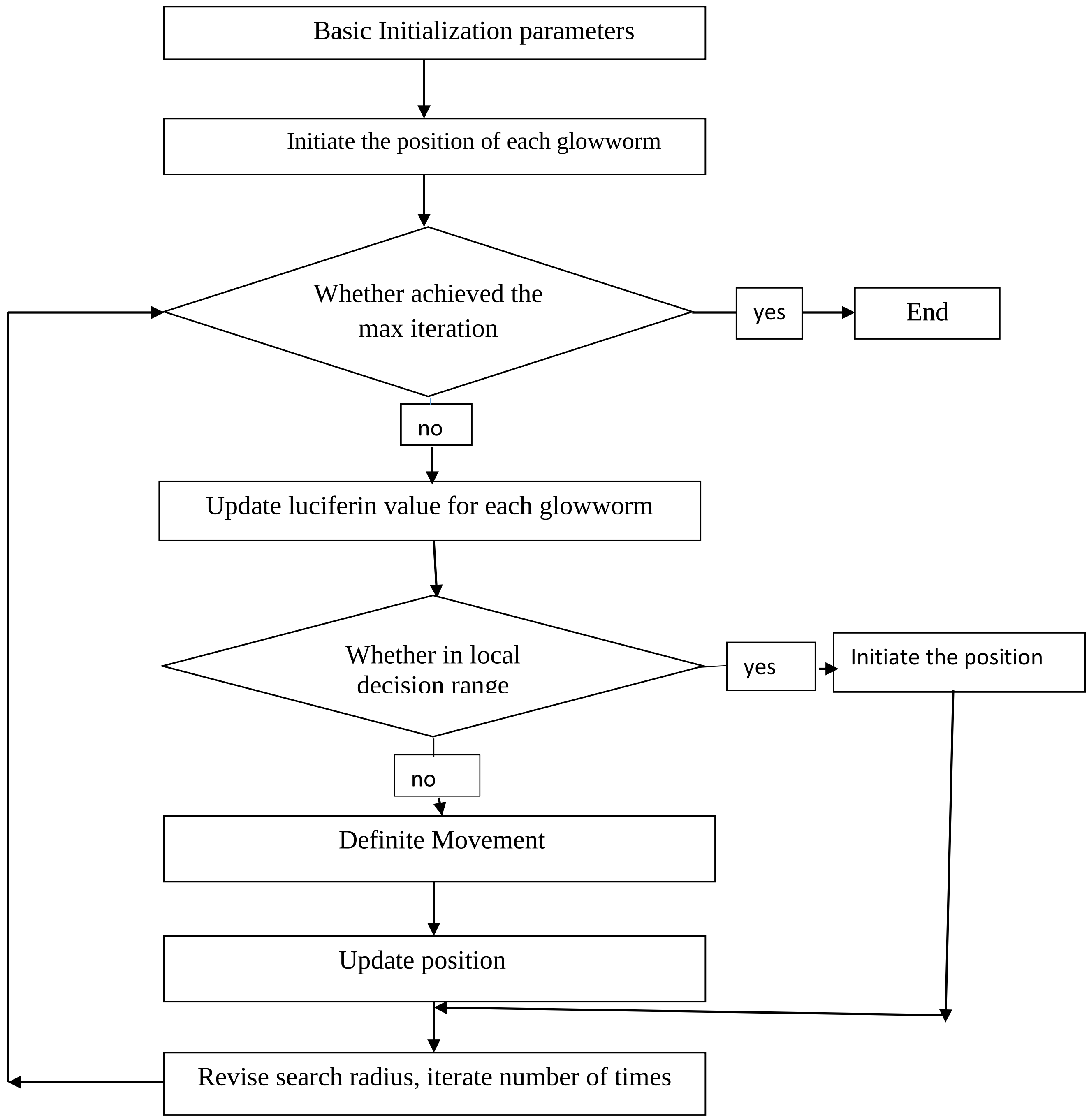


Figure 1.6. GSO flowchart

Chapter 2
LITERATURE SURVEY

Huabei Nie, *et.al* (2014) discussed the problem of GSO [3] of falling into local optima, slow convergence speed and low optimization. In this shuffled frog leaping algorithm (SLFA) is used to divide glowworms into various ethnic groups and local search and global information exchange are done for improving the performance of GSO. In this using the chaos optimization the population is initialized and the glowworms can obtain a high quality group. This paper also puts forward an improved GSO by using ideas based on SFLA. IGSO divides the glowworms into different groups on the same scale. Every glowworm does a local search and then when all the ethnic groups finish local search then all the glowworms are mixed and also sorted on the objective function of fitness value. This is done till it reaches the maximum iteration. The simulations show that IGSO shows better results than GSO. Also the IGSO has better precision and high convergence speed. For verifying the effectiveness of the IGSO algorithm, 6 benchmark test functions are selected, the basic GSO algorithm is taken for the comparison. In all these improved GSO was found better than GSO .

Du Pengzhen, *et.al (*2014) Standard GSO has poor search ability and it is easily trapped into local minima. This paper proposes a new algorithm to solve these kinds of problems, a Quantum Glowworm Swarm Optimization Algorithm based on Chaotic Sequence (QCSGSO) [4]. To initialize the population a chaotic sequence is generated having the higher probability to cover more local optimal areas, also provides good condition for further tuning and optimization. Here the quantum behavior is applied to elite population which locates individuals in any position of the solution space randomly with a certain probability. This enhances the performance of the algorithm. Also the global and the local optimum jumping is improved. In the last QCSGSO adopts single dimension loop swimming instead of the original fixed step movement mode, this improves the solution precision and convergence speed along with the robustness. This has solved the problem of standard GSO that sensitive to step-size. To verify the feasibility and the performance of the proposed algorithm, the proposed QCSGSO was made to compare with some existing methods on 10 well-known uni-modal/multi-modal benchmark functions. The QCSGSO's results were precise and convergence speed was significantly better than other algorithms.

Zhou Y , *et.al* (2013) focuses on the problem of GRC [5] (Garbage Recycling and Collection problem)using an application of swarm intelligence with the help of robots. The basic idea in this is to train multiple robots to interact with each other so as to behave as a single entity. This work in this is done with the help of two approaches PSO (particle swarm optimization) and ACO (Ant colony optimization). Star and circle topologies are used along with two prototypes in the experiments. The circle gave the best result between both of these. Both these topologies were mixed and more optimal solution was found. PSO has a specific type of memory system that meets requirements of the problem very effectively. This work of PSO working on robotics working as swarms was inspired by previous work done on robotics. A comparative evaluation and an explanation for the choice of topologies that enhanced the PSO algorithm is stated in this paper. This problem was also solved with ACO approach. The ACO approach presents an unusual grid implementation of robot physical simulation, generating new concepts and discussions about necessary modifications for the algorithm towards an improved performance. In this paper the objective is to find the optimized path to collect the garbage from various points and then dump them into the garbage station. Both ACO and PSO are then compared to get the best algorithm which gives optimum solution for the problem proposed.

Yongquan Zhou, *et.al* (2013) introduces a vehicle scheduling model which solves the problem of dispatching system of public transit vehicles as this needs to be made intelligent. This model is proposed so as to maintain a balance between the bus companies and the passengers to implement this model GSO with random disturbance factor, named R-GSO is applied to a schedule of vehicles. In tis the results of the R-GSO [6]are compared to other swarm intelligence algorithms and found that this has higher efficiency and is effective way to optimize the system. This paper divides the problem into two methods: to have a simulation model, to have an objective function used on the simulation model. This random disturbance factor, is inserted at the movement update phase so as to avoid it to fall into local optima. The results found were accurate than other swarm intelligence algorithms. From outcomes, it was calculated that this proposed algorithm can be used for an effective application in urban areas to solve the problem of vehicle dispatching system.

Yangquan Zhou,*et.al* (2013) discusses the TGSO [7](tribe glowworm swarm optimization) to solve the problem of low precision and easy to fall into local optimization of glowworm swarm optimization. In TGSO, glowworms are divided into tribes and then used in the flow shop scheduling problem to check the effectiveness of this algorithm. In TGSO the glowworms are divided into small tribes and each tribe has a leader. In tribe GSO algorithm, it has two layers: all the tribes from the first layer, from the second layer glowworm having the brightest light of each tribe. The second layer gives the global optimum according to basic GSO. In the first layer, tribes do not exchange any information, operate independently. In the second layer, using the brightest glowworm of each tribe, tribes communicate with each other and obtain the optimum. These tribes operate like a normal GSO algorithm and then choose a tbest i.e the leader of the tribe. Likewise all the tribes have one leader and in the end GSO is applied to all the leaders and then optimized solutions are obtained. The results show that great improvement is shown by this algorithm.

Yongquan Zhou,*et.al* (2013) proposes the Hybrid glowworm swarm optimization . In this the AFSA was embedded into GSO and then the obtained improved GSO along with differential evolution is combined on the basis of a two population co-evolution mechanism. In evolutionary process, HGSO [8] uses the constraint processing technology which is based on the feasibility rules for updating the optimal location of the glowworms which in turn makes the convergence faster and hence finds better solution. To avoid premature condition the local search technique to optimize the local optimal value based on simulated annealing is adopted. The results of this show that the HGSO has faster convergence speed and higher computational precision also it is more effective in solving constrained engineering problems. The proposed algorithm has IGSO-DE as its frame work. This is tested on welded design problem and also on the tension/compression string problem. HGSO is tested on five benchmark functions and five engineering design problems. The experimental results show that the HGSO proves to be the best among other algorithms in the literature in terms of efficiency, precision, reliability and robustness. Hence, the HGSO is very effective for solving constrained design problems.

Mr.Amar K. katkar (2012) presents an optimization technique, used in Municipal Solid Waste (MSW) [9]collection for the identification of optimal routes. This identification is critical for the trucks as most of the money approximately 80% is wasted on collection purpose only, therefore in order to reduce the cost factor the collection process needs to be improved. The proposed method is based on the location of waste bin, the road network and also the population density. To locate the shortest possible path to collect the wastes from all the dustbins, Minimum spanning tree technique is used. Minimal spanning tree in MSW is introduced for monitoring, simulation, testing and route optimization of different scenarios. The main task in this is to find the minimum spanning tree, building a network of roads to connect numerous cities to get the minimum path . The proposed method was implemented in the city of Kolhapur to see the results and was found to be effective. This problem has been related to the travelling salesman problem, which aims to find the minimum route. This method ensured to find the effective and reliable results and can be carried to the, where the problem is more severe.

M. Brambilla, *et.al* (2012) discusses swarm robotics along with swarm engineering. Two taxonomies are proposed with respect to swarms: methods and collective behaviors [11]. Some methods are analyzed to design and analyze swarm robotic systems. Some of the collective swarm behaviors are also analyzed which swarm robotics system can exhibit. Problems of swarm robotics and swarm engineering are discussed in this literature.

Design phase deals with the system when it is planned and developed starting from the initial requirements and specifications. Till now also some human intervention is required for design. Design phase is divided into two phases: behavior-based design and automatic design.

- Behavior-based design **:** This design method is the common method of designing a swarm robotics system. each robot's **b**ehavior is implemented using an iterative approach. This deals with the swarm system implementation by analyzing social behavior of animals. This makes the process very easy as the details of a any behavior are already understood and mathematical models are available.
- Automatic design method : This reduces the effort of developers in creating a collective behavior.

- Analysis methods: In this the swarm engineer is willing to see whether a general property of the designed collective behavior holds or not. Swarm robotics can be modeled at two levels: the individual level, or microscopic level.
- Collective behavior: Collective behavior of swarms can be combined to tackle complex real world applications like forging. They are categorized into many categories.

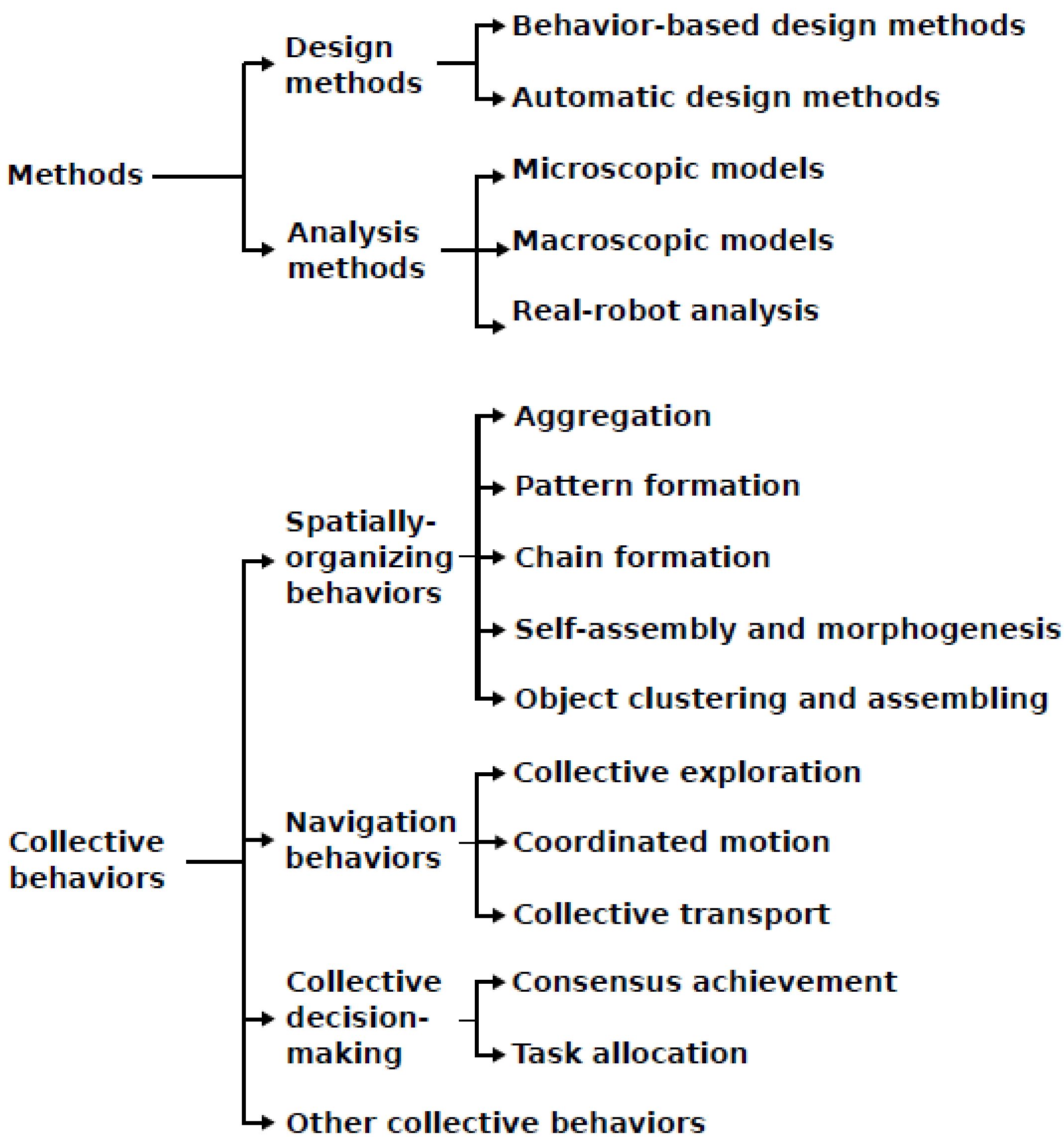


Figure 2.1. Methods of swarm engineering

Jiakun LIU, *et.al* (2011) introduces a inception of definite updating search field at glowworm updating position phase. As the GSO algorithm is easy to fall into local optimization, having a low speed of convergence and low accuracy. This paper introduces a new algorithm GSO-D [12]to make the position updating glowworm move closer to the best glowworm so that to improve the accuracy and speeding up the convergence. This method uses eight functions, to improve the optimization global ability with the help of testing. The results show that this method has a strong global searching capability. This GSO –D updates each particle to determine the range of domains presented, so that the position which is updated, is always better than the glowworms around it, so as to improve the convergence speed and accuracy.

Yongquan ZHOU, *et.al*(2011) proposes a new niching Glowworm Swarm optimization with some mating behavior [13] (MNGSO) to solve the problem of low precision and slow convergence and easy to be trapped in local optima of GSO. Both these techniques together improve GSO. Diversity of the algorithm can be maintained by the niching strategy as it can be incorporated with population elimination strategy. The mating behavior improves the convergence quality and precision. Both these techniques together enable the algorithm to solve the high dimensional global optimization and get a good solution. The solution is tested with some classical global optimization algorithms like ACO, PSO etc. The result of MNGSO is found to be efficient and feasible for global- optimization.

Niche strategy

Niche is defined as the living environment of biological population in specific environment. Individuals in the same niche live together, reproduce, communicate with each other and co-evolve. The individuals squeeze between individuals belonging to different niche. This strategy is used to solve global or local optimization. This paper uses the RCS niching strategy which form independent search spaces dynamically with the subpopulation. This will enable the algorithm to search several local optima and avoids being trapped in the local optima and also obtains more precise global optima.

Mating Behavior

In nature mating is done with respect to the luciferin intensity of the female glowworms. If a glowworm emits more bright light it will attract numerous male glowworms. Here it is supposed that the emitting pattern and emitting time of a generated male glowworm is proportional to its fitness. At last, the position of the male glowworm is obtained where the best female glowworm whose fitness is highest among others. In this the availability of MNGSO was tested with nine other functions. MNGSO was compared with other algorithms. MNGSO has advantages of high-precision, good convergent, speed, good stability.

Shu-Chuan Chu, *et.al*(2011 **)** talks about various algorithms in swarm intelligence which can be applied to variety of fields in engineering and social sciences. Algorithms like PSO, ACO [14]and others are reviewed in to the with experiments. In PSO potential solution is given by an individual known as swarm. Each particle has some fitness value and velocity, also learns from experience of the swarm to search for the global optima. This algorithm covers initialization, velocity updating, particle position updating, memory updating. In ACS (Ant Colony Systems) a cooperative population based search algorithm is inspired by food particle behavior of real ants. Each ant makes its root from nest to food particle by following the quantities of pheromone level. The intensity of pheromone level would bias the path choosing, decision making of subsequent ants. Enhanced algorithms are also discussed in this study like parallel PSO, in this the computation time of PSO is can be reduced with parallel structure. With a goal of reducing the run time parallel processing aims at producing the same results achievable using multiple processors. Just like PPSO this concept is applied to PACO, getting the same benefits. Both of these algorithms are experimented on travelling sales man problem.

B. Samanta,*et.al* (2009) presents an application of PSO in combination to some other computational intelligence techniques i.e proximal support vector machine (PSVM) [10] for machinery fault detection. Both the variants of PSO linear and binary were considered. This approach combines advantages of both the PSVM and PSO. All the input features are selected using the PSO algorithm. Subsets of experimental data are used to train the classifiers for known machine conditions and also tested using the remaining data. Whole of the procedure is illustrated on a vibration of a rotating machine. The influence of number of features like the PSO model and the PSVM are investigated. In the end the results were compared with a Genetic Algorithm (GA) and also with Principal component Analysis (PCA).t The accuracy was found to be 90% which is better as compared with GA and PCA. In this many topologies of PSO were used. Also the performance of linear was better than the non linear one.

K.N. Krishnanand, *et.al*(2009) represents a problem of driving groups of mobile agents on a two dimensional workspace to multiple sources of a some nutrient profile that is distributed spatially. The same problem is faced in wide variety of applications which includes detection of multiple radiating sources like nuclear spills. This report describes Glowworm Swarm Optimization that enables splitting of robot swarms into subgroups, exhibiting simultaneous taxis towards and rendezvous at multiple unknown radiation sources locations. GSO finds multiple optima of multimodal functions. This approach to compute their movements , uses a variable local- decision domain by the robots/agents.

GSO has several significant differences from ACO and PSO. [17]ACO and PSO techniques are used for locating global optima. The basic objective is to locate as many peaks as possible.

	Standard ACO	GSO
1.	Most effective in discrete settings.	Applied to continuous domain.
2.	Equal value of global optimum or multiple global optima.	Equal or unequal values for multiple optima.
3.	Cannot be applied to ants having limited sensing range.	This is useful in robots having limited sensing range.
4.	Global information used.	Local information used.
5.	Deals with pheromones to move from nest to region.	Deals with luciferin value to navigate from one position to other.

Table 2.1. Comparison of ACO and PSO

K.N. Krishnanand, *et al*(2009) presents a novel algorithm GSO that simultaneously finds a multiple optima of multimodal functions. The GSO algorithm is evaluated on many standard multimodal functions. This algorithm can handle discontinuities in the objective function. Also a comparison of PSO with GSO is shown in this.

The Leapfrogging Effect: In this paper GSO [15] is represented that with respect to any given iteration the glowworm with the maximum luciferin remains constant. This property may lead to deadlock situation as all the glowworms in a vicinity move to the brightest glowworm that is located in the peak. As all the movements of agents are restricted to the interior region of the convex hull, all the glowworms get together to the brightest glowworm having the maximum luciferin value during its movements within the convex hull. This problem is automatically looked upon by the discrete nature of movement update phase. In this phase a glowworm moves a distance of definite size s toward a neighbor. Now when the glowworm i approaches the glowworm j, with distance between a then less than s, i leapfrogs over the position of j and becomes a leader to j. In the next step j regains its position by overtaking i, and becomes the leader. This process repeats and a local search behavior is found along a single ascent direction.

Many test functions are considered in this like unequal peaks, equal peaks, peaks of concentric circles, peak-regions involving step-discontinuities, and plateaus of equal heights.

Multimodal test functions

GSO is tested on the following set of multimodal functions:

Rastrigin's function:

$$J2(x, y) = 20+x^2 - 10\cos(2\pi x)+ y^2 -10\cos(2\pi y). \qquad (2.1)$$

This function was proposed by Rastrigin as a 2-D function. This functions represents a difficult problem due to its large search space and large number of local minima and maxima. For eg the peak function ($J1(x, y)$) consists of only three peaks, whereas this function has 100 of such peaks in this range. This is a benchmark to test various algorithms which are designed to solve global and multimodal function optimization problems.

Circles Function:

$$J2(x, y) = 20+x^2- 10\cos(2\pi x)+ y^2 -10\cos(2\pi y). \qquad (2.2)$$

This function contains multiple concentric circles as a region of local maxima.in this the circular lines re*present* infinite peak cases.

Staircase function:

$J4(x, y) = 25 - x - y.$ (2.3)

This contains a series of stairs .This function presents a case where as we move the function value increases from one stair to the next, toward the tallest stair.

Plateaus Function:

$J5(x, y) = \sin\_\cos(x)+\cos(y)\_.$

This function contains multiple plateaus. This is similar to the stair case function in terms of nature of peaks, the plateaus in the $J5(x, y)$ *function have equal objective function values.*

(K. N. Krishnanand and D. Ghose,2005) presents a glowworm swarm based algorithm [16]to find solution to optimization of multiple optima continuous functions. In this optimization scenario the problem is solved where a set of autonomous robots are engaged to form a mobile sensor network. The problem of multiple sources detection of a general nutrient, on a two dimensional workspace distributed in a space, using numerous robots is addressed. The algorithm developed in this paper can be applied to any class of problems related to collective robots. In GSO the agents are based entirely on local information, exhibit behavior for nutrient sources. In this the author of the paper observed number of source locations that were detected, are strong function of the local decision range of the agent. So in this the decision range is varied as a function of neighborhood density, which in turn improved the performance and the number of peaks were maximized.

Techniques used so far to solve the problem

Previously some work has tried to solve the problem of Garbage and Recycling Collection (GRC) Problem using different techniques which are biologically inspired. Earlier Watanabe et al. used some immune network based system on new behavior arbitration. They did this with by using fig 1.1 some simulations were carried out to ensure efficiency of the invented mechanism. The simulator represented some environmental problem, just the same as this one .The environment contained a Charging Station (CS), a Recycle station(RS) ,and a Garbage station(GS). The work previously done is also inspired from swarm robotics. Robots are used as swarms and do the task. Different prototypes are used by different techniques to solve the problem. The robots will have the maximum energy level at the beginning of implementation, without carrying any garbage. The environment has no battery in the charging station. The robot will go to the garbage station which contains items of garbage, and collects them. After this it goes to the Recycle station to change this garbage into energy. A behavior Arbitration mechanism based on immune system was used to achieve their goals.

The work of Waltanabe and collaborators investigated an autonomous control system or a mobile robot based on the immune network hypothesis using some constructive approach. Fig 1.2 illustrates this problem environment.

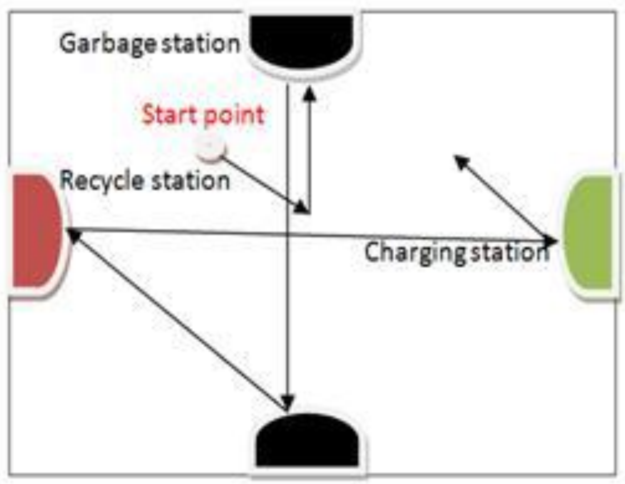


Figure2.2.trajectory of immunoid

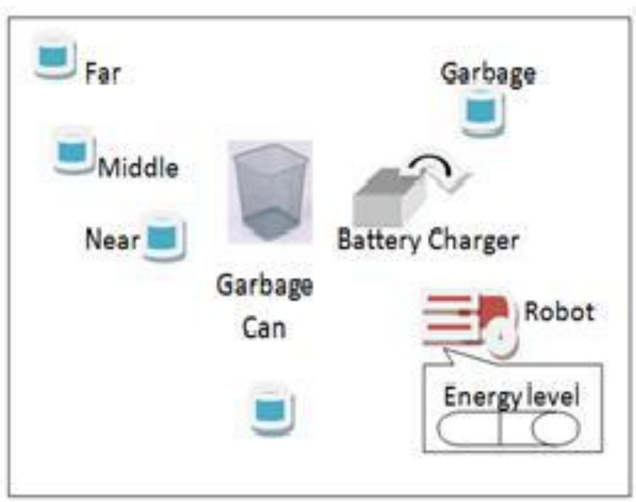


Figure 2.3. problem environment

Finally, Vargas et al.in which they implemented a new immune-genetic network which takes a evolutionary algorithm with a continuous immune network model applying it to a Real Khepera II robot. They used the simulated environment with the garbage, the base and the obstacles. In this the obstacles are avoided by the robot to reach the station by collecting the garbage.

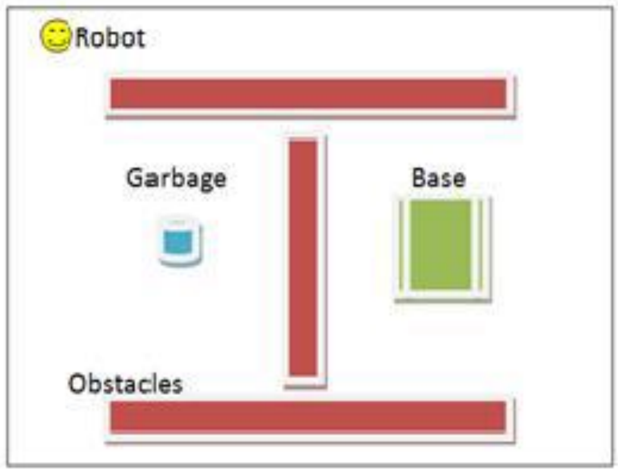


Figure 2.47. Simulation environment

All the simulated robots were trained so that they can avoid the obstacles like walls or other robots i.e collisions should be avoided.

CHAPTER 3
PRESENT WORK

After studying the idea behind the swarm intelligence, it is understood that this intelligent natural behavior helps to reduce the cost and time by finding the optimum solution. Swarms inspire themselves by the collective behavior of living beings like birds, ants, glowworms etc. Swarm also deals with robots and the study is swarm robotics. Swarm robotics introduced the concept of cellular robotics systems which consist of collections of autonomous, non-synchronized and non- intelligent robots cooperating on a finite n-dimensional cellular space under distributed control. Swarm intelligent has many algorithms which are used in many applications to get optimized results. All the algorithms are based on the collective behavior of individuals. All the techniques of swarm intelligence are bio-inspired.

Garbage and Recycle Collection problem was earlier solved with many other techniques so as to find the best solution. The basic aim of this work is to use one of the bio inspired techniques based on swarm intelligence (Denby and Hegarat-Mascleb, 2003) on an optimization problem.

Basically this work will concentrate on Glowworm swarm optimization to solve the problem of garbage collection and recycling problem. For doing this, simulated robots will be used and trained so as to distinguish between the items of garbage and material for recycling and the robots should find the best possible path to collect these items and then dump it into the garbage station.

3.1 Scope of Work

The scope of this work is wide as this can be used in the near future to find the best possible way to collect the desired things. As in GRC problem if the optimized path is not found it would result in more cost, so as to reduce this cost and time factor the GSO, an optimization technique is used. This can be used with sensors and the desired work can be done with it. As now we have many cleanliness programs so this can be a great help in that process. Also GSO is a new technique so can be used with many other problems and then can be integrated with many systems. Glowworm can be used in all the applications where local optima is required.

- Some more enhancements can be done to this algorithm so as to improve the efficiency and results.
- In the further work a camera in the simulator can be used for the detection of the colour of various stations i.e whether garbage or recycle station.
- By adding this camera items can be differentiated not only by color but also by shape.
- Improvement can be done in the GSO algorithm to have better efficiency and reliability.
- This approach can be integrated with many systems and an optimum route can be found so as to reduce the cost and time factor.
- This application of Garbage and Recycling Problem(GRC) can also be solved with other optimization techniques and more efficient results can be found.

3.2 Objectives

The aim is for the robots to interact as a swarm of animals, cooperating with each other to have an efficient and accurate solution. Some of the objectives of this are:

1. To gain understanding of the MATLAB.
2. To enable the addition of robots and the modification of their behavior.
3. To develop an algorithm of needs (Glowworm Swarm Optimization).
4. To have the best possible route to reach the garbage and deposit it in the minimum possible time.
5. To apply the code on the MATLAB by adding number of robots and for the robots to behave as swarms to accomplish the tasks:
    - Every robot in the arena, following the best immediate neighbor to that target. must reach the same target.
    - Robot must avoid all the barrier including other robots and walls of the arena and this can be done by activating sonar and bumper of each robot to calculate the distance between itself and each obstacle.
    - The garbage from the area must be collected and then dumped into the garbage station in the minimum time possible. The robots must be able to distinguish between the items of garbage and the material for recycling, and deposit each of these types in its allocated station without being exhausted out of energy**.**

3.3 Problem Formualtion

The problem of GRC (Garbage Recycling and Collection problem) using an application of swarm intelligence with the help of robots is earlier implemented using many other techniques and also using different methods. The basic idea in this is to train multiple robots to interact with each other so as to behave as a single entity. This work in this is done with the help of two approaches PSO (particle swarm optimization) and ACO (Ant colony optimization). While using PSO star and circle topologies are used along with two prototypes in the experiments. The circle gave the best results between both of these. When both these topologies were mixed, more optimal solution was found. PSO has a specific type of memory system that fulfills the requirements of the problem very effectively. This work of PSO working on robotics working as swarms was inspired by previous work done on robotics. A comparative evaluation and an explanation for the choice of topologies that enhanced the PSO algorithm is stated in this work. This problem was also solved with ACO approach. The ACO approach presents an unusual grid implementation of robot physical simulation, generating new concepts and discussions about necessary modifications for the algorithm towards an improved performance. The main objective is to find the optimized path to collect the garbage from various points and then dump them into the garbage station. Both ACO and PSO are then compared to get the best algorithm which gives optimum solution for the problem proposed. Between both of these PSO and ACO PSO came out to be the best with much higher accuracy. But PSO has many drawbacks which effects the accuracy of this application. As the Glowworm Swarm Optimization has glowworms as its agents, any physical entities are considered to be randomly distributed in a work area. The agents in GSO carry luminescence quantity along with them known as luciferin. Glowworms are considered as agents which emits light , the intensity of which is proportional to the associated luciferin value and have a variable decision range , which is bounded by a circular range.

3.4 Disdvantages of PSO

Compared with Particle Swarm Optimization algorithm, ant colony algorithm, and other traditional swarm intelligence optimization algorithms, GSO algorithm has rapid computing speed, less adjustable parameters, easy to realize. Local decision domain based on varying range. Also they are used in continuous domain.

	PSO	GSO
1.	Movement direction based on previous best positions.	Movement of agent along line-of-sight with a neighbor.
2.	Dynamic neighborhood based on n nearest neighbors.	Local decision domain based on varying range.
3.	Entire search space covered by neighborhood range.	Maximum range limited to finite sensor range.
4.	Limited to numerical optimization models	In addition to numerical optimization models detects effective multiple peaks

Table 3.1. Comparison of PSO and GSO

Due to significant differences among the two algorithms and also some advantages of GSO over PSO, GSO is applied to GRC to have more optimized results. GSO is also a new algorithm and with some more and more enhancements into this algorithm many applications can have more better results as compared to other computational intelligence techniques.

GSO has been used in many fields to achieve optimal solutions. GSO has been used in many applications with continuous domain. GSO finds solutions to optimization of multiple optima continuous functions. Detection of Multiple Source Locations is done with the help of GSO. GSO is used during nuclear spills, or hazardous chemical spill in an industrial plant for detecting multiple sources of spills and also contains all the spill in a much effective manner before they can cause damage to the environment and people living in the premises. Many other applications use GSO like search and rescue in some building to depend on temperature gradients, another application to localize sensors transmitted over landscape etc.

3.5 RESEARCH METHODOLOGY

The Garbage and Recycle Collection (GRC) problem uses robots for its implementation and obtain some results with the help of GSO. This application makes use of swarm bots and exploit their behavior and advantages efficiently. The work is implemented using MATLAB. As MATLAB is an interactive system and the performance graphs obtained will give more insight to the problem. It integrates computation, visualization, and programming environment. it is a modern programming language having sophisticated data structures, contains built-in editing and debugging tools, and supports object oriented programming. It allows matrix manipulations; plotting of functions and data; implementation of algorithms; creation of user interfaces; interfacing with programs written in other languages,

This problem makes use of a GSO algorithm to work on collective swarms. A prototyping approach is used, the problem is divided into three levels. The first level refers to prototype one and so on.

- The first prototype consist of some simulated robots in a limited area with a single target station in the area. This prototype shows the collective behavior of swarms in GSO to train the robots to interact with each other and communicate in order to reach the goal i.e the target station following the leader.
- The second prototype approach is more challenging, designed for when the robots have reached the goal in the previous level. In this more items of garbage are added at different random places in the same arena. The basic task of these robots is to collect the garbage and deposit the same in the garbage station as quickly and efficiently as possible. To do this task, GSO trains the robots to find the most efficient and optimal way to follow the brightest neighbor.
- The third prototype extends the goal of the second one by adding more complexity by requiring the robots to distinguish between the items of the garbage and the items to be recycled. For this prototype, recycling materials and a recycled station is also added. Robot checks is the material a garbage or material for recycling? and belongs to which station –garbage station or recycling station.

Description

The GRC application using the GSO algorithm performs efficiently and the results obtained are optimized. The three phases in GSO are responsible for the working of particles**.** GSO has some steps to be followed for the implementation of the application.

Step 1. Initialize the parameters and initialize the robots randomly in the search space.

Step 2. Now decide the case among the three and calculate the values of all the parameters.

Step 3. Calculate the fitness of each robot according to the distance from the target as the robot near to the target will have more fitness value and will attract others towards it.

Step 4 Using the equation 1.1 the luciferin will be updated in turn the fitness will be updated.

Steps 5. According to the fitness the robots will change their locations. Using the roulette method the robot selects a neighbor the probability is calculated and move towards it, then

using the eq 1.3 location of the robot is updated.

Step 6. Using the eq 1.4 neighborhood range is updated with respect to all the robots.

Step 7. The robot will check for the item that whether it is garbage or other one to recycle with respect to this it will select the station.

Step 8. All the steps from the step 3 are repeated till maximum iteration are reached.

Step 9. The process will stop when the maximum iterations are reached. The process will end and the performance can be analyzed with the help of graphs.

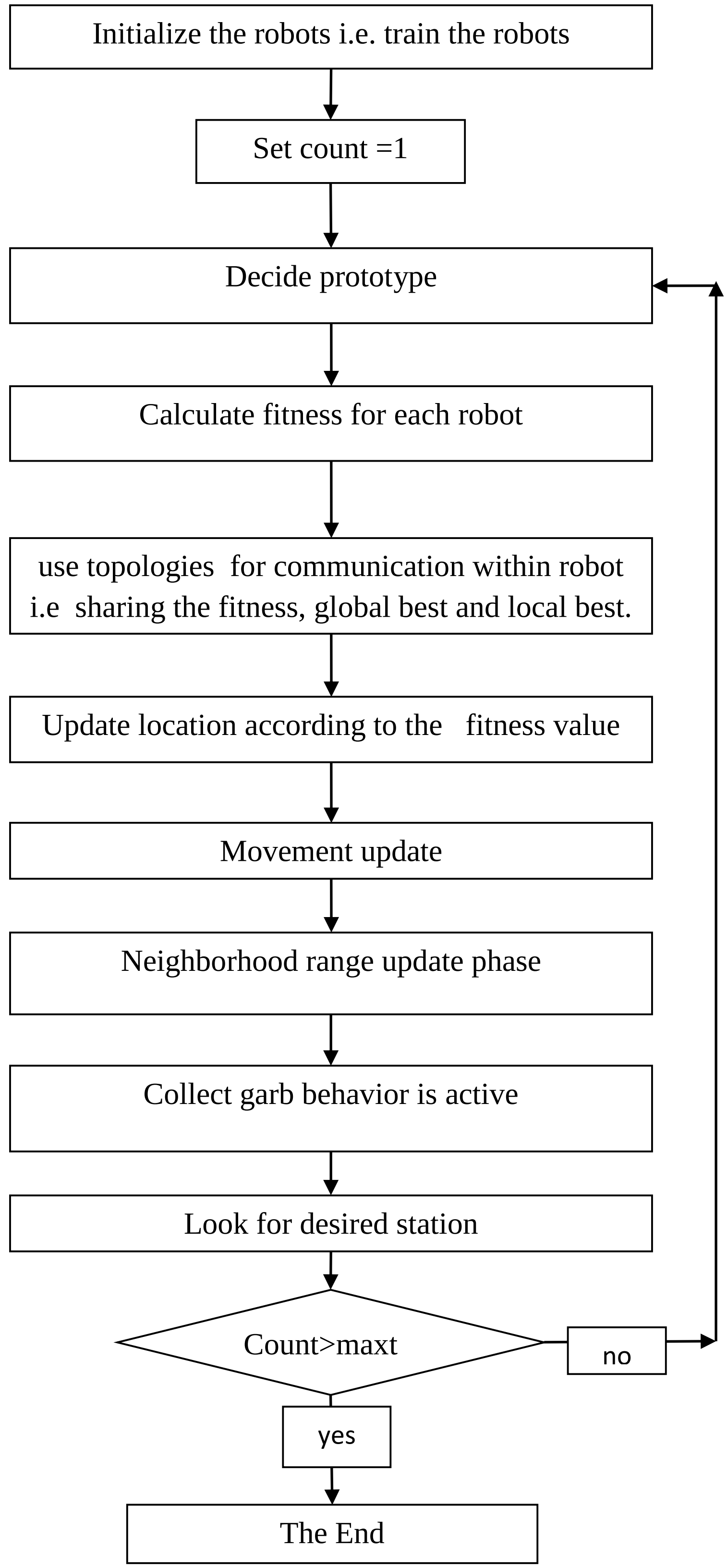


Figure 3.1. GRC working with GSO

Chapter 4

RESULTS AND DISCUSSION

This chapter presents the results of experiments carried out on GRC by Glowworm Swarm Optimization. Various graphs are generated to give the fitness of the robots and efficiency of the application with GSO. With the results it is clear that GSO has higher fitness value as compared to previously used techniques. The results are shown for 1000 units of garbage which are collected by the robots. In glowworm swarm optimization the glowworms work with the help of some steps. This algorithm works in three phases: Luciferin Update, Movement phase and the Local decision range update phase. Some standard benchmark functions are also used to find the best solution and for the comparison with other algorithms. These benchmark functions are minimized as much possible Some of the benchmark functions are given:

Funciton	Function Formula	Domain	Type
Sphere	$f_1(x) = \sum_{i=1}^{n} x_i^2$	[-100,100]	UM
SumSquares	$f_2(x) = \sum_{i=1}^{n} ix_i^2$	[-10,10]	UM
Quartic	$f_3(x) = \sum_{i=1}^{n} ix_i^4 + random[0,1)$	[-1.28,1.28]	UM
Schwefel 2.22	$f_4(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,10]	UM
Schwefel 1.2	$f_5(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2$	[-100,100]	UM
Rosenbrock	$f_6(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	[-30,30]	UM
Dixon-Price	$f_7(x) = (x_1 - 1)^2 + \sum_{i=2}^{n} i(2x_i^2 - x_{i-1})^2$	[-10,10]	UM
Griewank	$f_8(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]	MM
Ackley	$f_9(x) = -20 / \exp(\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)) + 20 + e$	[-32,32]	MM
Rastrigin	$f_{10}(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	[-5.12,5.12]	MM

*UM: Uni-modal, MM:Multi-modal

Table 4.1. Benchmark functions

The luciferin decay constant p=0.4, the luciferin enhancement constant gamma=0.6, the neighborhood change rate beta=0.08, the neighborhood threshold n_t =5. The step-size s= 0.8. These values are constant and standard as these are calculated from many standard functions. The whole process in GSO algorithm is based upon the intensity of the glowworm. More the intensity of glowworm more glowworms it will attract. The GSO has some predefined constants which are used as it is in the algorithm. The simulations are carried on MATLAB R2014a and the simulation platform used is Windows 8.1, i3 , 4GB memory. The maximum iterations are 1000. This work has been carried out in three prototypes and the results are then compared. 3 cases are made with respect of 3 prototypes having different number of robots in each. Robots behave differently in different environment. Their fitness also changes with respect to the target. The performance of GSO can be analyzed by various graphs.

The value for lbest and gbest can be obtained from the GSO and performance can be evaluated. The snapshots for the experimental results are shown :

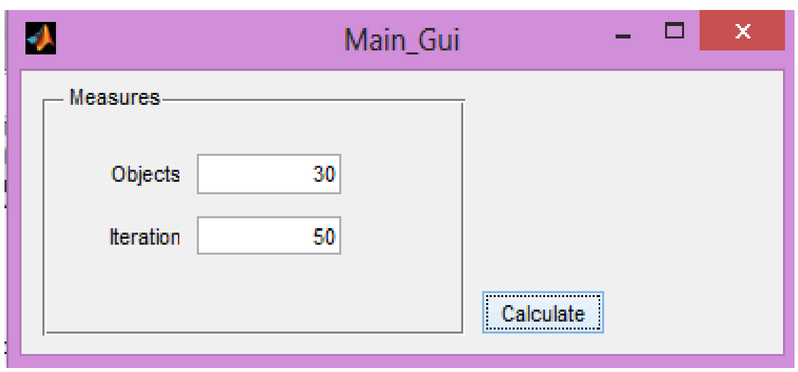


Figure 4.1. Simple GUI

A simple GUI shown in fig 4.1 to enter number of robots and specify number of iterations to perform the garbage collection. The number of iterations should be large enough so as to get a clear output and a clear understanding of the final results. Calculation will be performed on the bases of given output. Objects here are the number of agents i.e robots. The three cases are discussed below:

Case 1: In this case garbage is not added into the arena. Only the agents i.e the glowworms have their definite positions so all will have the same luciferin count means same fitness value. Number of robots =20

Number of iterations = 10

Units of garbage =0

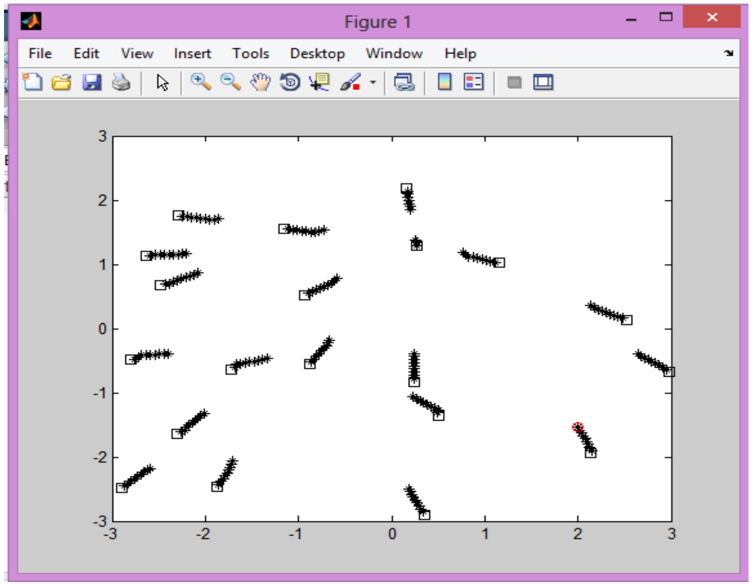


Figure 4.2. initializing the population with no garbage

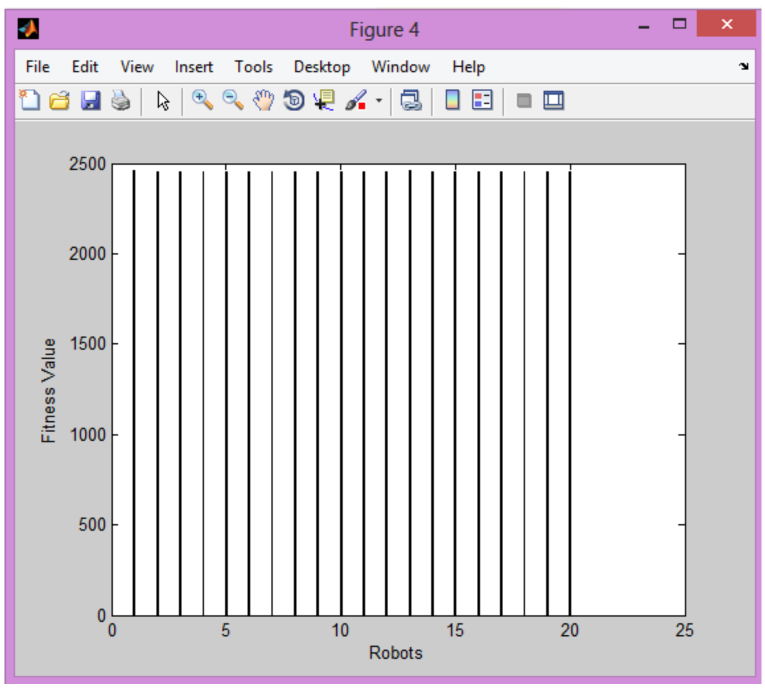


Figure 4.3. Fitness graph

Case 2: In this case the items of garbage are added and the intensity of each glowworm will vary with respect to its distance from the target.

Number of robots = 20

Number of iterations =100

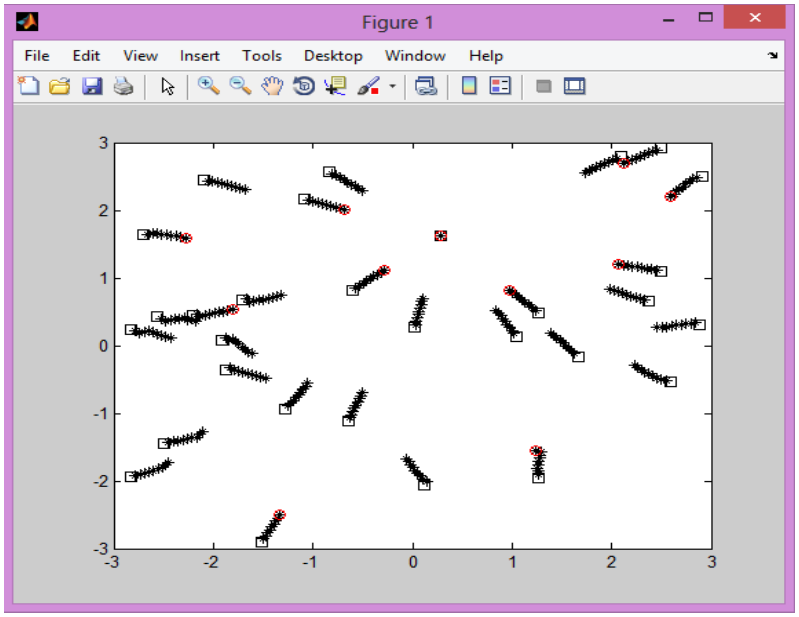


Figure 4.4. Robots with garbage

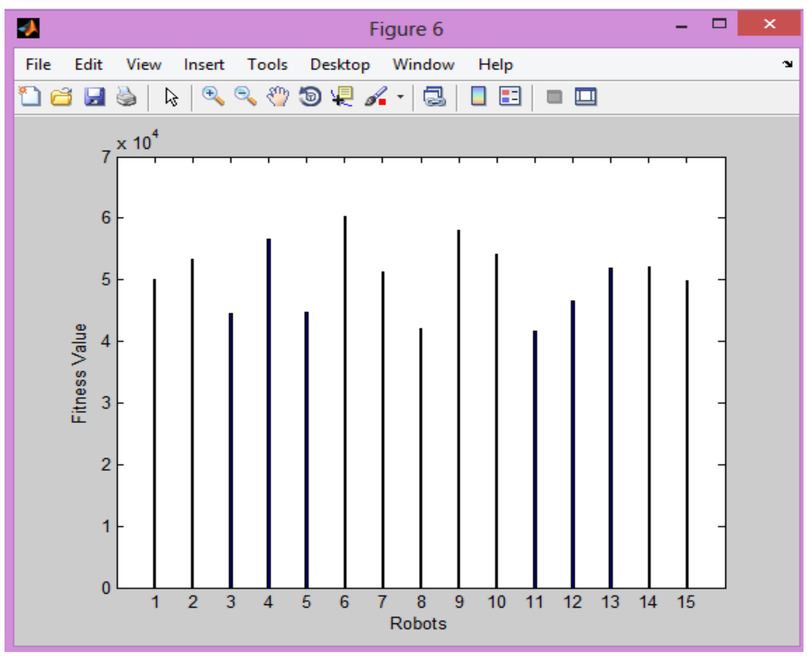


Figure 4.5. Fitness of each robots

Case 3: Brightest glowworm attract other glowworms i.e robots will move towards the robot with highest fitness value and will reach the target with an optimized path. The glowworms are attracted by the brightest glowworm. These glowworms are agents i.e the robots collecting garbage from the arena. The glowworm nearest to the target will have high luciferin count i.e the robot nearest to the target will have maximum fitness value to which others will be attracted and by this their cooperative behavior will be shown. The red circles are the items of garbage and the near by robot has higher fitness value and is the brightest so all the other agents will move towards that following the optimized path. In this case the collision rate is also taken into account i.e robots should avoid walls and other robots coming on its way.

Number of robots =40

Number of iterations =200

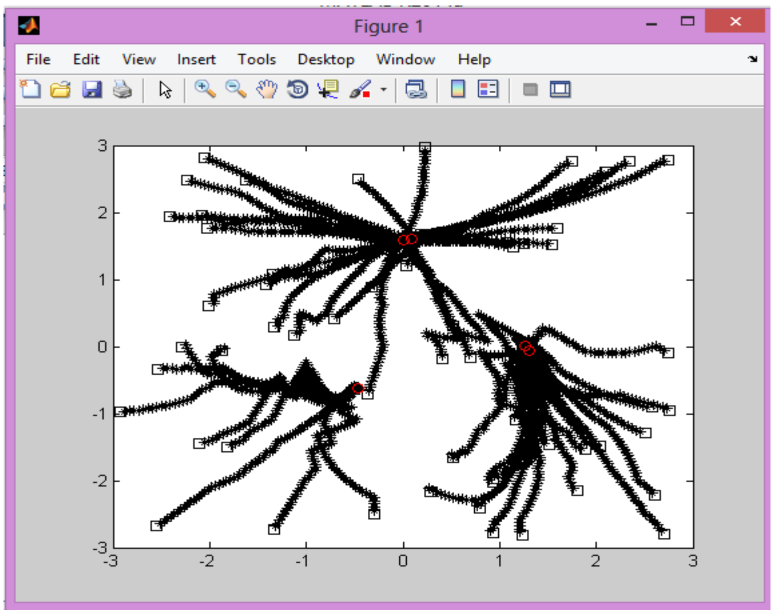


Figure 4.6. Glowworm attracted to the brightest

The fitness of all the robots at this stage is shown in figure , the leader the robot having the highest fitness will have more intensity and will attract more agents. This fitness in total gives the gbest and lbest values. The fitness of the robot depends on the distance from the garbage point i. e the target. Initially, the fitness of each robot is very less. This fitness is also dependent on the path taken by the robot to reach its destination. More the fitness of the robot, more optimized will be the results.

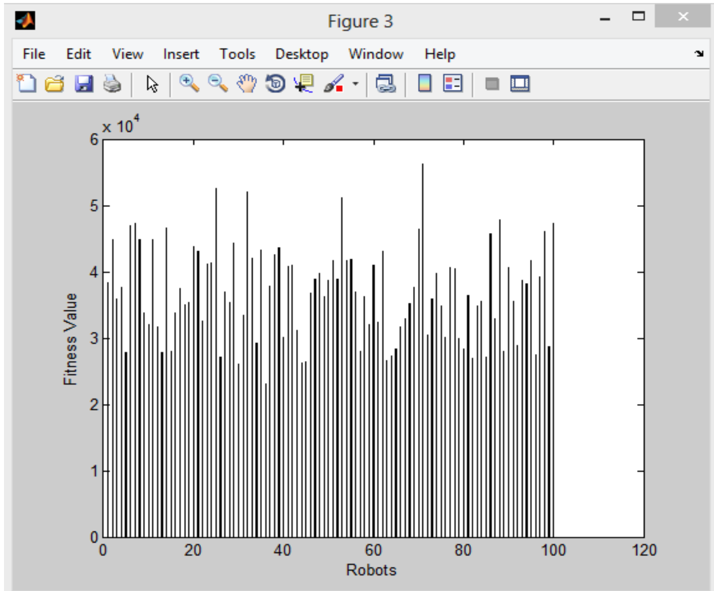


Figure 4.78. Fitness of each robot individually

Case	Robots	Iterations	Gbest value
	3	1	7.3861e+04
1	5	5	7.0032e+04
	20	10	4.7623e+04
	20	100	2.4538e+03
2	30	150	1.0155e+04
	35	180	1.0e+04
	40	200	0.385e+01
3	80	400	0.58e+01
	100	500	0.02e+01

Table 4.2 Gbest of all the cases

$$\text{Average gbest of case 1} = \frac{7.3861e{+}04+7.0032e{+}04+4.7623e{+}04}{3}$$

$= 6.3838e+04$

Average gbest of case 2 $= \dfrac{2.4538e+04+1.0155e+04+1.0e+04}{3}$

$= 1.4897e+04$

Average gbest of case 3 $= \dfrac{0.385+04+0.58e+04+0.02e+04}{3}$

$= 0.3283e+04$

The gbest values of the three acses are calculated and it can be seen that the value increases when the robot approaches the garbage and the number of iterations are increased. Gbest while approaching to zero is the best for all the functions. Here the experiments are done with one of the benchmark functions.

The robots in the beginning are scattered and look for the better fitness in the neighborhood. Initially all the robots take different paths to choose the brightest i.e with every iteration the results will be refined. Now in this it can be seen that all the robots take different positions in the first iteration. This blue region shows all the robots taking different path initially. This is because at this point the population is initialized randomly, they find the agent with the best fitness value and are attracted towards it.

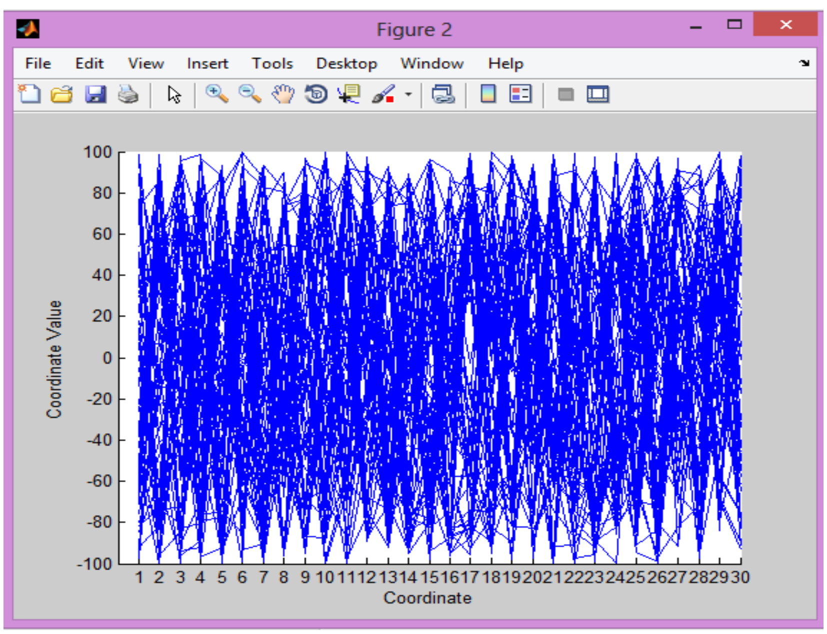


Figure4.8. Working of GRC

The figure 4.9 shows the path of the agents after some iterations and it can be seen that the path is now more refined. The peaks in the figure show the target i.e the garbage which is collected by the agents and dumped. The peaks also show the best fitness value among all the agents. Here, coordinate and coordinate value is plotted which gives different points in the arena where the application of GRC is working. The robots still take many paths i.e they search for the best possible path to reach the target by GSO.in the end an optimized path is obtained and also the time consumption is less.

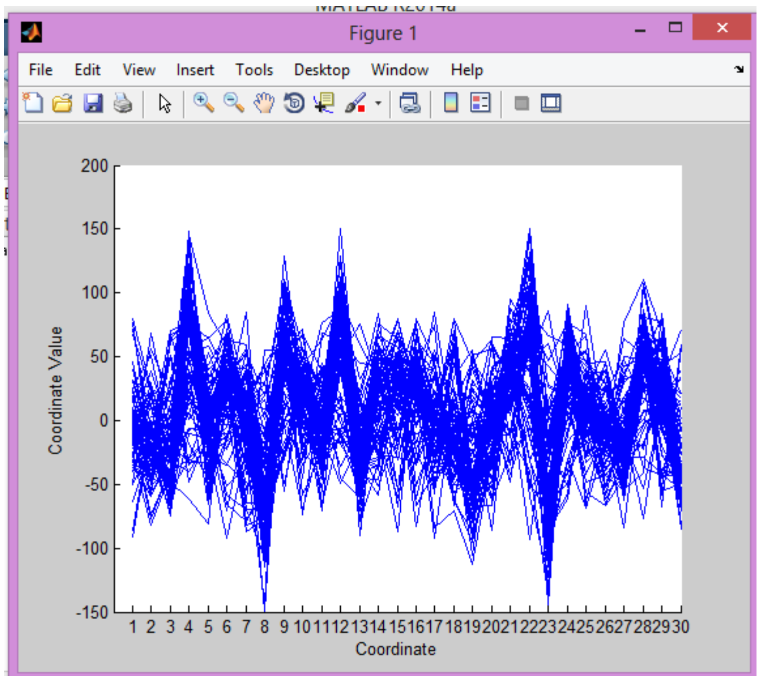


Figure 4.9. Converged path

This figure shows the final output of GRC with the help of GSO. The agents looked for the targets i.e the garbage at different points and found the best possible path to reach the station. Initially, the glowworms take various paths to reach to the destination. Better results can be found with large number of iterations. From the number of results i.e paths, the agents find the best possible solution to reach the destinations. This path is optimized with application of GSO. The randomly initialized robots are trained first to do the job. In the final graph a simple line is obtained which gives the path followed by the robots to reach to the target.

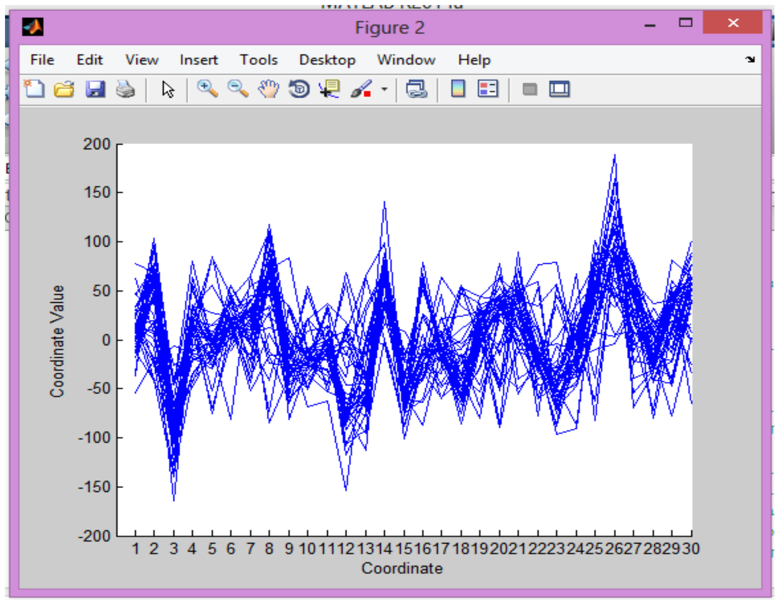


Figure 4.10. Final path

In this figure some bench mark functions are used to calculate the values. Twenty three bench mark functions are used to find the best fit. The algorithm can be tested for various standard functions to calculate the fitness value. In this graph, the fitness value is compared with an ideal value, the fitness value is highest in the starting and as the number of iterations decrease, the fitness also decreases as the units of garbage to be collected are very less now.

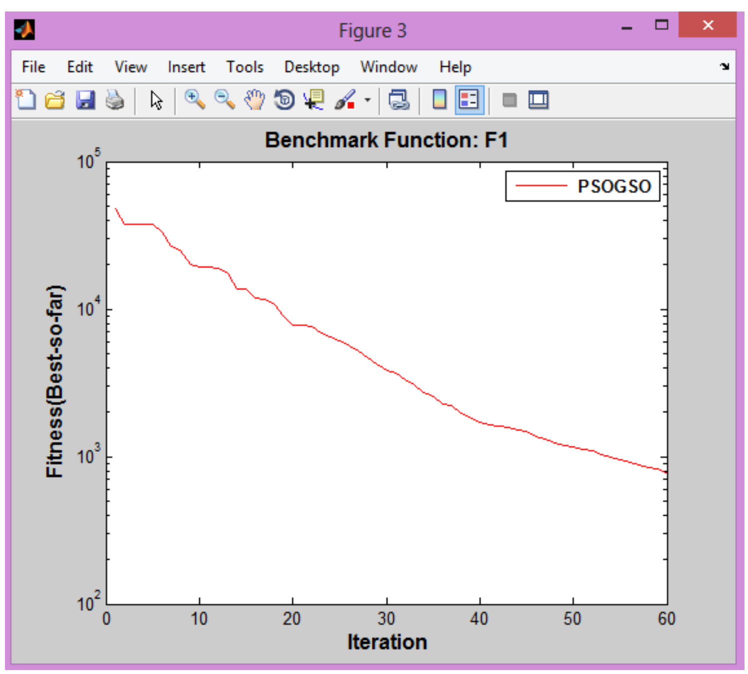


Figure 4.11. Comparison with ideal value

This figure shows the graph for GSO for the fitness of the algorithm with the number of iterations. Initially, the fitness value is higher but then dropped suddenly as we initialize the population randomly, the gents are not able to find the brightest agent or the agent with the maximum fitness value. With the increase in number of iterations, the fitness of the algorithm increases as the research is more refined now. In the end, the dropped suddenly as the number of units to be collected are finished. More the number of iterations, more accurate will be the results.

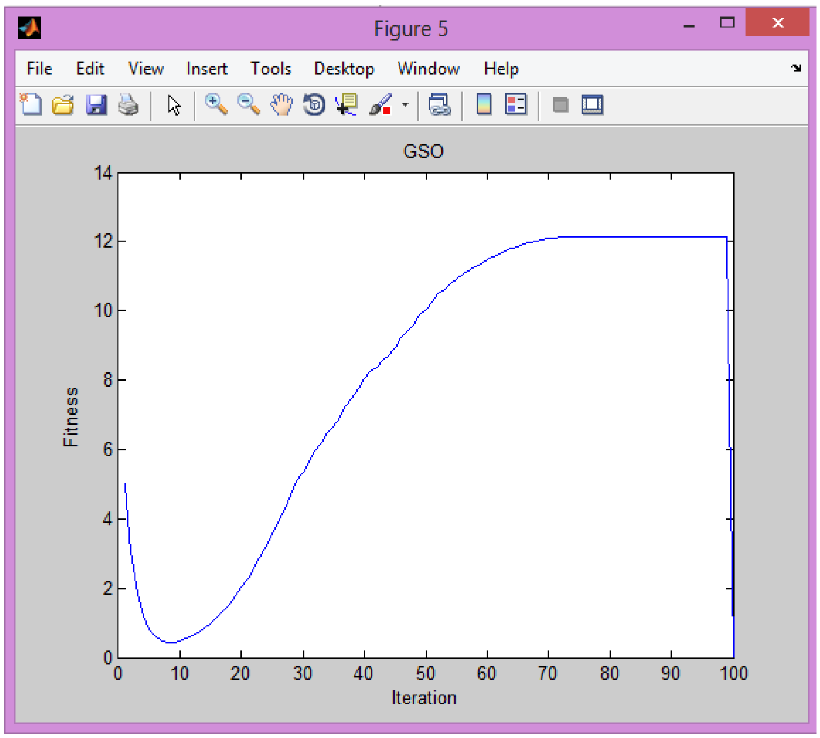


Figure 4.12. Fitness graph of GSO

The figure shows the graph for garbage collection by two methods: one represents the GRC application with glow worm swarm optimization. Second method represents the garbage collection with the application of PSO which was implemented earlier. The value for the collection is much higher in case of GSO. More of units of garbage are collected as the target in the GRC application Is the garbage and the agent near the garbage having the highest fitness value will glow bright. Hence, attracting the fellow agents. So no garbage is left in the arena while using GSO.

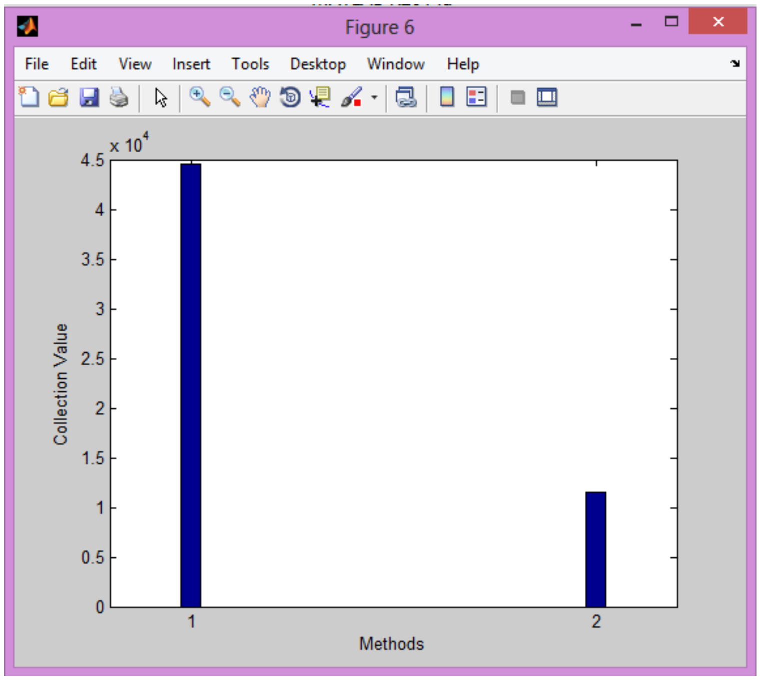


Figure 4.13. Comparison of GSO with PSO for garbage collection

The time taken by the GRC in optimizing the problem and reaching the target is less than the other techniques. The graph for the same is shown in figure

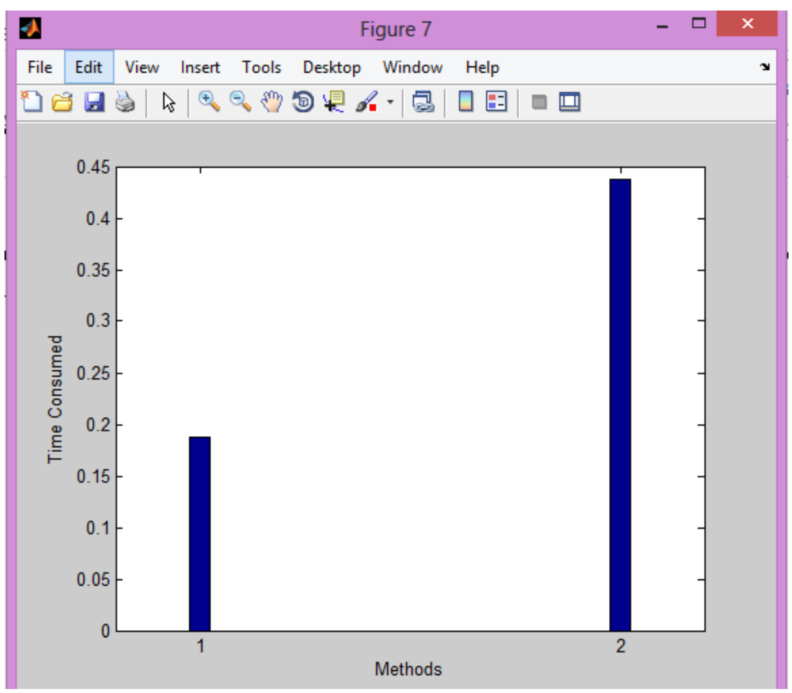


Figure 4.14. Time comparison

This figure represents the comparison between the collision rates in the GRC application by two methods: PSO and GSO. The collision rate in the PSO is much higher than the GSO. By collision, all the obstacles including walls and other robots are considered, each robot must not collide with any other robot or wall while traversing the distance towards the destination. By this collision, a lot of time is wasted and optimized results are not achieved. Lesser the number of collisions, less is the time taken to reach the destination and more optimized are the outcomes by using GSO.

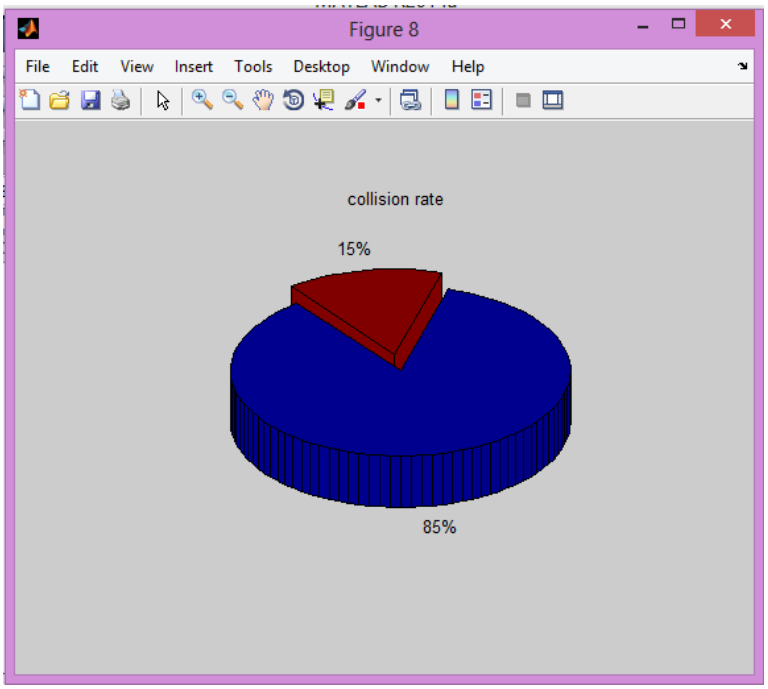


Figure 4.15.Collision rate of GSO

Chapter 5
SUMMARY AND CONCLUSION

This chapter presents the summary of what is proposed and done so far to achieve the goal and why the GSO algorithm is the choice to solve the problem of Garbage and Recycling Problem (GRC). This work includes the usage of GSO to solve the GRC and to find the best possible route to collect the garbage and the recycle the same in the station. GSO uses glowworms its agents to find the optimal path, behaving as a cognitive entity. In this the work is divided into four prototypes having goal in each of the prototypes and when the goal in first is reached, next level is processed and so on. And in every perspective glowworms i.e the agents will following the algorithm will find a way with the help of the other glowworms having the higher luciferin value. By this an optimized way is found to reach the target.

In this study a optimization approach is proposed with the help of GSO, a swarm intelligence technique. This work was previously done with PSO and ACO, the results were compared to find the optimal path. In this algorithm the efficiency can be improved and can also be enhanced further with some modifications. It assures the best possible way with the help of agents i.e robots can communicate with each other and will find an optimum path to reach the target. This work also has a future scope and can also be used in real time environment so as to reduce the cost and time factor. Robots are trained and simulated to collect the items of garbage and deposit them in respective stations. Also a camera can be used so as to monitor the proper working of the robots.

REFERENCES

[1] A. P. Engelbrecht, Computational Intelligence, University of Pretoria, South Africa: Wiley, 2007.

[2] K. Krishnanand and D. Ghose, "Glowworm swarm based optimazion algorithm for multimodal functions with collective robotics applications," *ISSN*, no. 2, pp. 209-222, 2006.

[3] H. Nie and J. Shen, "Research on Glowworm Swarm Optimization with Ethnic Division," *JOURNAL OF NETWORKS,* , vol. 9, no. 2, FEBRUARY 2014.

[4] D. Pengzhen, . T. Zhenmin and S. Yan, "A Quantum Glowworm Swarm Optimization Algorithm based on Chaotic Sequence," *International Journal of Control and Automation,* vol. 7, no. 9, pp. 165-178, 2014.

[5] G. Pessin, D. O. Sales, M. A. Dias, R. L. Klaser, D. F. Wolf, J. Ueyama, F. S. Osório and P. A. Vargas, "Swarm intelligence and the quest to solve a garbage and recycling collection problem," © *Springer-Verlag Berlin Heidelberg,* pp. 2311-2325, 2013.

[6] Y. Zhou, Q. luo and J. liu, "Glowworm swarm optimization for optimiztion dispatching system of public transit vehicles," *ISSN,* vol. 52, no. 2, pp. 205-210, 2013.

[7] Y. Zhou, G. Zhou, Y. Wang and G. Zhao, "A Glowworm Swarm Optimization Algorithm Based Tribes," *An International Journal*, pp. 537-541, 2013.

[8] Y. Zhou, G. Zhou and . J. Zhang, "A Hybrid Glowworm Swarm Optimization Algorithm for Constrained Engineering Design Problems," *Applied Mathematics & Information Sciences,* vol. 7, no. 1, pp. 379-388, 2013.

[9] A. A.Katkar, "Improvement of solid waste collection by using optimization technique," *ISSN,* vol. 2, no. 4, pp. 298 - 307, 2012.

[10] B. Samanta and C. Nataraj, "Application of particle swarm optimization and proximal support vector machines for fault detection," *Springer*, vol. 3, p. 303–325, 2009.

[11] M. Brambilla, E. Ferrante and M. Birattari, "Swarm robotics:A review from the swarm engineering," IRIDIA, 2012.

[12] Y. Z. H. O. W. Jiakun LIU, "a Glowworm Swarm Optimization algorithm based on definite updating search domains," *journal of Computational Intelligence,* pp. 3698-3705, 2011.

[13] K. HUANG , Y. ZHOU and Y. WANG, "Niching Glowworm Swarm Optimization Algorithm with Mating Behavior," *Journal of Information & Computational Science,* vol. 8, no. 16, p. 4175–4184, 2011.

[14] X.-m. T. Yan-fei Zhu, "Overview of swarm Intelligence," *IEEE,* vol. 9, pp. 400-403, 2010.

[15] K. N. Krishnanand and . D. Ghose, "Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions," *Springer,* vol. 3, p. 87–124, 2009.

[16] K. Krishnanand and D. Ghose, "Detection of Multiple Source Locations using a Glowworm Metaphor with Applications to Collective Robotics," *IEEE,* p. 14, 2005.

[17] K. Krishnanand and D. Ghose, "Theoretical Foundations for Multiple Rendezvous of Glowworm-inspired Mobile Agents with Variable Local-decision Domains," *IEEE,* pp. 3588-3593, 2006.

[18] S.-C. Chu, H. C. Huang, J. F. Roddick and J.-S. Pan, "Overview of Algorithms for Swarm Intelligence," *Springer-Verlag Berlin Heidelberg,* pp. 28-41, 2011.

[19] M. P. Asha Gowda Karegowda, "A survey of applications of glowworm swarm optimization algorithm," *IC2IT,* pp. 39-42, 2013.

APPENDIX

ABBREVIATIONS

a) **ANN-** Artificial Neural Network

b) **SI-** Swarm Intelligence

c) **PSO-** Particle Swarm Optimization

d) **GA-** Genetic Algorithm

e) **SLFA -** Shuffled frog leaping algorithm

f) **QCSGSO** - Quantum Glowworm Swarm Optimization Algorithm based on Chaotic Sequence

g) **TGSO** - Tribe glowworm swarm optimization

h) **HGSO** - Hybrid glowworm swarm optimization

i) **PCA** - Principal component Analysis

j) **GRC** - Garbage and Recycling Problem

k) **ACO-** Ant Colony Optimization

PUBLICATIONS

- Paper accepted in ICAAET 2015 and in process for publication.
- Paper accepted in International Journal of Applied Engineering Research (IJAER).
- Paper accepted in Advanced Computational Intelligence: An International Journal (ACII)