2D SWARM MEERKATS BEHAVIOR MODELLING

NG HONG SHEN

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by

NG HONG SHEN

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PEMODELAN SIFAT DUA DIMENSI KUMPULAN MEERKATS

ABSTRAK

Tingkah laku atau sifat binatang mempunyai sambungan atau hubungan antara aspek molekul dan fisiologi biologi dan ekologi. Kelakuan adalah hubungan antara organisma dan alam sekitar antara sistem saraf dan ekosistem. Selain itu, tingkah laku secara umumnya adalah "barisan pertahanan pertama" sebagai tindak balas kepada perubahan alam sekitar. Oleh itu, pemerhatian yang teliti terhadap tingkah laku dapat memberi kita maklumat yang berguna. Kelakuan adalah salah satu ciri penting kehidupan haiwan. Sebagai manusia, kelakuan memainkan peranan penting dalam kehidupan kita. Hal ini kerana tingkah laku adalah sebahagian daripada organisma yang berinteraksi dengan persekitarannya. Banyak masalah yang berlaku dalam masyarakat manusia sering dikaitkan dengan interaksi antara alam sekitar atau genetik dengan tingkah laku. Bidang sosioekologi dan tingkah laku haiwan berurusan dengan isu interaksi tingkah laku persekitaran baik pada tahap evolusi dan tahap proksimat. Oleh itu, sosial saintis fokus kepada tingkah laku haiwan sebagai rangka untuk menafsirkan masyarakat manusia dan mencari sumber kemungkinan masalah masyarakat. Dalam tesis ini, tingkah laku meerkat Meerkat akan dikaji dan parameter untuk simulasi tingkah laku Meerkats foraging direka. Parameter yang direka termasuk bilangan ejen, bilangan kumpulan, pelbagai persepsi dan bilangan makanan. Tetapi, tidak banyak penyelidikan dilakukan terhadap tingkah laku meerkat jadi borang tinjauan digunakan untuk mereka 14 set parameter. Hanya pilihan yang mempunyai peratusan yang tinggi sahaja akan ditumpu dalam mereka bentuk 14 set parameter untuk simulasi. Prestasi 14 set simulasi dibandingkan dengan hasil yang diperoleh daripada simulasi seperti kualiti min tertinggi yang boleh dicapai oleh simulasi dan bilangan kutu yang diperlukan untuk mencapai kualiti purata tertinggi. Semakin tinggi kualiti min lebih baik prestasi. Simulasi yang memerlukan jumlah tik yang kurang untuk mencapai kualiti min tertinggi mempunyai prestasi yang lebih baik.

2D SWARM MEERKATS BEHAVIOR MODELLING

ABSTRACT

Animal behavior is the connection or link between the molecular and physiological aspects of biology and the ecological. Behavior is the bridge between organisms and environment also between the nervous system and the ecosystem. Besides that, behavior is generally the animal's "first line of defense" in response to environmental change. Therefore, careful observation of the behavior can provide us a great information. Behavior is one of the most important features of animal life. As a human, behavior plays a critical role in our lives. This is because behavior is the part of an organism that interacts with its environment. Many problems occur in human society are often related to the interaction between environment or genetics with behavior. The fields of socioecology and animal behavior deal with the issue of environment behavioral interactions at an accurate level and a proximate level. Therefore, social scientists are turning to animal behavior as a framework to interpret human society and to find out possible sources of societal problems. In this study, the foraging behavior of Meerkat will be studied. In this thesis, the foraging behavior of Meerkat will be studied and the parameters for simulation of Meerkats foraging behavior are designed. The designed parameters including the number of agents, number of group, range of perception and number of food. However, there are not much works done on Meerkats therefore, survey form is used in designing these 14 sets of parameters. Only the choices that have higher percentage is focused in designing the 14 sets of parameters for simulation. The performance of each 14 sets of simulation are compared based on the result obtained from the simulations such as the highest mean quality the simulation can achieve and the number of ticks required to reach the highest mean quality. The higher the mean quality the better the performance. The smaller the number of ticks required to reach the highest mean quality the better the performance.

CHAPTER 1

INTRODUCTION

1.1 Background

The suricate or more known as meerkat is one of the species that belong to the mongoose family. Its scientific name is Suricata Suricatta. The meerkat is belonged to mammal class which mean they are a warm-blooded vertebrate animal and they are omnivores. Meerkats are mostly found in Kalahari Desert in Botswana, southwestern Angola, South Africa and Namib Desert in Namibia.

Meerkats only active during daytime and the average weight of male meerkats is about 731 grams, for the female meerkats the average weight is about 720 grams. The height of the meerkats is between the range of 25-35 centimeters and the length of their tail is about 17-25 centimeters. While standing, the meerkats will use their tail to balance their body and their eyes are surrounding by the black color. The black color surrounds their eyes helps meerkats to inspect a thing very clearly even though the surrounding is very bright and the meerkats can even see the sun directly without any damage to their eyes. This characteristic is very important to meerkats because they can detect the predators that fly in the sky easily and prevent their clan from being the food to the predators.

Besides that, meerkats are social and living in colonies which can contain up to 40 meerkats. Meerkats groom each other regularly to increase the bond between each other. One or more meerkats will act as a guard to look for the predators when the other meerkats are hunting for food [1]. When there is a predator, the guard meerkat will give a warning bark to inform the other meerkats to hide into the holes. The guard will be the first one to come out from the holes to ensure whether the predator had left or not and if the predator had left the guard meerkat will stop the warning bark and the other meerkats can continue their routine.

Swarming robotic is basically contain many homogeneous and simple robots that operate autonomously without a global controller. The interactions between each robot or between the robots and the environment allow the swarm robotics to simulate the behavior of the studied population [2].

Foraging is the process that searching for food resources. Meerkats normally will forage or hunt in a small group. Meerkats have only a little fat to store energy so they have to searching for food every day if not they will unable to survive. In this project, the behavior of the meerkats during foraging will be studied and analyzed for example the food is distributed non-uniformly and simulate the foraging of meerkats [3]. The meerkats will find their own way to search for the food in order to survive [4].

Netlogo is a software that authored by Uri Wilensky in 1999 and has been in continuous development ever since at the Center for Connected Learning and Computer-Based Modeling. It was used by many of researchers, students and teachers. It is a multi-agent programming language and modeling environment for simulating complex phenomena [5, 6].

Agent-based modelling (ABM) is a method for simulating the interactions between each individual agent which can be simulated using Netlogo. ABM is to simulate a complex dynamic model. “Dynamics” is define as continuously changing or developing and always involve in many complex elements. ABM makes the problems easily to solve and that would be very difficult to solve using traditional dynamical methods [7]. Several examples of Agent Based Modelling application for swarm intelligence are ant colony optimization (ACO), bee colony optimization (BCO) and so on.

In this project the meerkat swarm dynamics behavior will be simulated by using agent-based modelling (ABM) method. The parameters such as number of groups, chances to go for the best food, range of perception and number of foods are designed and the simulation result of different input values of parameter is studied.

1.2 Problem statement

Meerkat is a fascinating social-animal that can live in a desert and there is not much analysis done on the behavior of meerkat. Therefore, in this project, study and simulation on the foraging behavior of the meerkat are constructed. The parameters which are number of groups, chances to go for the best food, range of perception and number of foods are designed and the simulation result of different input values of parameter is studied. However, in order to simulate the behavior of meerkat, computer-based modelling is used due to its ability to provide effective tools for analysis.

1.3 Objectives

There are 2 objectives need to be achieved to complete the project:

1. To study and design the parameter for simulation of the behavior of meerkats in term of hunting and guarding.
2. To study the performance of the modelling with different input values of parameters.

1.4 Research scope

The behavior of meerkat is studied through many different sources such as youtube, Journal of Zoology and so on. Based on the studies of the behavior of meerkats, the behavior is simulated with the aid of computer. There are two types of agents with different behavior let say agent type-A and agent type-B. Agent type-A is the agent that perform foraging process while agent type-B is the agent that act as a sentry to warn the foraging meerkat if there is any danger.

For the simulation part, a set of parameters which are number of groups, chances to go for the best food, range of perception and number of foods is stated and analysis should be done to interpret the relationship between the behavior of meerkat and the changes of parameters. This is because a slightly change in the parameters may cause a deviation from normal meerkat's behavior.

Netlogo 6.0.2 is used in the simulation of the behavior of meerkats. Netlogo is a multi-agent programmable modeling environment. The parameters used in simulation of the behavior of meerkats should be simulated by using the Netlogo. Besides that, the result of simulation by using Netlogo should be analyzed and studied the interaction between the set of parameters with the meerkats' behavior.

1.5 Report outline

This research report comprises five chapters. Chapter 1 briefly explains on the research background, problem statement, objectives followed by project scope and then report outline of this project.

Chapter 2 presents the literature review about this project. The previous work such as Agent Based Modelling, optimization from the social insect behavior, flocks, herds and schools behavior and so on are studied in this chapter. Besides that, the methodology of the previous work will briefly discuss in this chapter.

Chapter 3 focuses on the methodology to design and simulate the meerkat's behavior. Agent-based models are becoming very popular in simulate the behavior of animals. Therefore agent-based models will be used in Chapter 3 to design the meerkat's behavior. Netlogo is one of the softwares that offers the agent-based modelling platform. Hence, Netlogo will be used to simulate the behavior of meerkats.

Chapter 4 explains about the result and discussion. In this chapter, the results obtained from the simulation in Chapter 3 will be evaluated. Discussion is made based on the result that obtained in Chapter 3.

Chapter 5 represents the conclusion of the project. In this chapter, the overall project is summarized. Besides that, the future development and suggestion of the project is also included in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

In this project, the foraging behavior of meerkats will be studied and analyzed. Therefore, the previous works that relevant to the fundamental theories and concept about the research topics will be studied and explained in this chapter. Agent-based model is used to approach the simulation of behavior of meerkats. By using the agent-based models, the interaction between the meerkats or agents can be studied and analyzed.

Section 2.2 discussed about the agent-based modelling and simulation. In the next section, expectation transformation in a housing market under different exogenous conditions by using an agent-based modeling approach is discussed. Section 2.4 a case study in HIV Epidemic by using agent -based modeling is discussed. In section 2.5 and section 2.6, poverty and the emergence of Tuberculosis using the agent-based models and agent-based event simulation approach for modelling large scale disaster evacuation network is studied. For section 2.7 until section 2.16, the social animal behavior is briefly explained. The social animal behaviors include social insect behavior, flocks, herds, schools, meerkat clan, schooling of fish, grey wolf with invasion-based migration, bee colony, cat and social spider. Finally, last section summaries the research and studied done on this chapter.

2.2 Agent-Based Modelling And Simulation

Tutorial on agent based modelling (ABM) simulation by Charles M. Macal and Michael J. North in 2012 is an appropriate modelling approach for a large class of problems [7]. Agent-based modelling is mathematical model of an item and the item can be human, animal and so on. It creates an artificial population of agents and let them interact between each other to simulate the behavior of the item. First, the type or class of the agents such as human, animals and so on need to be identified. Once the agents are defined, we need to specify their behaviors by studying the behavior of the agents such as social behavior or foraging behavior. After specifying the behavior, we need to add the rules that control which agents interact, when they interact and how they interact. After that, the interaction between the agents with different parameters is observed and analyze. When to use Agent-based Modelling (ABM) [7]?

1. When the problem has a natural representation as being comprised of agents.
2. When there are decisions and behaviors that can be well-defined.
3. When it is important that agents have behaviors that reflect how individuals behave.
4. When it is important that agents adapt and change their behaviors.
5. When it is important that agents learn and engage in dynamic strategic interactions.
6. When it is important that agents have a dynamic relationship with other agents, and agent relationships form, change, and decay.
7. When it is important to model the processes by which agents form organizations, and adaptation and learning are important at the organization level.
8. When it is important that agents have a spatial component to their behaviors and interactions.
9. When the past is no predictor of the future because the processes of growth and change are dynamic.
10. When scaling-up to arbitrary levels is important in terms of the number of agents, agent interactions and agent states.
11. When process structural change needs to be an endogenous result of the model, rather than an input to the model.

ABMS offer many opportunities and has advantages with respect to conventional modeling and simulation paradigms. Due to the explanatory power that arises from its generative nature, it allows observation and analysis of model dynamics on at least two levels: the local agent and the macroscopic level, the latter being generated from the actions and interactions on the former. Figure 2.1 explains the concept of an agent in an agent-based models. Agents interact with the environment they lived in and other agents around them. All agents have different attributes such as fitness, ability to learn and so on. Since the learning process is involving in, therefore memory is required for agents to learn. Agents will have different behavior by varying their sophistication such as how much information is taken care when agents making a decision.

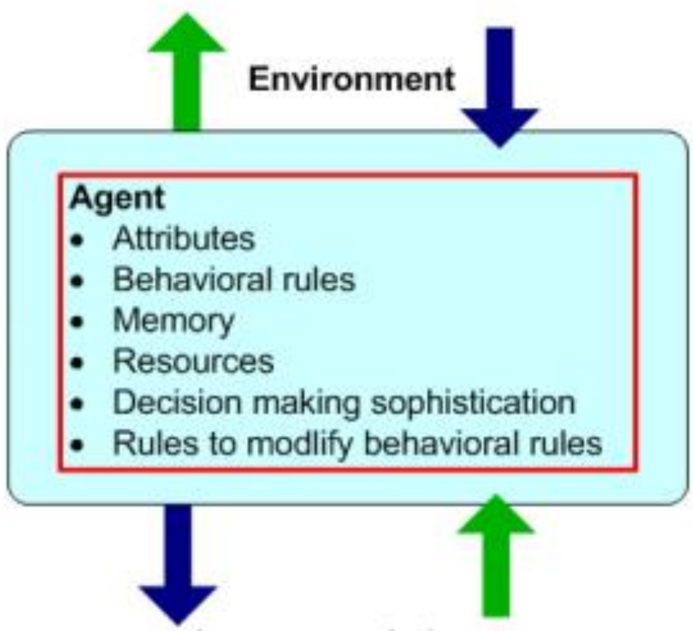

Figure 2. 1 Concept of an agent in an agent-based models [7].

2.2.1 Identifying Expectation Transformation In A Housing Market Under Different Exogenous Conditions: An Agent-Based Modeling Approach

Research done by X. Ruhang and L. Zhilin in 2017 [8] on identifying expectation transformation in a housing market under different exogenous conditions by an Agent-Based Modeling approach stated that market of houses is one of the main concern of social issues. There are many crises arise from housing market such as economic crises happened in 90s in Japan and 2008 in the USA. Agent based modelling is applied in this paper. Genetic based is introduced in the agent decision making and behavior simulation. This paper builds an agent-based housing market model based on a novel Genetic Programming method which consider the supply, transaction, credit and bankruptcy and auction. First the agent will be characterized as a rigid demand agent. As in the real world, an ABM of a market consists of a large number of buyers and sellers who act autonomously, making decisions of buying and selling based on their information and behavioral traits [9]. In this paper, there is an unified producer who will produce all houses in the market and the producer will supply some houses at regular interval [8]. There are 3 different types of decisions that the agents will do which are buy, hold and sell [8]. When an agent believes that the market will rise then it will buy the house. If an agent believes that the market will decrease in the future, it will sell the house. When an agent believes that the future market is neither not rise or drop then it will hold the house [8]. Besides that, every purchase of house is by using the loan and there are two types of loan. First type is the agent apply when it need to buy a house and second type is the unsecured loans which happen during the liquidity of an agent is insufficient [8]. The agent will be marked bankrupt when their cash become zero. At this point, the agent can only sell house but cannot buy house and only when all the loans have been cleared, the agent is in non-bankruptcy and can trade again. When the price of house increase, the agent will buy the house because in the rule if the agent believes that the market will rise, it will buy the house. Then the percentage of no house will decrease, this will increase the society wealth and lower down the poverty. However, this situation also arises the unevenness of wealth distribution problem [8].

2.2.2 Agent-Based Modelling: A Case Study in HIV Epidemic

The human immunodeficiency virus or know as HIV is a virus that causes the AIDS. AIDS is a condition where the human's immune system had failed to function and allow the growth of cancer cells or viruses. HIV mainly a sexually transmitted disease and causes the failure of immune system. The virus is transmitted from person to person through different factors. Modelling the HIV epidemic is difficult because the true incidence1 of the HIV/AIDS-epidemic is uncertain since many people may be unaware of their infection [10]. Secondly, HIV progression has a very long asymptomatic period which makes studies of the actual infection spreading a very complicated task [10]. The various routes of infection and the inhomogeneity of the involved population pose additional challenges to understanding the underlying knowledge of HIV epidemics [10]. The research had done by E. Teweldemedhin, T. Marwala and C. Mueller in 2004 [11] to develop the simulation tool by modelling these factors by agents. The agent-based modelling has advantage of observing the interaction between agents which is difficult problem for the other modelling methods. Figure 2.2 show that there are 4 agents introduced in this research which are Controller agent, Person agents, Environment agent and Statistical agent [11]. The controller agent starts the simulation process and controls the creation of all other agents. It provides input to agents [11]. The inputs are population size, characteristics, behaviors, assumptions about the population, time for completing the simulation and number of executions [11]. The person agents represent the individuals in the populations. Thus, the number of the individuals are the size of population. Each Person agent has characteristics and behaviors that represent it which are person's gender, HIV-status, type of personality, experience with safe sex, alcohol or drug addiction status, outgoing and having stable relationship [11]. The environment agent represents the environment in which the Person agents live. The statistical agent receives the average result of the expected output [11]. The agent contains the results of all the information obtained from the simulation process. It has number of persons living with HIV-positive and number of new HIV infections. There are four decisions used to calibrate the output of the model [11]:

- The number of agents a person agent need to approach
- Decision to propose for sex
- Decision to reply for the proposal for sex
- Decision to be infected during interaction

From the research, there is a stable oscillation for each simulation of different size population. The prevalence predicted by the simulation has accuracy about 90% [11] when compared to the findings of the Department of Health.

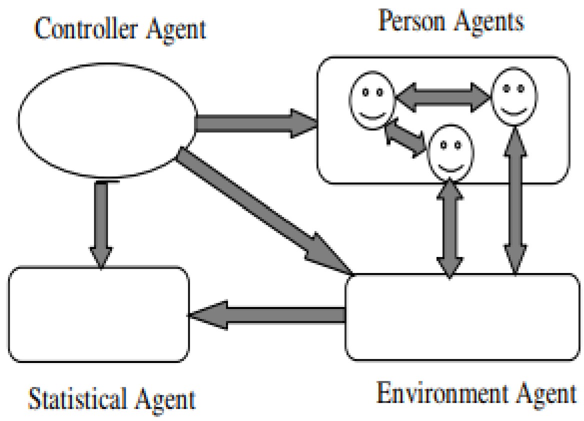

Figure 2. 2 Multi-agent system architecture of the simulation process[10].

2.2.3 Poverty And The Emergence Of Tuberculosis: An Agent –Based Modelling Approach

Tuberculosis (TB) is a disease caused by bacteria called Mycobacterium tuberculosis and the bacteria usually attack the lungs. Tuberculosis can spread during sneezes, talk or coughs through air. Therefore, there is a need to consider from the epidemiological perspective, the factors relating to poverty that increases the risk of emergence of the tuberculosis infection and the disease. In the research done by O. Badmus, S. Camorlinga and O. Simpson in 2016 [12], the agent-based modelling was used to have better understanding of the complex host-pathogen interplay considering some of the related factors relevant to poverty. The agents are living in absolute poverty which is undernutrition, overcrowding, inadequate ventilation and inadequate health care access. Each agent has their own CD4+ to CD8+ ratio which represents the immunity of the agent and a bacilli load which represents the quanta of infected droplet nuclei carrying the mycobacterium tuberculosis inhaled by the agents [12]. There are 2 stages of tuberculosis which are latent tuberculosis infection stage and the active tuberculosis stage. Latent tuberculosis is a state of equilibrium in which the host is able to control the infection but not completely eradicate the bacteria [12]. Four parameters relating to poverty are studied. First parameter is undernutrition and the level of undernutrition is converted to numerals 0, 1 and 2 to represent mild undernutrition, moderate undernutrition and severe undernutrition [12]. Overcrowding and inadequate ventilation parameters are represented as Occupancy density and air changes per hour. The

ACH is a measure of how many times the air within a confined space is replaced. Next, the access to health care parameter is either set to true or false. The Occupancy density, air changes per hour and access to health care are connected to bacilli load in the agents [12]. There are increase in the number of active TB disease cases as the undernutrition parameter changes from mild to severe (0- 2) when the access to health care parameter was set to false [12]. A steady number of active TB disease cases while increasing the undernutrition parameter and setting the access to health care parameter to true.

2.2.4 An Agent-Based Discrete Event Simulation Approach For Modelling Large-Scale Disaster Evacuation Network

When facing with a large-scale natural disaster, an appropriate evacuation strategy is always a daunting problem. A disaster can be defined as any occurrence that causes damage, ecological disruption, loss of human life, and deterioration of health. Natural disasters such as hurricanes, floods, earthquakes, volcanic eruptions, famine, and drought are often occurred in large-scale, rapid-onset, and overwhelming catastrophes relative to the scale of damage and the toll of casualties. It is most important to provide a rapid and efficient medical treatment when there are disasters. A research done by H. S. Na and A. Banerjee in 2014 was to study the large-scale disaster evacuation network to transport the patients to medical facilities efficiently [13]. DSG is a disaster scenario generator, a GIS is a geographic information system to solve a network evacuation problem and ABDES is an agent-based discrete event simulation. An ABDES evacuation framework based on an embedded GIS module is introduced to solve the large-scale natural disasters evacuation network problem that involves multiple candidate shelters, multi-priorities patients, and multiple vehicle types as shown in the Figure 2.3. First, the decision rules are considered to simulate the flow of each individual patient and vehicle during the whole evacuation procedure. The flowchart of this paper shown in Figure 2.4 shows that patients will be moved to the staging area which is a spacious area located around the disaster when they are found by rescue workers [13]. They will be prioritized in the staging areas based on their severity levels. At staging area, the patients will stay and receive the first-aid treatment, then the patients will be transferred to a proper shelter by a suitable vehicle [13]. The patient's priority will not be changed to a higher priority if a patient with a lower priority is waiting for a long time at a staging area and still yet not be transferred to a shelter [13]. While transporting patients to shelters, the decision-makers need to consider some factors such as transportation costs of evacuation vehicles arising from traffic congestion situations, any change of patients' condition or unexpected accidents. ABDES evacuation framework based on an embedded GIS module is proposed to act as a foundation for large-scale natural disasters evacuation decision support system [13].

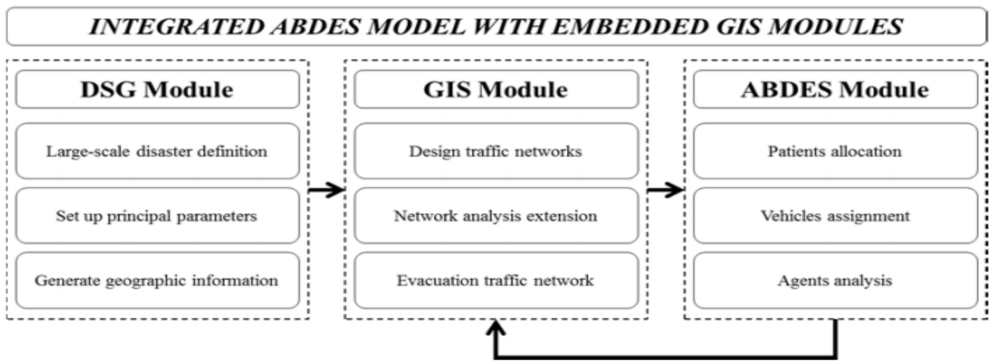

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Figure 2. 3 Overall evacuation framework with three modules[13].

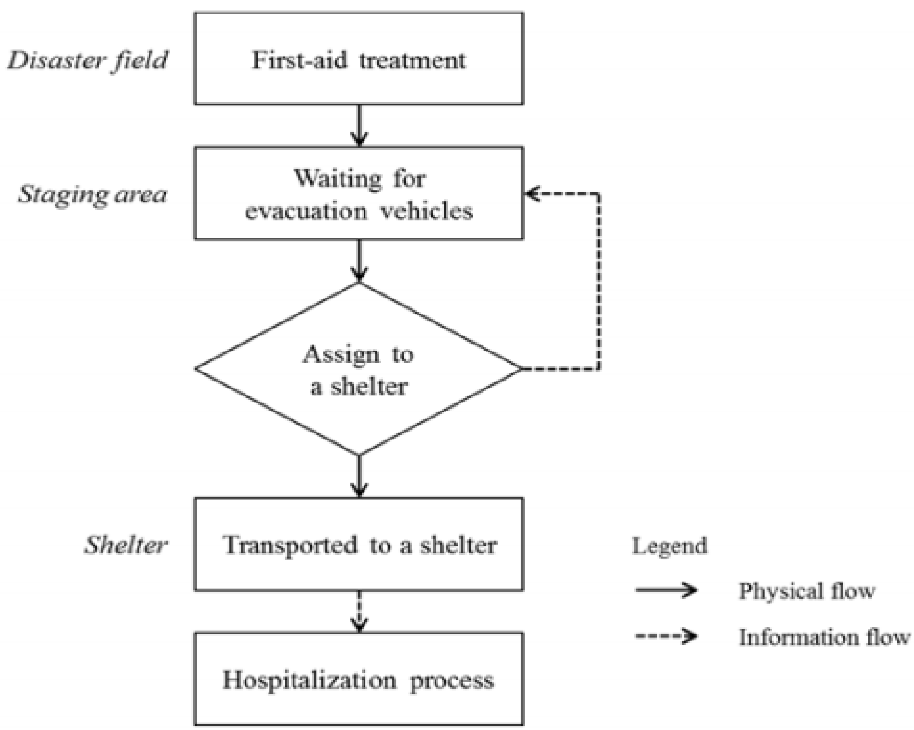

Figure 2. 4 Flowchart of patient agents transported to shelters[13].

2.3 Social Insect and Animal Behavior Modelling

Social behavior of insect and animal is studied in this section. The social behavior is very interesting in how the interactions among individuals of the same species able to solve the complex problems. For instance, ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs.

2.3.1 Inspiration For Optimization From Social Insect Behavior

Ethologists use modelling to understand animal behavior. In year 2000, a research had done by E. Bonabeau, M. Dorigo and G. Theraulaz in social insect behavior suggests that models based on self-organization can help explain how complex colony-level behavior emerges out of interactions among individual insects [14]. The final goal in understand animal behavior is to transform the models of social insect behavior into a useful algorithm that can help in solving problem. Ant Colony Optimization (ACO) and Ant Colony Routing (ACR) are the Optimization and control algorithms inspired by models of co-operative food retrieval in ants [15, 16]. ACO and ACR are being applied successfully to solve some of the engineering problems [14]. One of the ACO example is “How ants find the shortest path”. In this example, food is separate from the nest by a bridge with two branches as shown in Figure 2.5. These two branches have different length, the longer branch is *r* times longer than the shorter branch. Next example is “Travelling Salesman Problem”. In this example, ants will find the shortest tour between *n* number of cities visiting each once and only and ending at starting point. There are four steps in one iteration of ACO algorithm [14]:

- A set of *m* artificial ants are initially located at randomly selected cities.
- Each ant makes a complete tour, visiting each city exactly once.
- An ant located at current city hops to another city by selecting among the cities that have not yet been visited.
- When every ant has completed a tour, pheromone trails are updated. The pheromone refers to a chemical substance produced and released into the environment by an

animal, especially a mammal or an insect, affecting the behavior or physiology of others of its species.

Ant Colony Optimization (ACO) does not always work well [19]. Ant Colony Optimization does not perform as well as other heuristics on any problem's instances that have been uniformly randomly generated. The reason is that Ant Colony Optimization tends to reinforce portions of solutions that belong to many good solutions which the better solutions a given portion belongs to, the more virtual pheromone it receives. If a large number of portions of solutions are equally likely to be part of good solutions, ACO cannot differentiate them and therefore performs poorly [14]. However, many of real-world problems contain enough of the require information to allow this approach to perform efficiently.

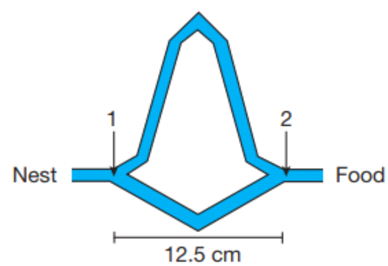

Figure 2. 5 The multiple branches with different distance [14].

2.3.2 Flocks, Herds, and Schools: A Distributed Behavioral Model

The research was done by Craig W. Reynolds on behavior of flock, herds and schools of animal [17]. The motion of a flock of birds is one of nature's delights. A flock of birds is made up of many of individual birds and overall motion seems smooth. The coordinate flight formation of bird have been simulated with a model that assumes no leadership within the flock [18]. Therefore, flocks and related synchronized group behaviors such as herds of land animals or schools of fish are both worth to study and interpret. The aggregate motion of a flock of birds, a herd of land animals, or a school of fish is a beautiful and familiar part of the natural world. However, the motion is rarely seen in computer animation due to its complexity. It seems randomly arrayed and yet is magnificently synchronized. Perhaps most puzzling is the strong impression of intentional, centralized control. To build a simulated flock, a boid model that supports geometric flight is started [17]. The behaviors that correspond to the opposing forces of collision avoidance and the urge to join the flock is added. Stated briefly as rules, and in order of decreasing priority, the behaviors that lead to simulated flocking are [19]:

- Separation: steer to avoid crowding local flockmates.
- Alignment: steer towards the average heading of local flockmates.
- Cohesion: steer to move toward the average position of local flockmates.

Static collision avoidance and dynamic velocity matching are complementary because they ensure that the members of a simulated flock are free to fly within the crowded skies of the flock's interior without bumping into one another. Collision avoidance is to steer away from an imminent impact. Static collision avoidance is based on the relative position of the flock mates and ignores their velocity [17]. Velocity matching is based only on velocity and ignores position. It is a predictive version of collision avoidance. If the boid does has a good matching, it is unlikely that it will collide with any of flock mates. With velocity matching, separations between boids remains approximately constant with respect to ongoing geometric flight. Static collision avoidance is used to define the minimum required separation distance [17]. This paper has presented a model of polarized, noncolliding aggregate motion. The model is based on simulating the behavior of each bird independently. The birds will try both to stick together and avoid collisions with one another and with other objects in their environment.

2.3.3 A Simulation Study on the Schooling Mechanism in Fish

In year 1981, a research done by Ichiro AOKI to study on the schooling mechanism in fish [20]. Schooling mechanism is referring to a group of fish swimming in the same direction in a coordinate manner. The individuals interact with each other to perform schooling. Many investigators interest in study the mutual attraction and attribute of schooling behavior. This is because the schooling behavior may be subject to different neural mechanisms and emphasized the significance of the distinction between polarized and nonpolarized forms shown by groups which were based on mutual attraction. In this research, few basic assumptions are made [20]:

- Time is quantized, and movement is decided at intervals of time. Decisions are independent of the previous step.
- A hypothetical organism moves in two dimensions on the horizontal plane.
- There are two components of movement which are speed and direction. They are stochastic variables characterized by probability distributions. However, speed and direction are mutually independent.
- Interactions between individuals are restricted to the directional component. Thus, the velocity component at any time is determined independently of other individual.
- In the initial state, individuals are distributed at random within a square area with certain length of each sides and their directions of orientation are given with uniform distribution over the range 0^o to 360^o.

The Figure 2.6 concludes the methodology of the schooling mechanism of the fish. This research paper assumes that the speed and direction of individual movement are stochastic variables [20]. Therefore, individual movements and the resultant group movement could be simulated by repeatedly generating random numbers which determined the moved distance and direction at each step [20]. Hence, the simulation model is simple to take care of due to its concrete expression. This method has been widely employed in behavioral and ecological research because some stochastic aspects are found in animal movement.

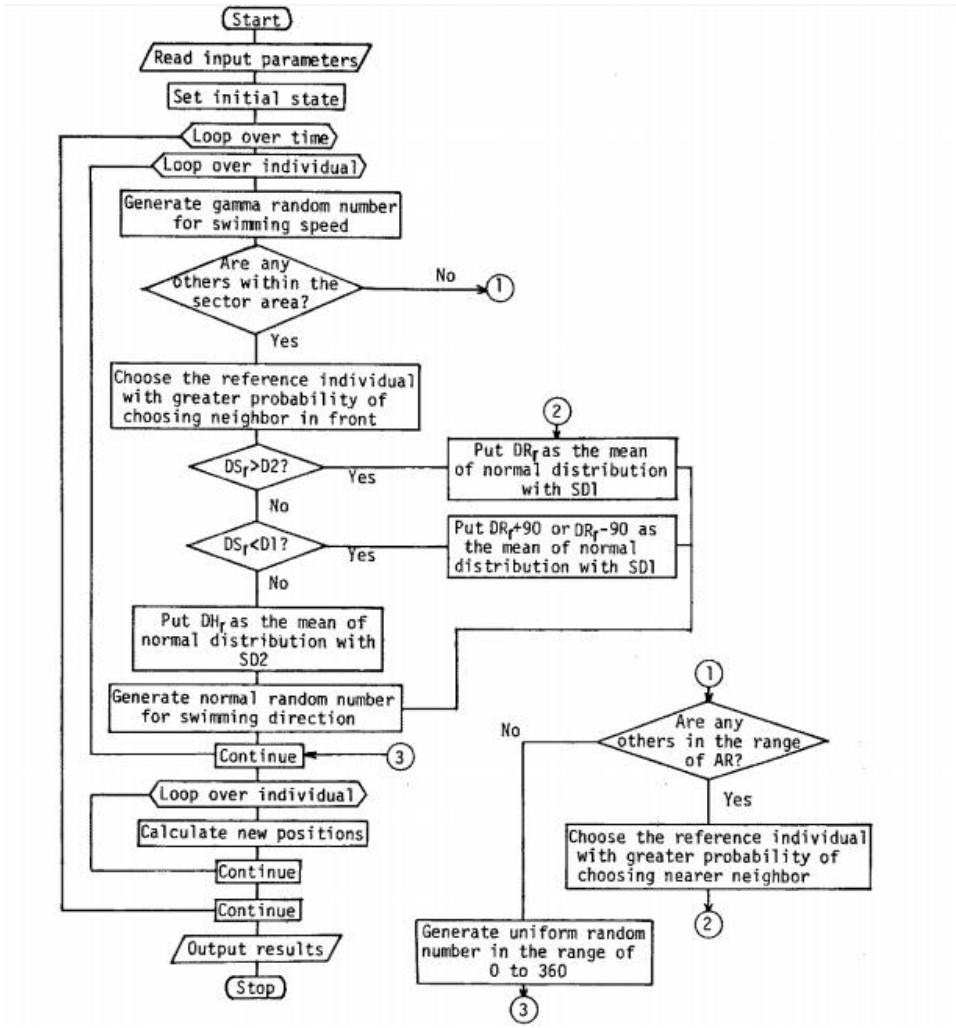

Figure 2. 6 Flow chart of the schooling mechanism in fish simulation models [20].

2.3.4 Grey Wolf Optimization Algorithm with Invasion-based Migration Operation

The research done by D. Jitkongchuen, P. Phaidang and P. Pongtawevirat in 2016 focused on the optimization of grey wolf [21]. As we know the grey wolves live, travel and hunt in pack. Therefore, the concept of grey wolf optimizer (GWO) algorithm is to resemble the grey wolf behavior to live in a pack. The grey wolf optimizer algorithm proposed an alternative solution to enhance the grey wolf optimizer performance by integrating the migration operation. The information exchange within population and generates new candidate individuals due to the migration operation. The main concept in grey wolf optimizer algorithm is to simulate the behavior of grey wolf that live in a pack [21]. Grey wolves have very strict rules in social dominant hierarchy. The alphas are leading the pack, the alpha wolves are responsible for making decisions. The alphas decisions are dictated to the pack [22]. The betas are subordinate wolves that help the alpha in decision making or other activities. The beta can be either male or female, and he/she is probably the best candidate to be the alpha [22]. The third level in the group of grey wolves is called delta [21]. In this category contain scouts, sentinels, elders, hunters and caretakers. Scouts are responsible to observe the boundaries of region and give out warning if there is any danger. Sentinels is responsible to protect and guarantee the safety of the pack [21]. Elders are the expertise wolves who used to be alpha or beta. Besides, hunters will help the alphas and betas when hunting prey and providing food for the pack. The caretakers are responsible for caring for the weak, injured, and wounded wolves in the pack. The lowest level in the group of grey wolves is omega. The omegas will obey all the command from the other dominant wolves. Figure 2.7 shows the pseudocode how the grey wolf optimization choose the alpha, beta and delta. This paper simulates the invasion-based migration operation [21]. The operation is an alternative solution to improve the grey wolf optimizer performance. There are 3 main steps in traditional grey wolf optimizer algorithm which are hunting, searching for prey, encircling prey and attacking prey whereas the wolves have only one pack. The wolves in this proposed algorithm have more pack and have migrated between them. The migration operation only will be used when the algorithm is trapped in the local optimum.

```
Initialize the grey wolf population X_i (i = 1, 2, ..., n)
Initialize a, A and C
Calculate the fitness of each search agent
X_α = the best search agent
X_β = the second best search agent
X_δ = the third best search agent
while (t < Max number of iterations)
    for ( X_i in each pack)
        Update current wolf's position by Eq. (5)
        Update a, A and C
        Calculate the fitness of all search agents
        Update X_α, X_β, X_δ
    end for
    if (is trapped local optimum)
        Evaluate the average fitness of each pack
        for ( X_i in each pack and is not best pack)
            Select i individuals that have better fitness than average fitness of pack
            Insert i selected individuals into a migration ( M_i )
        end for
        Insert a migration ( M_i ) to best pack
        Select new individuals of best pack by evaluate fitness value
        Random new individuals for emigration
    end if
end while
```

Figure 2. 7 Pseudo code of the GWO with invasion-based migration operation [21].

2.3.5 Animal Aggregation: Experimental Simulation Using Vision-Based Behavioral Rules

In animal behavior, aggregation is any form of gathering of animal. The research done by GD Peterson comprises the structure of the simulation environment and a description of simulated aggregate behavior [23]. Besides that, a discussion of the directions also describes in this paper. The simulation program models a simple artificial world, containing a population of animals who move according to specified vision-based behavioral rules. The simulation environment contains a population of simulated animals. These animals are referring to Zooids following the model set by Reynold's Boids [24]. Zooids are circle in shape, a form that simplifies the simulation of vision [23]. The world of the zooids is two dimensional and time passes in discrete increments. In order to move, zooids need to exert force continually. However, there is a limit to the velocity of the zooids. They cannot exceed the maximum value and drop below the minimum value of the velocity. Figure 2.8 shows that each zooid will have 180^0 field of view and cannot recognize any object that occupy less than half of arc. If a zooid sees other zooids, then the zooid which occupies the greatest amount of its visual field is consider as leader and it will follow the leader. The leader is the zooid that cannot see any other zooids. Therefore, the leader is actually following nothing [23]. By following simple behavioral rules to simulate animals will form aggregates. An expansion of the present simulation environment is required to test a more complete repertoire of aggregate behavior. Experimental computing provides a method for testing the emergent properties of behavioral theories, allowing the set of plausible theories to be reduced in number and refined in detail [23].

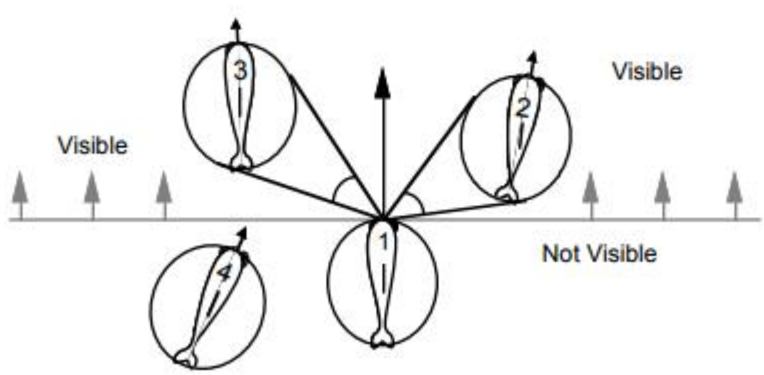

Figure 2. 8 A zooid perceives a 180 degrees zone[23].

2.3.6 Particle Swarm Optimization

In year 2011, the research done by James Kennedy describes the particle swarm optimization concept in terms of its precursors, briefly reviewing the stages of its development from social simulation to optimizer. Particle swarm optimization [25] has roots in two main component methodologies. It is related to evolutionary computation and has ties to both genetic algorithms and evolutionary programming. However, it is more obvious related to artificial life (A-life) in general, and to fish schooling, bird flocking and swarming theory. In this paper, agents were present as collision-proof birds [26]. During each iteration a loop in the program, every agent will determine which other agent was its nearest neighbor, then assigned the X and Y velocities based on the nearest neighbor. Unfortunately, the flock quickly settled on a unanimous, unchanging direction. Therefore, the paper introduced a stochastic variable called craziness. At each iteration some change was added to randomly chosen *X* and *Y* velocities [26]. This able to introduce enough variation into the system so that the simulation will become an interesting and “lifelike” appearance, but the variation was wholly artificial. Each agent “remembered” the best value and the *XY* position which had resulted in that value. The value was called *pbest[]* and the positions *pbestx[]* and *pbesty[]*. Each agent knows the globally best position that had be found by one member of the flock. All member’s *vx[]* and *vy[]* will adjust as follows, where *g-increment* is a system parameter. Equation 2.1, Equation 2.1, Equation 2.1 and Equation 2.1 shows the calculation of new *vx[]* and *vy[]* for different condition.

$$\text{I}f\ presentx\,[\,] > pbestx\,[gbest]\ then\ vx\,[\,] = vx\,[\,] - rand\,(\,) * g\_increment \qquad 2.1$$
$$If\ presentx\,[\,] < pbestx\,[gbest]\ then\ vx\,[\,] = vx\,[\,] - rand\,(\,) * g\_increment \qquad 2.2$$
$$If\ presenty\,[\,] > pbesty\,[gbest]\ then\ vy\,[\,] = vy\,[\,] - rand\,(\,) * g\_increment \qquad 2.3$$
$$If\ presenty\,[\,] < pbesty\,[gbest]\ then\ vy\,[\,] = vy\,[\,] - rand\,(\,) * g\_increment \qquad 2.4$$

The particle swarm paradigm [25] found the global optimum each iteration and appears to approximate the results reported for elementary genetic algorithms in terms of the number of evaluations required to reach certain performance levels [26].

2.3.7 Bee Colony Optimization (BCO)

There are many species in the nature can be characterized by swarm behavior. For instance, fish schools, flocks of birds, and herds of land animals and so on. They are formed because of the biological needs to stay together. For example, they stay together in herd, fish school, or flock of birds because they have higher probability to survive compare to when they are alone. This is because predator usually assault only one individual. Therefore, they will stay together to avoid most of the attack by the predator. In year 2009, the Bee Colony Optimization (BCO) researched by Dušan Teodorović [27] is introduced and has been successfully applied to various engineering and management problems [28]. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance [29]. The BCO is a population-based algorithm. Population of artificial bees search for the optimal solution. Artificial bees represent agents, which collaboratively solve complex combinatorial optimization problem. Every artificial bee generates one solution to the problem. The algorithm consists of two alternating phases: forward pass and backward pass. In each forward pass, every artificial bee is exploring the search space. Below are the steps in simulating the bees colony algorithm [28]:

1. Initialization: every bee is set to an empty solution;
2. For every bee do the forward pass:
   a) Set k = 1 //counter for constructive moves in the forward pass;
   b) Evaluate all possible constructive moves
   c) According to evaluation, choose one move using the roulette wheel;
   d) k = k + 1 and if k ≤ NC, go to step b.
3. All bees are back to the hive // backward pass starts;
4. Sort the bees by their objective function value
5. Every bee decides randomly whether to continue its own exploration and become a recruiter, or to become a follower (bees with higher objective function value have greater chance to continue its own exploration)
6. For every follower, choose a new solution from recruiters by the roulette wheel
7. If the stopping condition is not met, go to step 2
8. Output the best result.

The main concept of BCO is to build multi agent system. The system is able to figure out problems related to combinatorial optimization problems [28].

2.3.8 Cat Swarm Optimization (CSO)

In the field of optimization, many algorithms were being proposed recent years. For example, Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and so on. In the year 2006, Chu SC, Tsai P and Pan JS proposed the algorithm of Cat Swarm Optimization (CSO) [30]. This algorithm is motivated from Particle Swarm Optimization and Ant Colony Optimization. Besides that, Cat Swarm Optimization have better performance than the pure Particle Swarm Optimization [30]. There are two modes in Cat Swarm Optimization which is seeking mode and tracing mode. In seeking mode, the cat is resting, being cautious of their environment, looking around and seeking the next position to move to. Tracing mode is the sub-model for modeling the case of the cat in tracing some targets [30]. In Particle Cat Swarm Optimization (PCSO), the virtual cats share the isolated near best solution between different clusters via information exchanging process [31]. PCSO performs better than CSO and much better than PSO when the population size is small and the iteration is less [32].

1. Create number of cats stated by the users.
2. Randomly sprinkle the cats into the M-dimensional solution space and randomly select values, which are in-range of the maximum velocity, to the velocities of each cat. Then haphazardly pick number of cats and set them into tracing mode according to mixture ratio, and the others set into seeking mode.
3. Evaluate the fitness value of each cat by applying the positions of cats into the fitness function, which represents the criteria of our goal, and keep the best cat into memory. Note that we only need to remember the position of the best cat (xbest) due to it represents the best solution so far.
4. Move the cats according to their flags, if cat is in seeking mode, the cat is applied to the seeking mode process, otherwise it is applied to the tracing mode process.
5. Re-pick number of cats and set them into tracing mode according to mixture ratio, then set the other cats into seeking mode.
6. If the termination condition is satisfied, terminate the program, and otherwise repeat step 3 to step 5.

Six test functions are applied to CSO, PSO and PSO with weighting factor to compare the performance. The performance of CSO is superior compare to other [30].

2.3.9 A swarm optimization algorithm inspired in the behavior of the social-spider

In the year 2013, the Social Spider Optimization (SSO) is proposed by Erik Cuevas, Miguel Cienfuegos, Daniel Zaldívar and Marco Pérez-Cisneros in solving optimization problems [33]. The Social Spider Optimization algorithm is based on the simulation of the cooperative behavior of social-spiders. In the proposed algorithm, individuals imitate the interaction between each individual spider with another based on the biological laws of the cooperative colony [33]. In Social Spider Optimization algorithm, it considers two different search agents which is males and females as shown in Figure 2.9. Depending on gender, each individual is conducted by a set of different evolutionary operators which mimic different cooperative behaviors that are typical in a colony. Social Spider Optimization is different to most of existent swarm algorithms because Social Spider Optimization algorithm is considering two genders [33]. In the paper, the operational principles from the social-spider colony have been used as guidelines for developing a new swarm optimization algorithm. The Social Spider Optimization assumes the whole search space as a communal web [33]. The web serves as the transmission media of the vibrations generated by the spiders [34]. In the proposed algorithm, each solution within the search space represents a spider position in the communal web. According to the fitness value of the solution every spider will receive a weight that symbolized by the social-spider. The Social Spider Optimization algorithm is applied to 19 functions collected from Storn and Price (1995), Yang, Barton, Arslan, and Erdogan (2008), Duan et al. (2009), Vesterstrom and Thomsen (2004), Mezura-Montes, Velázquez-Reyes, and Coello Coello (2006), Karaboga and Akay (2009) and Krishnanand, Nayak, Panigrahi, and Rout (2009) [33]. The results were then compared to the result produced by the Particle Swarm Optimization (PSO) method and the Artificial Bee Colony (ABC) algorithm. Based on the result, Social Spider Optimization offer a better solution than Particle Swarm Optimization and Artificial Bee Colony for all functions [33].

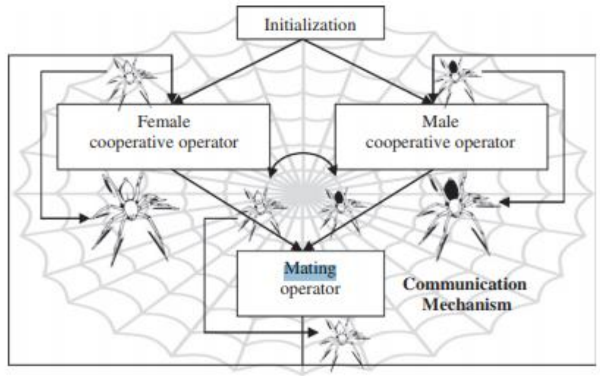

Figure 2. 9 Schematic of the Social Spider Optimization algorithm data flow[33].

2.4 Meerkat Behavior Modelling

In this thesis, the Meerkats foraging behavior will be simulated. Therefore, the analysis and interpretation of previous work about the Meerkats behavior need to be done. Thus, in this section the Meerkat behavior will be studied and the fundamental knowledge or concept of simulation of Meerkat behavior will be discussed.

2.4.1 Meerkat Behavior Modelling Clan Algorithm: A New Swarm Intelligence Algorithm

In year 2018, Ahmed T. Sadiq Al-Obaidi, Hasanen S. Abdullah and Zied O. Ahmed studied the Meerkat Clan Algorithm [35]. Optimization practices of swarm intelligence have become popular more and more recently. They are described by a decentralized manner of working in which it imitates the performance of swarms of social insects, flocks of birds, or schools of fish. The benefit of optimization practices of swarm intelligence over old-fashioned methods is their strength and flexibility [35]. These characteristics make swarm intelligence a useful project paradigm for algorithms the complex problems. There are 3 behaviors of Meerkat being simulated in this paper which are sentry behavior, foraging behavior and baby-sitter behavior [35]. Sentry behavior is one or more meerkats will lookout while the others are hunting or to inform the other Meerkats if there is anything dangerous event happens. Foraging behavior is where Meerkats forage separately while upholding visual and vocal contact. Baby-sitter behavior is one of the supportive actions perform by the Meerkats where helpers offer an amount of their food stuffs to pups. Figure 2.10 shows the general steps for Meerkats Clan Algorithm which can be describe as follow [35].