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Stingless Bee Foraging Behaviour Algorithm for Optimisation

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ABSTRACT

Foraging behaviour of stingless bee has specific characteristics and it is of interest to be adapted as an optimisation algorithm. Foraging behaviour of stingless bee either as an individual worker or as a colony is different from the foraging behaviour of other group of bees. This paper considers an optimisation algorithm based on specific characters of stingless bee. The developed stingless bee algorithm is then tested for solving an optimisation problem of a wireless network routing with residual energy cognizance. Elapsed time of the computation of the stingless bee algorithm is examined by varying node number using 5 nodes, 10 nodes, 15 nodes, 20 nodes, and 25 nodes. The larger number of nodes means there are more candidate of solutions. The reduction mechanism and the early termination mechanism used in the stingless bee algorithm are the important parts of the developed stingless bee algorithm. The two mechanisms distinguish the algorithm from other bee colony based algorithms.

Keywords: Stingless bee algorithm, foraging behaviour, optimisation, reduction mechanism, early-termination mechanism, energy cognizance routing.

Mathematics Subject Classification: 68T99, 92B20

Computing Classification System: I.2

1. INTRODUCTION

Stingless bees (Meliponini) belong to a tribe of Apidae family among others different tribes i.e. honey bees (Apini), bumble bees (Bombini) and orchid bees (Euglossini), the taxonomi is shown in figure 1. Stingless bees have an interesting pattern of foraging behaviour to be adopted into an optimisation algorithm as part of the swarm intelligence, in which, the foraging behaviour of honey bees (Apini) has received considerable attention and has been adopted into Artificial Bee Colony algorithm (Karaboga, 2005) and some other algorithms (Nakrani and Tovey, 2003), (Teodorovic and Dell'Orco, 2005), (Yang, 2005). Foraging behaviour of honey bees has inspired a population based search algorithm to find the optimal solution which was firstly proposed by D. Karaboga in 2005 (Karaboga, 2005). The algorithm exploits the food foraging behaviour of honey bee swarms. Karaboga and his team have investigated the artificial bee colony (ABC) algorithm and its applications to real problems.

Karaboga and Basturk have studied the performance of the ABC algorithm on either unconstrained (Basturk and Karaboga, 2006), (Karaboga and Basturk, 2007a), (Karaboga and Basturk, 2008) or constrained numerical optimisation problems (Karaboga and Basturk, 2007b).

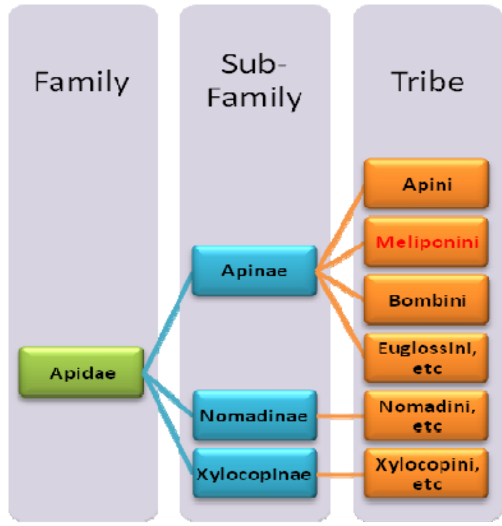


Figure 1. The taxonomi tree of meliponini in Apidae family.

The ABC algorithm has also been implemented in neural network training in (Karaboga and Akay, 2007), (Karaboga et al., 2007). In (Hadidi et al., 2010), it was considered an Artificial Bee Colony (ABC) algorithm based approach for structural optimisation. In 2011, Zhang et al. implemented the ABC algorithm for various applications, such that optimal multi-level thresholding (Zhang and Wu, 2011a), MR brain image classification (Zhang et al., 2011a), cluster analysis (Zhang et al., 2011b), face pose estimation (Zhang and Wu, 2011b), and 2D protein folding (Zhang and Wu, 2012). The application of honey bee algorithm in smart lights by using feedback control has been considered in (Alfonso et al., 2016). The honey bee algorithm proposed in (Karaboga, 2005) is an algorithm which has received considerable attention since the first publication. Another honey bee algorithm has been developed by (Nakrani and Tovey, 2003). More inspired algorithms by the behaviour of honey bee have been studied in (Ozturk et al., 2010), (Chitra and Subbaraj, 2010). .

An Australian research (Heard, 1994) described comparison between honey bee species and a specie of stingless bees. The research showed that stingless bees visit less flower for exploitation than honey bees in the same interval time. Variation communications made by stingless bees are more diverse with more types of information transmitted (Nieh, 2004). The stingless bee does not only performing the waggle dance in the nest but also using chemical communication by spreading special odour in the feeder, around the feeder or some places on the path to the feeder. The uniqueness of stingless bee colony is its fastidious selection in feeder exploration. It inspires to develop an algorithm which fastidious in candidates selection. Moreover, it can reduce the candidates before further execution and eliminates some candidates before the final calculation in selection process.

Stingless bees use and communicate with more information than honey bees. Research on three Sumatran stingless bees (in Sumatra Island, Indonesia) has shown that an individual of stingless bees which flies to exploite floral resources will also perform exploration eventhough the floral resources have not been fully consumed (Inoue et al., 1985). In contrast, honey bees will perform continuous exploitation until the floral resources is emptied (Von Frisch, 1967). Information of floral resources given by stingless bees includes direction, height and amount of nectar compared to honey bees that only give direction and amount (Nieh, 2004).

The paper proposes an optimisation algorithm based on the stingless bee foraging behaviour by adopting the unique characteristics studied in (Heard, 1994), (Nieh, 2004), (Inoue et al., 1985), (Von Frisch, 1967), (Roselino and Hencir, 2012), (Kakutani et al., 1993), (Jarau et al., 2004), (Reichle et al., 2013), (Jacobus and Judith, 2004), (Peter et al., 2010), (Jarau, 2009), (Sanchez et al., 2008). This work is motivated by the experimental result in (Kakutani et al., 1993) in which the stingless bees foraged well than the honey bees that foraged inefficiently. The paper considers the development of a stingless bee algorithm (SBA) by using less number of visited flowers in an interval time characteristic. The behaviours of stingless bees are used for reduction of states of solution candidates. The main different with the well known honey bee algorithm and various variants of the original algorithm is in the alteration of the reduction part. The proposed algorithm is then tested for solving an optimisation problem in a wireless sensor network routing to find the best route either by setting the value of the residual energy at each node or without pre-defined routes by searching and calculating any possible routes randomly.

2. STINGLESS BEE ALGORITHM

The bee optimisation algorithms have been developed by mimicking the behaviour of colonies in exploring and exploiting floral resources. In wild habitat, there are similarities between honey bees and stingless bees. Foraging behaviour of bees can be divided into two types, i.e. colony and individual behaviours (Heard, 1994), (Nieh, 2004). There are similarities and also differences on behavioural patterns among tribes in Apidae family. Several entomology studies have made comparison between the two types of bees that are stingless bees (Meliponini) and honey bees (Apini) (Heard, 1994), (Nieh, 2004). The foraging behaviour of stingless bees, i.e, the colony behaviour and individual behaviours are as follow.

2.1. Colony Behaviour

In foraging activity, as very social colonies, the honey bees, stingless bees and the bumble bees distribute tasks among the colony members (Sanchez et al., 2008). However, only some colony members are going out in the same time while the majority members are in the nest. The colony members that stay in the nest (onlookers/unemployed/un-experienced workers) are waiting the foragers bringing information of floral resources. In addition, several foragers who explore and find the floral resources then recruit colony members in order to exploit found floral resources. Some members fly out of the nest as the explorer to find feeder, but some members stay in the nest to observe any information brought by the explorers that fly back into the nest.

Bees communicate each other by using visual and chemical communications. Waggle dance as a visual communication presents the profitability and location information of the feeder. The waggle dance of honey bees foraging behaviour is adopted by D. Karaboga (Karaboga, 2005) as an important part of Artificial Bee Colony (ABC) algorithm. Stingless bees also perform waggle dance as a visual communication to recruit observer bees. However, the waggle dance on stingless bee is more varied and contains more information compared to the waggle dance of honey bees. It presents complete information of related feeders (Jarau, 2009).

In addition to waggle dance, stingless bees also communicate with the chemical signal. It provides odour guidance which presents profitability and direction information of floral resources to be recognised by other members of colony (Roselino and Hencir, 2012), (Sanchez et al., 2008). Stingless bees have varied odour to broadcast different information (Roselino and Hencir, 2012), (Kakutani et al., 1993). Beside the odour produced by the body of bees, stingless bee also observe the floral odour of food. Then, the observer bees can switch to be the explorer for searching the food source based on their recognition to the odour of the food which brought to the nest by explorer bees in advance (Jarau et al., 2004). It has been shown in (Roselino and Hencir, 2012) that stingless bees will put repellent odour to the certain resources that are considered as not eligible or even fake resources. Hence, the others explorers will not explore the marked location. In this case, stingless bees have developed an efficient exploration mechanism.

2.2. Individual Behaviour

The individual workers of stingless bees are able to make decision during foraging activity. It has been observed that the foragers perform exploitation of resources and can switch to do exploration in their flight although the current food sources have not been exhausted (Von Frisch, 1967). In contrast to the behaviour of honey bees which still continue to visit the same food sources even until the next day after the food source have been exhausted (Heard, 1994), (Von Frisch, 1967). A single explorer of stingless bees can mark one or more feeder using odour as repellent signal in order to avoid other members visiting those locations. This shows that stingless bee foragers perform pre selection in their exploration. Moreover, individual explorers are also able to create full or partial trail by spreading odour that linking the feeder location and the nest (Roselino and Hencir, 2012).

2.3. Algorithm Based on Foraging Behaviour of Stingless Bee

An algorithm based on foraging behaviour of stingless bees is considered by adapting the information communication exchange during foraging. Before describing the algorithm, the following definition is required.

Definition:

- *Permanently ineligible candidate*:
  A candidate which does not fulfil the threshold to be chosen permanently.
- *Temporary unfit candidate*:
  A candidate which only unfits in a specific condition, but in principle it fulfils the threshold to be an acceptable solution.

The algorithm proposed in this paper is based on foraging behavioural patterns of stingless bees. The structure of the algorithm is described in the flowchart shown in figure 2.

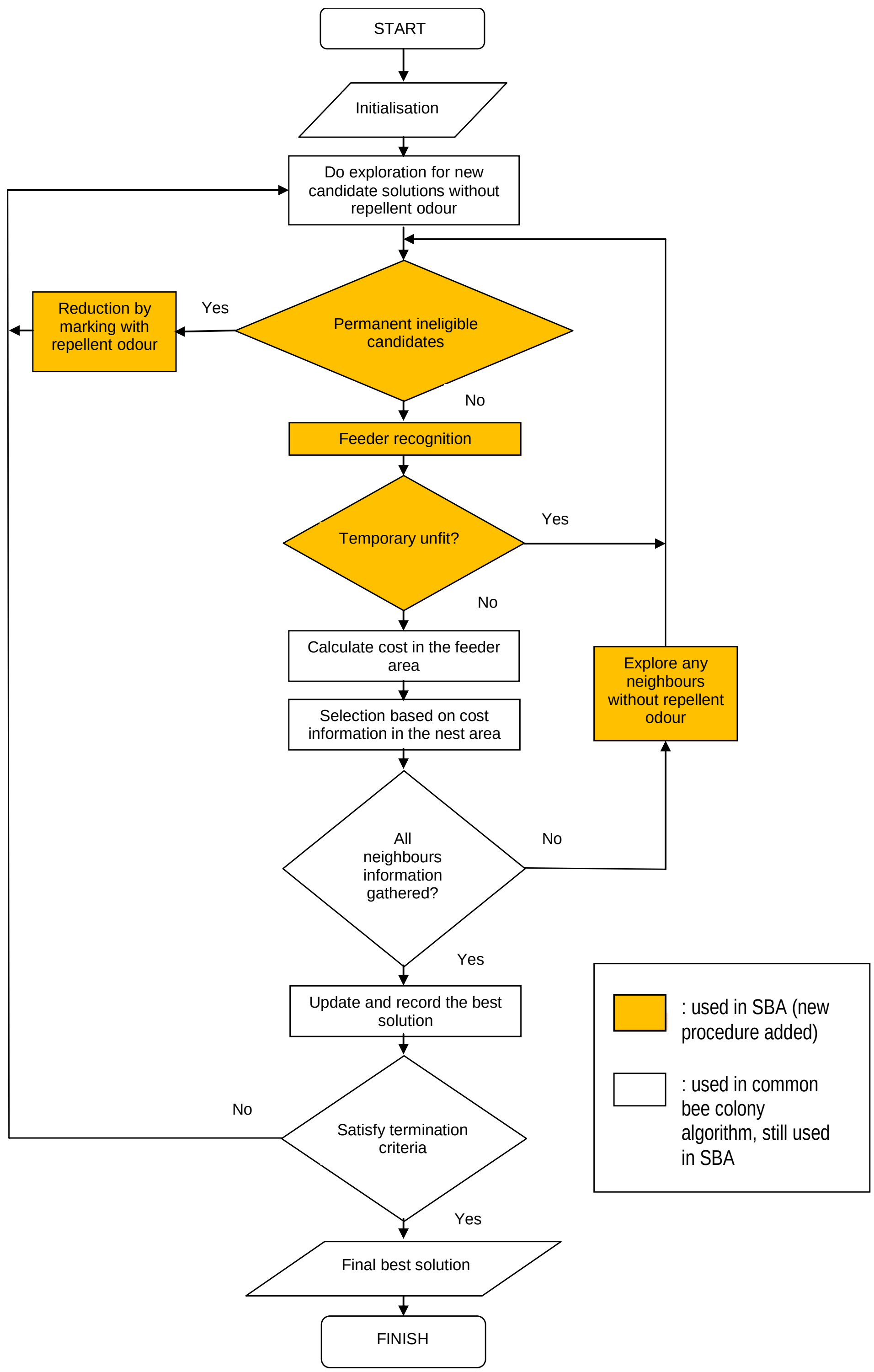


Figure 2. The Stingless Bee Algorithm Flowchart with relation to common bee colony algorithms

With the stingless bee algorithm (SBA) procedure, available observed edges (or candidate solutions) can be reduced in a significant number. Therefore, this makes a good impact on computation. The key process for presenting the final best result in SBA is the reduction of unfit candidate solutions with repellent odour. The explorer bees can perform selective decision to the colony in order to avoid inefficient foraging visit to the ineligible location. The explorers mark several feeder locations with repellent signal. These show that the individual forager can eliminate ineligible feeders in order to avoid the other foragers visit the ineligible feeders. The information is not necessarily to be sent to the nest for the response of the colony.

The algorithm described in the flowchart in figure 2 adopts the foraging behaviour of the stingless bees which have more information communication variaties. In principle, the algorithm is influenced by the honey bee algorithm developed in (Karaboga, 2005). The stingless bee algorithm is developed by performing the reduction of candidates by means of eliminating the permanent ineligible candidates. Hence, it does not need to be involved in further selection process. For real time applications, it is a very useful mechanism in order to reduce the computational load and to increase the searching speed.

In addition to the reduction mechanism, it is also considered an early termination mechanism. In the early termination of stingless bee algorithm, the looping process does not need to be run until the end of calculation. The algorithm will terminate the current process to the next process earlier without finishing the process in a loop. It is useful when the candidates of solutions that have been found are recognised as temporary unfit. The temporary unfit candidates do not need to be calculated in further process. In contrast with permanent ineligible candidates which are permanently unacceptable, since the temporary unfit is temporary unaccepted, it may be accepted in the next loop.

In the considered SBA algorithm, there are two mechanisms have been added, i.e. candidate reduction and early termination mechanisms compared to the ABC algorithm. The two mechanisms in the SBA algorithm make up two stages with the ABC algorithm. In recent years, algorithms with multi strategies have been developed with various combinations of heuristic and/or classical methods. The algorithms have been successfully implemented in solving, for example, nonlinear functions, combinatorial optimisation problems, high-dimensional and large-scale regression datasets, and have achieved the high performance of the results. To illustrate, El Sehiemy et al., 2013 has considered a multi-objective fuzzy-based procedure for solving reactive power management in practicable environment. The procedure comprises both economical and technical aspects of reactive power supports. Osaba et al., 2013 has proposed a parallel genetic algorithm for solving combinatorial optimisation problems. In the algorithm, a communication between subpopulations called migration has shown to increase the performance of the algorithm. Precup et al., 2013 has developed a reduced parametric sensitivity method using Gravitational Search Algorithms (GSAs) to minimise the objective functions of classified optimisation problems which increases the search accuracy. Gacto et al., 2014 has considered a two-stage method to yield proper fuzzy modelling in high-dimensional regression problems by means of an approximate Takagi–Sugeno–Kang fuzzy system. The stages consist of an inductive rule based learning process with an evolutionary data base learning, and a post-processing process acting as a rule selection and a scatter-based tuning of the membership functions of the determined solutions which include an efficient Kalman filter to find out the coefficients of the consequent polynomial function in the rules of the fuzzy system. The mechanisms in the both stages produce a fast convergence in optimisation problems of high-dimensional and large-scale regression datasets with enhanced accuracy.

3. PROBLEM FORMULATION AND IMPLEMENTATION OF ALGORITHM

3.1. Problem Formulation

Given an ad-hoc network which has N nodes, where each node has the same transmission range of coverage denoted by λ. Nodes are scattered at the position $k = \{k_1; k_2; k_3; \cdots; k_N\}$, where k_1, k_2 , $\cdots, k_N$ represent the coordinates (x, y) location of the node. Each node is assumed to have a residual energy which is expressed in the set $e = \{e_1; e_2; e_3; \cdots; e_N\}$.

The optimisation goal is to minimise a cost function, C, which defines the required energy from the source node to the destination node. The optimisation problem is then formulated mathematically as follows.

Minimise $\quad C \qquad (1)$

where

$$C_t = \alpha D_t + \frac{1}{\boldsymbol{e}_t} \qquad (2)$$

$$D = \sum_{(i,j)\in N} d_{ij} \boldsymbol{A}_{ij} \qquad (3)$$

$$\boldsymbol{A}_{ij} = \begin{cases} 1, if\, 0 < \left| k_j - k_i \right| \le \lambda \\ 0, else \end{cases} \qquad (4)$$

In equation (2), e_t denotes the value of residual energy at the node in *t* position, while the cost of distance from the current node to the next node in *t* position is denoted by D_t. For the node i to node j, d_{ij} is the distance between of these nodes and D_{ij} will be calculated if and only if the distance d_{ij} fulfils the range transmission criteria i.e. $d_{ij} \le \lambda$ which is marked on A_{ij}. Hence, the cost of distance on a full path transmission is given by D as shown in equation (3), α is a multiplier factor to make the cost value of the distance to be much smaller than the energy cost as the main issue in this paper is based on energy cognition. A is a matrix that shows the link availabilities refer to the coverage transmission of each sensor node. A_{ij} will be 0 (zero) if it does not meet the provisions.

3.2. Implementation of the procedure of stingless bee algorithm

The combinatorial solution is expressed by p which contains some partial solutions p_t, is a set of nodes that form a full path from the source node to the destination node. The p_t is defined by the following equation

$$p_t = \lceil lb + \phi(ub - lb) \rceil \Leftrightarrow t \succ 1 \tag{5}$$

and

$$p_t = ps \Leftrightarrow t = 1 \tag{6}$$

In this case ps is a source node, lb is the node with the lowest index while ub is the node with the highest index. ϕ in equation (5) is a random value between 0 and 1. A source node is given with the lowest index, while the destination node is given with the highest index in the range, whereas the other nodes are indexed randomly. All indexes are integer, hence the ceiling bracket ($\lceil \bullet \rceil$) is used in order to keep the equation provides integer value, such as the integer value of node's index in its range.

Explorers of stingless bees are trying to obtain information about any detected food sources and will decide whether it will be marked with a repellent odour or will be communicated about its cost to the observer in the nest. In this case, the criteria for repellent odour is the solution if the path does not meet the initial constraint, means represented with $A_{ij} = 0$ (equation (4)) and the additional constraint (equation (7))

$$D_{ij} = d_{ij} \leq \frac{\lambda}{2} \tag{7}$$

$$\boldsymbol{R}_{ij} = \begin{cases} 1, if \;\; d_{ij} \succ \frac{\lambda}{2} \\ 0, else \end{cases} \quad , \; d_{ij} = \left| k_j - k_i \right| \tag{8}$$

Equation (7) will reduce the number of edges. As a result, a number of solution paths that has one or more unmarked edges by the repellent odour $R_{ij} = 1$ will be eliminated. In other words, the full path solution contains repellent odour in one edge or more , $R_{path} \geq 1$, will be ignored.

$$R_{path} = \sum_{i,j \in N} R_{ij} \tag{9}$$

The next stage is to calculate the C value with the function in equation (2). In this step, the only path that is free from repellent odour (in the previous stage) will be proceeded in the selection stage.

The information of C value is then shared to the observer bees that are waiting in the nest. Next, on the exploitation phase, the worker bees in flight are also looking for the neighbour food sources. Equation (10) represents the neighbour exploration:

$$q_{ti} = \lceil lb + \phi(ub - lb) \rceil \Leftrightarrow q_t \neq p_t \neq ps \tag{10}$$

The observer bees in the nest are comparing the cost of neighbour solutions to previous solution. The solution with less cost is then selected as a new solution.

The early termination mechanism performs termination of the process in a loop when a temporary unfit feeder is found. Hence, it is not necessary to continue the process untill the final calculation, but it will jump to the next iteration immediately. In this case, the temporary unfit feeder is a candidate which has the residual energy below the average of residual energy, γ in one neighbourhood nodes.

$$fit = \begin{cases} 1, if \quad \mathbf{E}(q_t) \geq \gamma \\ 0, else \end{cases} \tag{11}$$

A node may unfit in one group of neighbourhood but it may be fit in other groups, so it is called a temporary unfit.

4. SIMULATION RESULTS

The simulation was performed by using MATLAB in order to test the performance of the proposed stingless bee algorithm in generating solutions. The results are shown in the figure 3, there are 25 nodes with 158 edges, and one node can have up to 21 neighbour nodes (node 22).

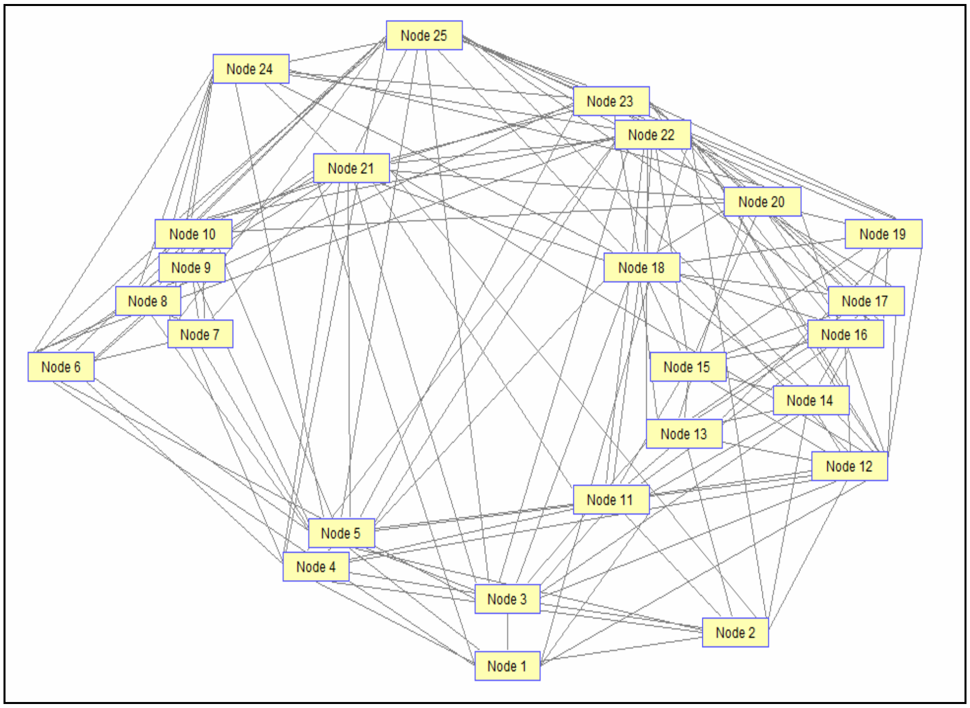


Figure 3. Available link on the network based on coverage transmission of each node

The simulation begins by setting the value of the residual energy at each node by 15 Joules. In this condition, the algorithm performed to get the optimal route from node 18 to node 25, as shown in figure 4.

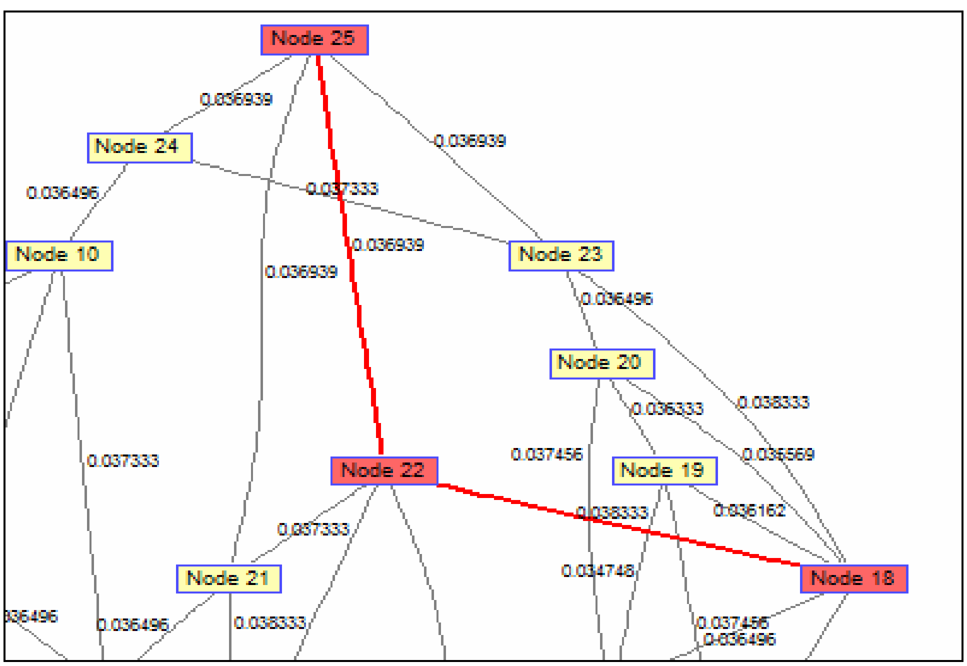


Figure 4. Simulation for optimal routing transmission of node 18 to node 25

In the first simulation, the result is presented in figure 4. The optimal route from node 18 to node 25 is known through the node 22. To test the algorithm in obtaining the optimal route, the next case, a scenario is run by changing the value of residual energy at node 22 of 15 Joules to 14 Joules. In this scenario the route was changed, as shown in figure 5.

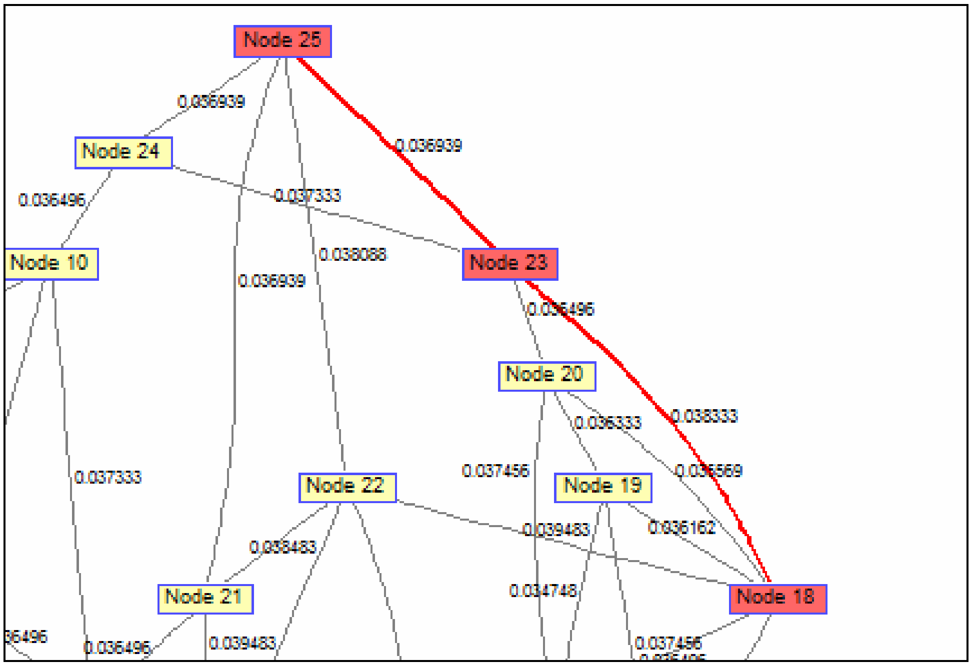


Figure 5. Second simulation for optimal route of node 18 to node 25

From the simulation results, it was obtained the route from node 18 to node 25.It can be seen that the algorithm can determine the optimal route by selecting the path through the node which has higher residual energy. The route 18-22-25 was originally the optimal route, when the value of the residual energy at node 22 is reduced then the algorithm will search for a new solution. The new solution is found as neighbours of the previous solution, i.e. 18-23-25 .

In the next simulation scenario, the selected nodes are located quite far from the sink node so that the simulation can be made with the two nodes on the residual energy value decreased significantly. In this scenario, node 1 is chosen as a source node and node 25 as a destination node. Each node is given by the residual energy of 15 Joules. The simulation result of this scenario is shown in the figure 6.

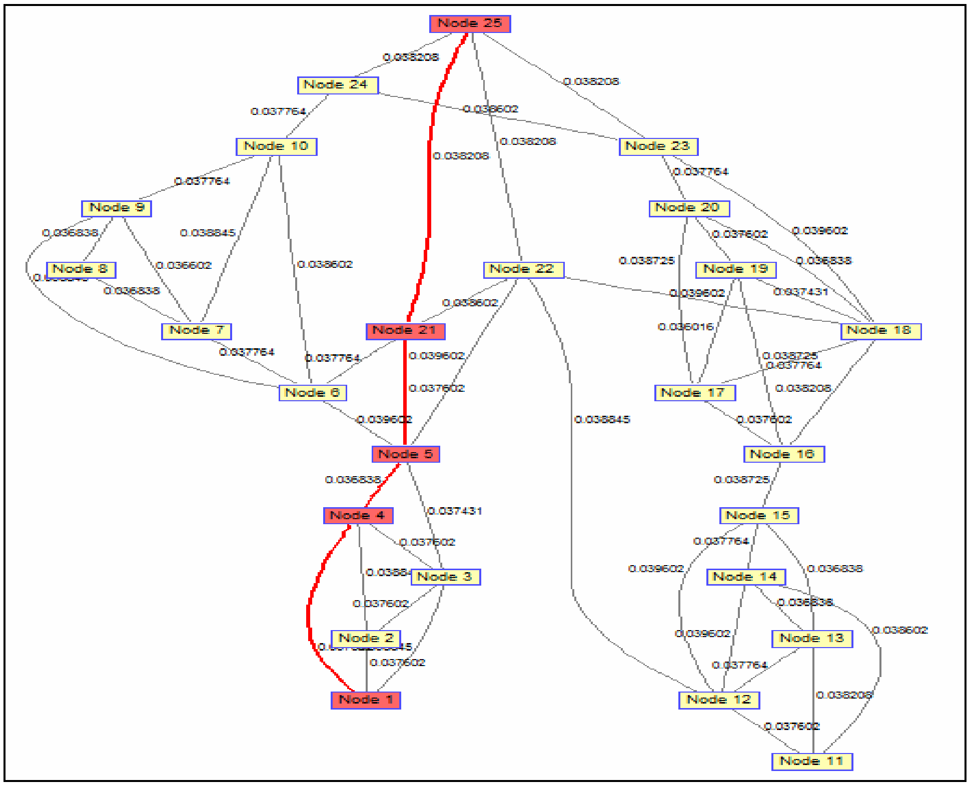


Figure 6. Simulation of 1st scenario for optimal route of node 1 to node 25

In the simulation results (figure 6), it is found the optimal route from node 1 to the node 25 through the path 1-4-5-21-25. In this scenario the entire value of each component of the energy matrix e is 15 Joules.

To test the algorithm, a second simulation on the route from the source node 1 to the sink node 25 is performed. The second scenario is run by changing the value of the residual energy at node 4 and node 21 of 15 Joules to 7 and 5 Joules respectively. The purpose of this simulation scenario is to determine whether the algorithm can find a new route solution if the old route runs into a lower residual energy level. Simulation result in this scenario presents the route changes, as shown in figure 7.

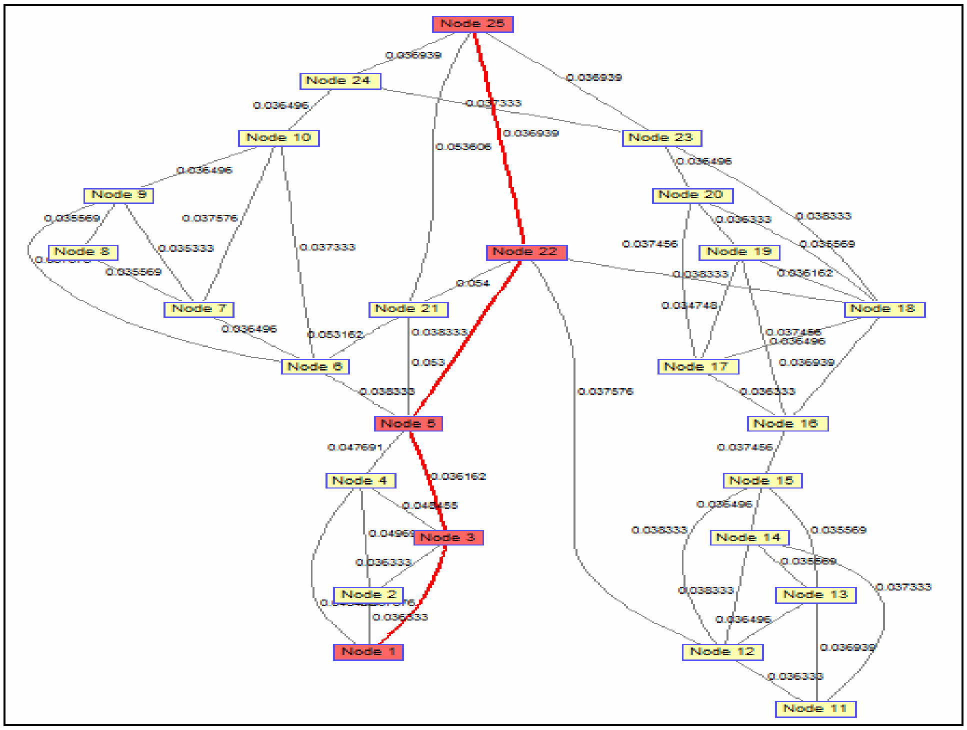


Figure 7. Simulation of 2nd scenario for optimal route of node 1 to node 25

For these scenarios, the numbers of node is 25 nodes. It is observed the reduction of candidate solutions by the algorithm as shown in table 1. The reduction of candidate solutions is represented by the reduction of the number of observed edges. The early termination and the reduction mechanism of the stingless bee algorithm lead to the reduced elapse time of execution to produce the optimal solution.

Table 1: Performance of the algorithm in simulation

Parameters	**Value**	
	Initial value	**stingless bee algorithm (with reduction)**
Number of observed nodes	25	25
Number of observed edges	158	50
The maximum number of neighbour nodes	21	6
The minimum number of neighbour nodes	8	3

The algorithm is then tested by changing the number of nodes into several scenarios (5 nodes, 10 nodes, 15 nodes, 20 nodes and 25 nodes). From this test, it is known the elapsed time of the algorithm which gives the required time of the searching process. The results are shown in table 2 and figure 8.

Table 2: Simulation results of elapsed time

Nodes / Run	5 nodes	10 nodes	15 nodes	20 nodes	25 nodes
1st	*0.924243 s*	*1.246057 s*	*1.930346 s*	*2.082516 s*	*2.660983 s*
2nd	*0.934927 s*	*1.231707 s*	*1.811621 s*	*2.0712 s*	*2.649989 s*
3rd	*0.800293 s*	*1.207068 s*	*1.803981 s*	*2.030206 s*	*2.559149 s*
4th	*0.778148 s*	*1.192857 s*	*1.730544 s*	*2.004045 s*	*2.444357 s*
5th	*0.768285 s*	*1.18623 s*	*1.720151 s*	*1.967595 s*	*2.330155 s*
Average	*0.841179 s*	*1.212784 s*	*1.799329 s*	*2.031112 s*	*2.528927 s*

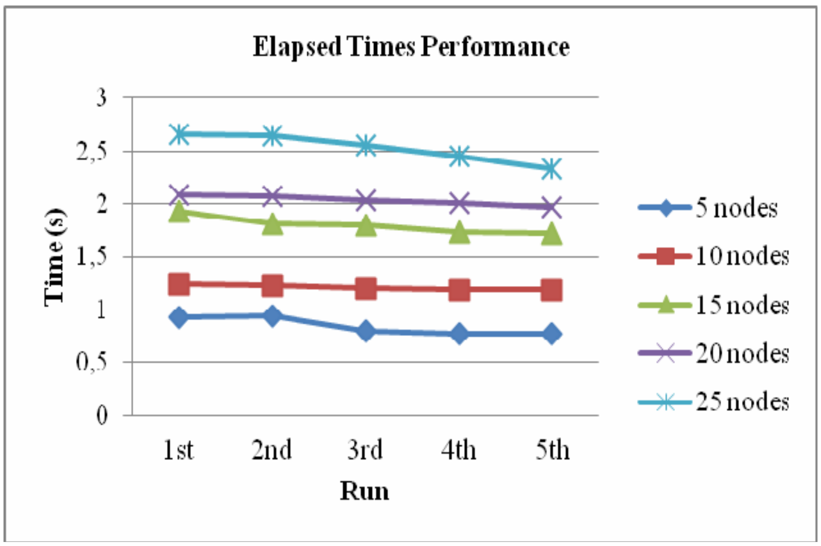


Figure 8. The elapsed time of computation performance of stingless bee algorithm

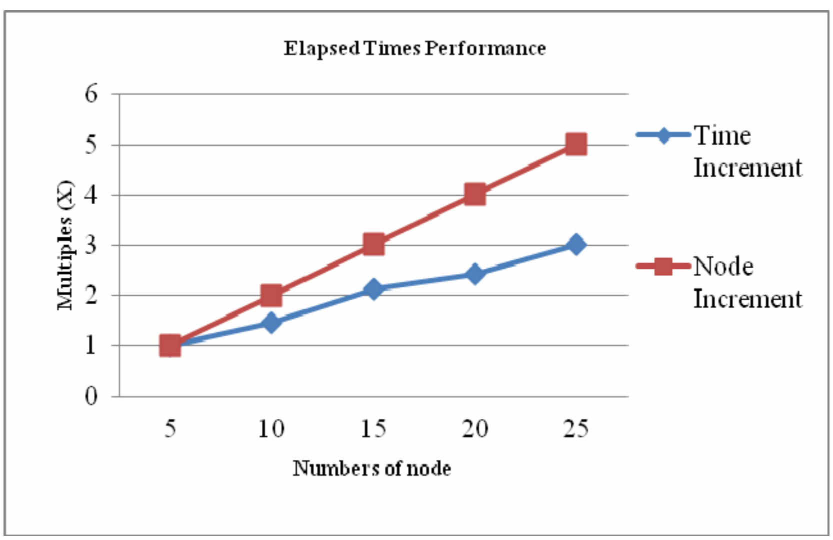


Figure 9. The multiples of average of elapsed times to the increment of nodes

In table 2 and figure 8, the searching process of the stingless bee algorithm becomes slower as the number of the nodes grows to be larger. However, the increasing of elapsed times is not linear as the linear increased of related numbers of node as shown in figure 9.

The next test was performed to find the best route from node 1 to 6. In the first test, all possible routes were defined (in MATLAB program) i.e :

```
rout1   = [1 2 3 4 5 6];
rout2   = [1 2 4 3 5 6];
rout3   = [1 2 4 5 3 6];
rout4   = [1 2 5 4 3 6];
rout5   = [1 2 5 3 4 6];
rout6   = [1 2 3 5 4 6];
rout7   = [1 3 2 4 5 6];
rout8   = [1 3 4 2 5 6];
rout9   =   [1 3 2 5 4 6];
rout10  =   [1 3 4 5 2 6];
rout11  =   [1 3 5 4 2 6];
rout12  =   [1 3 5 2 4 6];
rout13  =   [1 4 2 3 5 6];
rout14  =   [1 4 3 2 5 6];
rout15  =   [1 4 3 5 2 6];
rout16  =   [1 4 2 5 3 6];
rout17  =   [1 4 5 3 2 6];
rout18  =   [1 4 5 2 3 6];
rout19  =   [1 5 4 3 2 6];
rout20  =   [1 5 4 2 3 6];
rout21  =   [1 5 3 4 2 6];
rout22  =   [1 5 3 2 4 6];
rout23  =   [1 5 2 3 4 6];
rout24  =   [1 5 2 4 3 6];
rout25  =   [1 2 3 4 6];
rout26  =   [1 2 3 5 6];
rout27  =   [1 2 4 3 6];
rout28  =   [1 2 5 3 6];
rout29  =   [1 2 4 5 6];
rout30  =   [1 2 5 4 6];
rout31  =   [1 3 2 4 6];
rout32  =   [1 3 2 5 6];
rout33  =   [1 3 4 2 6];
rout34  =   [1 3 5 2 6];
rout35  =   [1 3 4 5 6];
rout36  =   [1 3 5 4 6];
rout37  =   [1 4 3 2 6];
rout38  =   [1 4 2 3 6];
rout39  =   [1 4 3 5 6];
rout40  =   [1 4 5 3 6];
rout41  =   [1 4 5 2 6];
rout42  =   [1 4 2 5 6];
rout43  =   [1 5 3 2 6];
rout44  =   [1 5 2 3 6];
rout45  =   [1 5 4 2 6];
rout46  =   [1 5 2 4 6];
rout47  =   [1 5 3 4 6];
rout48  =   [1 5 4 3 6];
rout49  =   [1 2 3 6];
rout50  =   [1 2 4 6];
```

```
rout51  =   [1 2 5 6];
rout52  =   [1 3 2 6];
rout53  =   [1 3 4 6];
rout54  =   [1 3 5 6];
rout55  =   [1 4 2 6];
rout56  =   [1 4 3 6];
rout57  =   [1 4 5 6];
rout58  =   [1 5 2 6];
rout59  =   [1 5 3 6];
rout60  =   [1 5 4 6];
rout61  =   [1 2 6];
rout62  =   [1 3 6];
rout63  =   [1 4 6];
rout64  =   [1 5 6];
rout65  =   [1 6];
```

The algorithm was then performed based on those fixed 65 routes. The second test was carried out without defined routes, it was fully random. The best route was found by searching and calculating any possible routes randomly.

Both Fixed and Random produce same route (1-3-2-4-6) in 10 tests, but the SBA yields different performances between them. With fixed parameters of routes are defined, the SBA finds the best route faster than randomly as shown in figure 10. The average of elapsed times for the fixed parameters is 0.20 seconds which is three times faster than 0.69 seconds of the random. However, the SBA with fixed route parameters needs more efforts such as higher capacity of memory and manual update for pre-defined all combination route in the plant than the random routes. More nodes added require more efforts. The SBA with random parameters causes the algorithm more flexible especially in dealing with huge number of nodes.

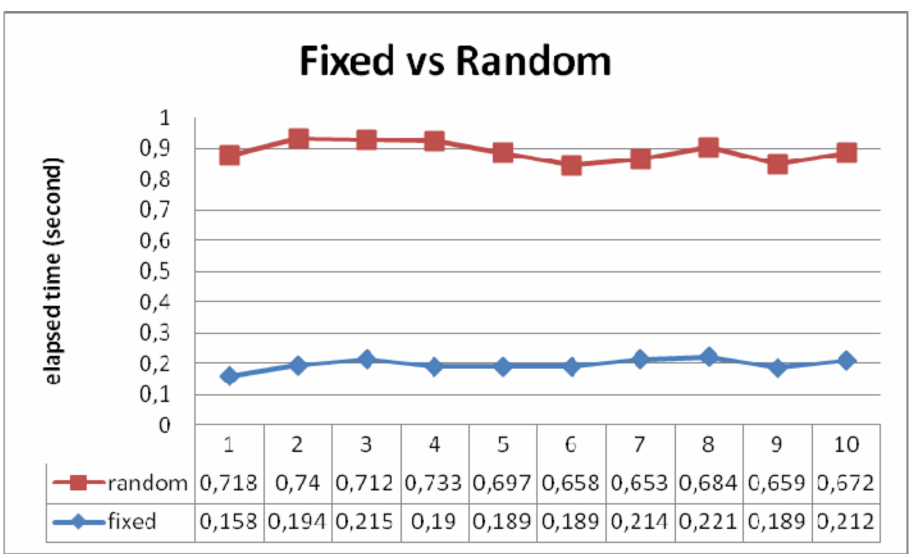


Figure 10. The elapsed time in 10 tests

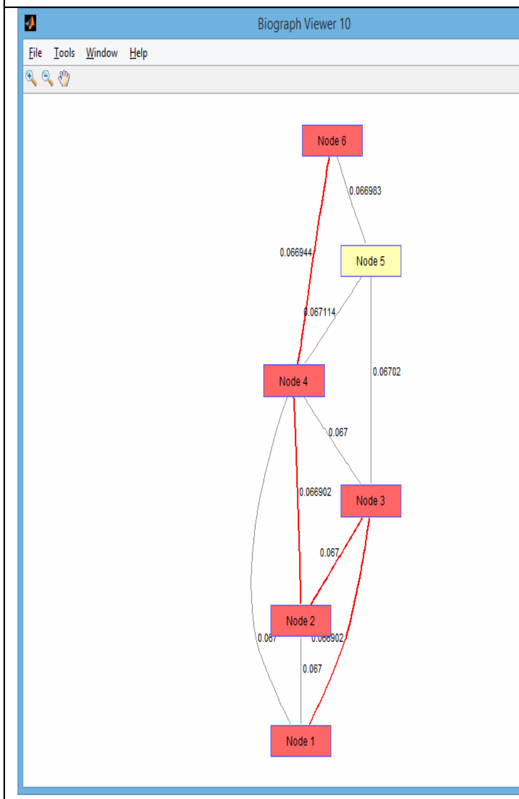
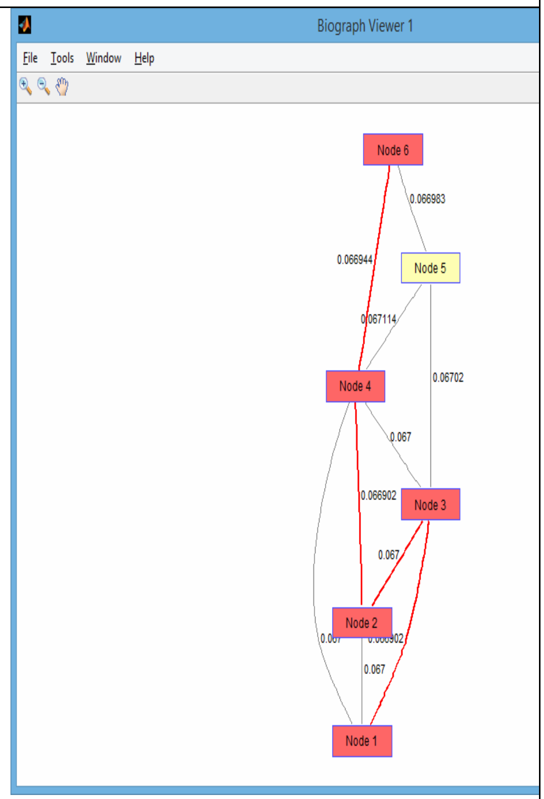
Fixed	*Random*
	

Figure 11. Simulation results

5. CONCLUSION

An algorithm based on foraging behaviour of stingless bee was developed in this paper. The main idea of the proposed algorithm was the inclusion of reduction mechanism and early termination mechanism. The reduction mechanism mimics the stingless bee foraging behaviour by marking ineligible feeders and the early termination mechanism mimics the stingless bee behaviour leaving the feeder during exploitation process to explore new fit feeders. The proposed stingless bee algorithm successfully found the optimal route rapidly in any environmental changes i.e. the changes of residual energy value distributed in the network. Only two foraging behaviours of stingless bee were adopted in the proposed algorithm. In fact, there are still many foraging behaviours of stingless bee that can be explored for future development in order to improve the algorithm. Future work is aimed to exploit the other foraging behaviours in order to produce an optimal algorithm.

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