International Journal of Sciences: Basic and Applied Research (IJSBAR)

ISSN 2307-4531
(Print & Online)

http://gssrr.org/index.php?journal=JournalOfBasicAndApplied

EIABC Optimization Approach for DSPRP in MANET

K. Mariyappan[a*], Dr. M.karnan[b]

[a]*Assistant Professor, Dept. of CSE, Aringer Anna College Of Engineering And technology , Palani, Dindigul, India*

[b]*Professor And Principal Aringer Anna College Of Engineering And technology , Palani, Dindigul, India*

[a]*Email: mariwithgold@gmail.com*

[b]*Email: drmkarnan@gmail.com*

Abstract

The very many optimization techniques like GA, PSO and ABC aid in crystallizing and addressing the static shortest path in the realm of wireless network routing. The motion of MANET is dynamic and hence the shortest path routing problem in MANET manifests into a dynamic optimization problem. The nodes are instilled with an awareness of the environmental conditions by making them operational through intelligence routing becomes a key concern as it has a significant impact towards network performance. The paper attempts to exploit and utilize Artificial Bee Colony to solve MANET because shortest Path problem turns out to be a dynamic optimization problem in MANETs. MANETs are kept and considered target systems because they do represent the next generation wireless network. The results of experiment explicate that Artificial Bee Colony is steadfast to adapt to the gradations in the environment.

Keywords: Mobile ad hoc networks (MANETs); dynamic Optimization problem (DOP); Genetic algorithms (GAs); Dynamic SP routing problem (DSPRP) ,Artificial bee colony(ABC);Particle swarm optimization(PSO).

----

* Corresponding author.

1. Introduction

Mobile ad-hoc is self encompassing wireless network which includes collective mobile hosts moving on packets on each other's behalf.

MANET supports exclusive and efficient operation by putting to use routing operation to mobile hosts [15,16,17]. Unicast routing helps establish the multi-hop forwarding for two nodes beyond wireless communication. The connectivity is unbroken by routing protocols as the links are vulnerable to breakage due to node movement, battery drainage, radio propagation.

In Topological routing the topological information is used by mobile nodes to construct routing tables or search routes and on the contrary geographic routing is unique for the node knows its position and makes routing decisions on destination and local neighbor's position.

The paper explores shortest path routing problem on the dimension of topological routing. The shortest path routing probability endeavors to find shortest path in a specific source pertaining to a certain destination thereby minimizing the lost associated with the path. The determinants of search Dijkstra's algorithm, the breadth-first search algorithm, the Bellman–Ford algorithm and prove effective only in fixed infrastructure wired or wireless network and do showcase high computational complexities in real time communications in even changing network topologies.

In DSPRP in MANETs is a contemporary dynamic optimization problem and has hence attracted evolutionary algorithms to study due to the fast interest in EA's real-world applications. The first best way to address dynamic optimization problems is to restart evolutionary algorithms whenever or wherever an environmental change arises. Restart schemes are reliable only in some cases , while in others DOPs is efficient from knowledge collected other environments.

The paper emphasizes the implementation and application of ABC for the resolution of dynamic shortest path problem. To begin with, an algorithm is designed specifically for dynamic shortest path problem. To maintain diversity a certain amount of population is generated with the gradation in topology, the novel design can help guides the search of solutions in the new ambiance. The routing path is mandatory to satisfy delay constrain so quality-of-service (QoS) metric is needed as a guarantee to real-data delivery. Moving further in second section the related work is highlighted.

MANET network model and DSPRP model are discussed in the next section. The following section throws light on design of ABC for static shortest path. Section five portages the extensive experimental study, followed by experimental results and analysis finally leading to the last section conclusion.

2. Related Works

Many search algorithms were formulated for solving shortest path routing problem [1,2], but Artificial Bee is extensively presented for solving the shortest path routing problem studies on simulation reflect that an algorithm is imperative in respect of optimality and convergence and the quality of solution has been found to be feasible than other deterministic algorithms [11].

It is proposed to employ a modified HNN for study. Information is used bit by bit at peripheral neurons coupled with highly correlated information at local neurons thereby helping it attain faster convergence and better rout optimality than HNN based algorithms. When a genetic algorithm approach was presented to shortest path routing problem, computer simulations inferred that ABC based algorithms did exhibit a higher rate of convergence than other algorithms. A population sizing equation to facilitate the solution with desired quality was developed and a PSO based algorithm was proposed too.

3. Models for Dynamic Shortest Path Routing

In this section a network model is presented and the formulation of the shortest path model takes into place. MANET operation is considered into a fixed geographical region. It is modeled on undirected and connected topology graph where $G_0(V_0, E_0)$, where V_0 represents the set of wireless nodes (i.e., routers) and E_0 represents the set of communication links connecting two neighboring routers falling into the radio transmission range. A communication link (i, j) cannot be used for packet transmission until both node i and node j have a radio interface each with a common channel.

Here, we review some notations that we use throughout this paper.

– $G_0(V_0, E_0)$, the initial MANET topology graph.

– $G_i(V_i, E_i)$, the MANET topology graph after the ith change.

– s, the source node.

– r, the destination node.

– $P_i(s, r)$, a path from s to r on the graph G_i.

– d_l, the communication link (l)transmission delay.

– c_l, the communication link (l) Cost.

– $\boldsymbol{\Delta}(P_i)$, the total transmission delay on the path P_i.

– $C(P_i)$, the total cost of the path P_i.

Source node it is endeavored to find delay bound least path on the graph of topology. Some nodes are either hibernated or activated depending on the conservation of energy. This results in the change of network topology gradation. The objective is to find optimal delay constrain past topological changes.

4. ABC algorithm for sp routing problem

The ABC algorithm proposed by Karaboga is progressed through inspection of the behaviors of real bees in finding food sources called nectar [10]. The sharing of food sources don to bees on nest. The resultant bees are categorized as viz-a-viz Employed Bees, Onlooker Bees and Scout Bees. The bees exploiting food source and transfer them to the onlooker bees that wait at the hive for the information to be shared by employed bees on the food discovery. Scout bees seek for new food sources the hive. Employed bees share information on food sources by the way of their designated dance inside the hive which is proportional to nectar content of food source exploited by dancing bees. Onlooker bees do watch the dance and select a food on the probability proportional to the quality of source. This results in good food sources attracting more onlooker bees than bad on exploiting the food source complexity. The employed bees associated with it become scout by abandoning the food.

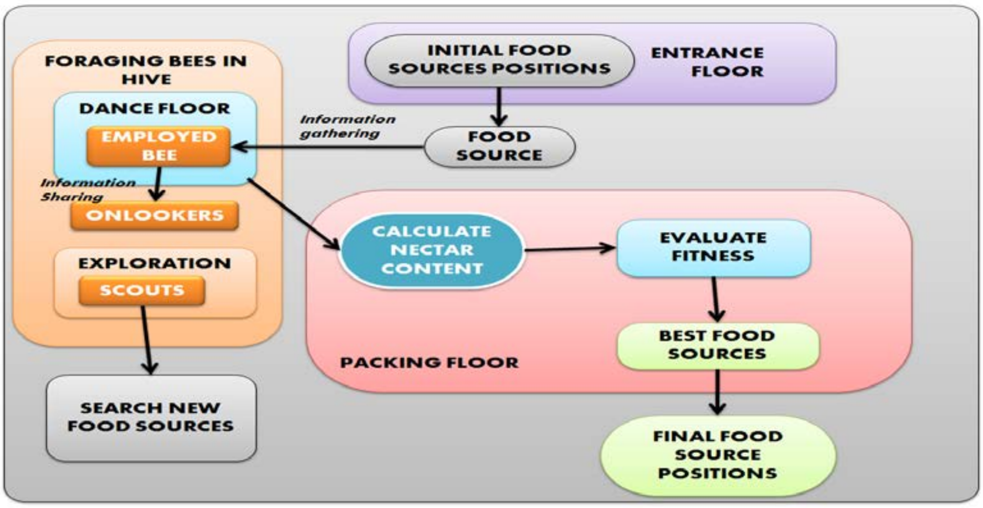

Figure 1: Flow Diagram for Artifical Bee Colony

Scout bees perform the job of exploration and the onlooker bees perform the task of exploitation. In ABC algorithm the food source becomes a solution of problem under consideration and nectar represents the quality of solution through fitness value and there is an employed bee for the food source each.

. Pseudo code for ABC algorithm

1. Initialize
2. REPEAT.
3. Shift the employed bees onto their food source and evaluate the fitness
4. Shift the onlookers onto the food source and evaluate their fitness
5. Shift the scouts for searching new food source

6. Store the best food source found so far

7. UNTIL (execution criteria fulfilled)

The algorithm operates with associating all employed bees with generating food resources. Every employed bee represents a food source adjacent to the current food source and the nectar amount is computed. The ith food designates the nectar food source at Xij on watching the dance movements of employed bees the onlooker bees get to region of source represented as

$$P_i = \frac{F(X_i)}{\sum_{k=1}^{s} F(X_k)}$$

Where S is total number of food sources. The onlooker finds a neighborhood food source in the vicinity of *Xi* by using

Xi(t+1) = Xi (t)+ δij * u

Where is the neighborhood patch size for *j* th dimension of *i*th food source defined as

δij = Xij – Xkj

The bees moves to the new food source thereby deserting the old one if the new fitness value is better than the best fitness salve else it stays in its own food source. The fitness information is shared on the employed bees going through with fitness information with the onlooker given in eq (1). There by making good food sources getting more on lookers than bad ones. Each bee seeks a better food source annexed to the patch for a limited number of cycles and when the fitness value shows improvement it becomes a scout bee.

5. ABC with Immigrants

In stationary environments, convergence at a correct pace is absolutely what we have a tendency to expect for ABCs to find the optimum solutions for several optimization issues. However, for DOPs, convergence sometimes becomes an enormous downside for ABCs as a result of ever-changing environments sometimes need ABC on keep a definite population diversity level to take care of their ability. To deal with this downside, the random immigrants approach may be a quite natural and straight forward method. It had been planned by Grefenstette with the inspiration from the flux of immigrants that wander in and out of a population between 2 generations in nature [8]. It maintains the variety level of the population through commutation some people of this population with random people, known as random immigrants, each generation. On that people within the population sought to get replaced, sometimes there are2 strategies: commutation random people or commutation the worst ones. so as to avoid that random immigrants disrupt the continued search progress an excessive amount of, particularly throughout the amount once the setting doesn't amendment, the quantitative relation of the quantity of random immigrants to the population size is sometimes set to a little price, e.g., 0.2. Supported the on top of thought, AN immigrants approach, known as elitism-based immigrants [9], is planned for ABCs to deal with DOPs [EIABC].

However, in a very slowly dynamic atmosphere, the introduced random immigrants could divert the looking out force of the basic principle throughout every atmosphere before a modification happens and thus could degrade the performance. On the opposite hand, if the atmosphere solely changes slightly in terms of severity of changes, random immigrants might not have any actual impact even once a modification happens as a result of people within the previous atmosphere should be quite slot in the new atmosphere. supported the on top of thought, associate immigrants approach, referred to as elitism-based immigrants [9], is planned for ABCs to handle DOPs.

Begin

t:=0 and initialize population P(0) randomly

evaluate population P(0)

repeat

P´(t)=selectForReproduction(P(t))

crossover(P´(t), pc) // pc is the crossover probability

mutate(P´(t), pm) // pm is the mutation probability

evaluate the interim population P´(t)

// perform elitism-based immigration

denote the elite in P(t-1) by E(t-1)

generate$r_{ei}\times n$ immigrants by mutating E(t-1) withp^{i}_{m}

evaluate these elitism-based immigrants

replace the worst **people** in in P´(t) with the generated

immigrants

$P(t+1):=P'(t)$

until the termination condition is met // e.g., *t >tmax*

end

above shows the pseudocode for EIABC. In our implementation of EIGA, if the mutation probability *pi m*is satisfied, the elite *E*(*t*-1) will be used to generate the new immigrants by the mutation operation; otherwise(*t*-1) itself will be directly used as the new immigrants.

The bees moves to the new food source thereby deserting the old one if the new fitness value is better than the best fitness salve else it stays in its own food source. The fitness information is shared on the employed bees going through with fitness information with the onlooker. There by making good food sources getting more on lookers than bad ones. Each bee seeks a better food source annexed to the patch for a limited number of cycles and when the fitness value shows improvement it becomes a scout bee.

6. Experimental Results and Analysis

In this first scenario, mobile ad hoc network consisting of 100 nodes placed randomly using uniform distribution in an area of 1000 X 1000 m^2 is considered for simulation study. The nodes in the network have the transmission range of 60 to 70 m and a channel capacity of minimum 750Kbps to maximum 2Mbps The mobility model Random Way Point (RWP) in this each node is randomly placed in the simulated area and remains stationary for a specified pause time. It then randomly chooses a destination and moves there at velocity chosen uniformly between a minimum velocity and maximum velocity. Each node independently repeats this movement pattern through the simulation. The experimental setup defined from 0 to 50 Sec and varies the pause time as the independent variable. The nectar generation rate at each node was set to 48Kbps. NS2 simulator is considered to implement the proposed routing protocol.

The performance of the proposed ABC algorithm is gauged in terms of packet delivery ratio, throughput, routing overhead, memory usage and end-to-end delay. The results presented here are the average of obtained for the same simulation configuration of 100 active sources. The results obtained after simulation are compared with the well-known algorithm GA and other.

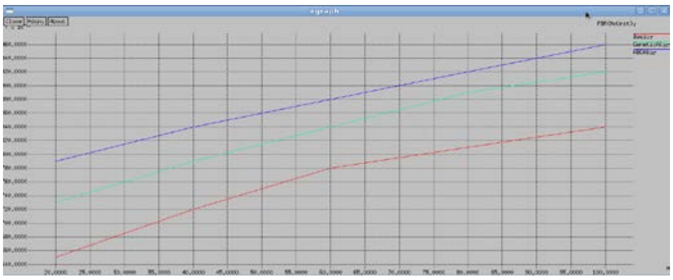

Figure 1: Comparison of Packet Delivery Ratio

The figure 1 shows the packet delivery ratio compared with GA. The packet delivery ratio is higher for bacteria foraging algorithm as compared with GA and others. At high mobility, the GA and other algorithm has to reinitiate the route discovery process again. This leads to lower packet delivery ratio. The proposed ABC proactively maintains the path to the destination, which leads to better performance. At lower mobility, the performance is comparable as expected.

The routing overhead is shown in Figure 2 gives the number of control packets per data packet to perform routing. The routing overhead is more for the proposed algorithm. The performance of ABC is relatively stable at lower mobility leading to a decrease in routing overhead.

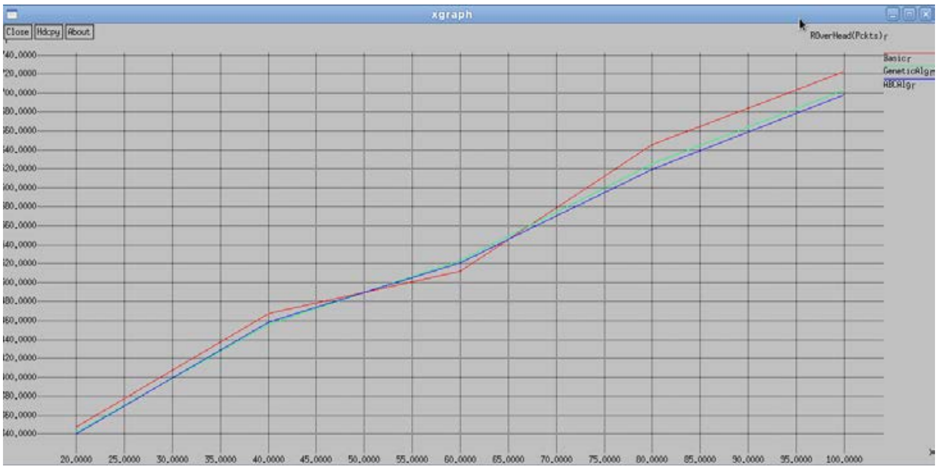

Figure 2: Comparison of Routing Overhead

The following Figure 3 shows the throughput performance of ABC with GA and other with respect to transmission time. It is depicted in the figure that the throughput increases as the data transmission time increases for all routing protocols. It is evident that the throughput of ABC increased with data transmission and highest throughput occurred at 2.6 sec.

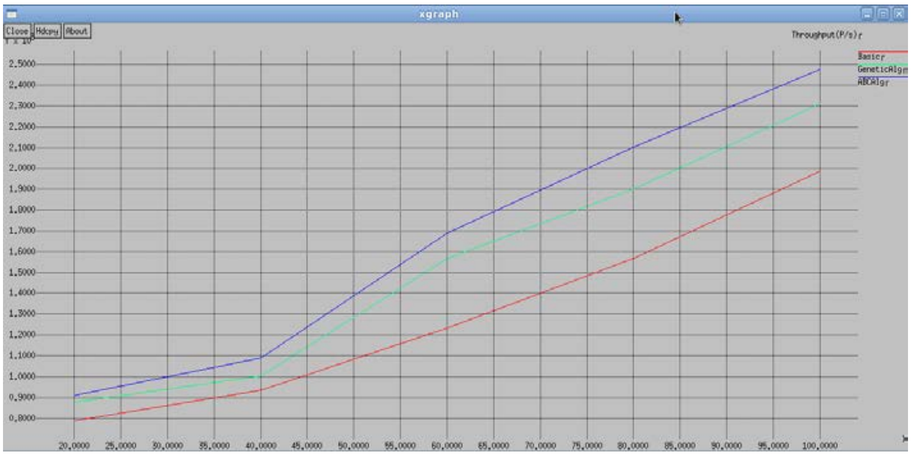

Figure 3: Comparison of Throughput

Figure 4 shows the memory usage of ABC with GA and other. We investigate the memory size that ensures a specified quality of solution for the memory-related schemes. Since there are 20 different topologies in this cyclic series, we set the minimum memory size to 40. Then we increase it to 30 and 50, respectively. We repeat 20 different topologies five times, and the memories schemes will show more power when the same environments are visited more times we sample the data from the latter part of the evolutionary process in ABC. Fig. 5 shows the results. it can be seen that 40 is good enough in both Basic and ABC. The increase of the memory size wastes more resources instead of benefiting the quality of solutions.

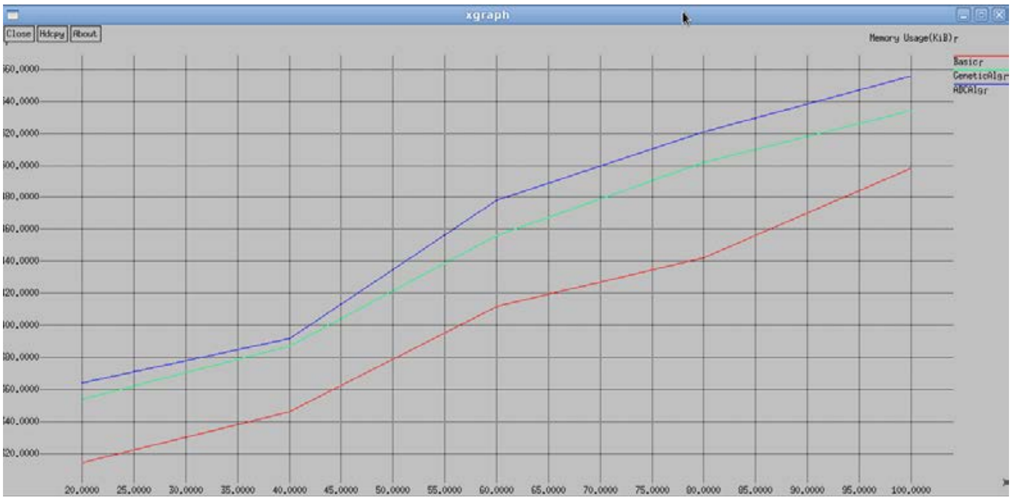

Figure 4: Comparison of Memory Usage

Finally we investigate the impact of the change interval on the algorithm performance for end-to-end delay. Figure 5 shows that the comparison packet end-to-end delays of ABC with GA and other. From the below figure, it can be seen that the end-to-end delay becomes better when the change in GA becomes larger. Therefore, in a relatively slowly changing environment, the studied ABC can achieve a good performance.

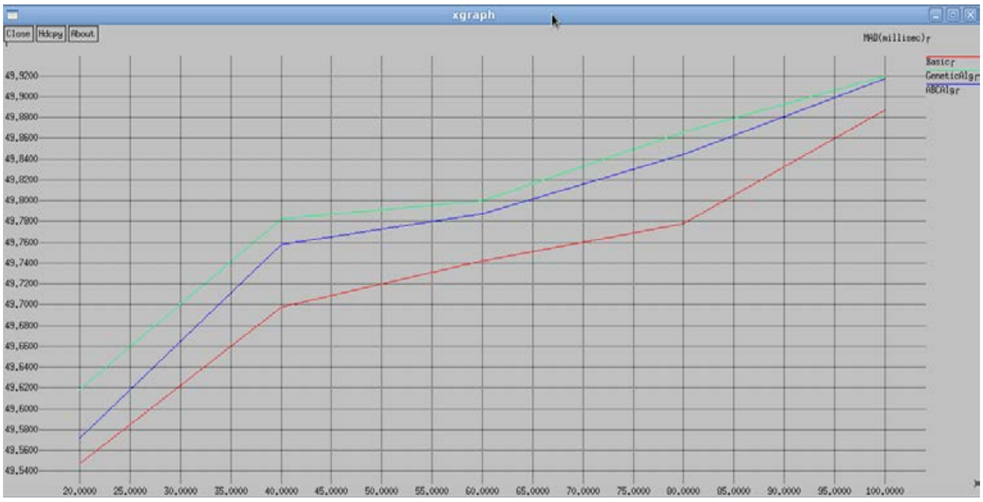

Figure 5: Comparison of Average End-to-End Delay**.**

The Table 1 shows the comparison of SGA, and ABC, depending upon the values of average fitness of given generation of chromosomes.

Table 1: comparison of fitness value for SGA and ABC

Generations(or)Iteration	**SGA (Fitness Value) (meters)**	**ABC (Fitness Value) (meters)**
10	2458	2201
20	2210	1980
30	1985	1733
40	1765	1828
50	1560	1907

The table illustrates the best possible optimal path that can be obtained using the schemes as mentioned above.

7. Conclusion

MANET is a self-organizing and self-configuring multihop wireless network, which has a wide usage nowadays. The SP routing problem aims to establish a multihop forwarding path from a source node to a destination node and is one important issue that significantly affects the performance of MANETs. So far, most SP routing algorithms in the literature consider only the fixed network topology. It is much more challenging to deal with the SP routing problem in a continuously changing network like MANETs than to solve the static one in a fixed infrastructure

This paper investigates the application of ABCs for solving the DSPRP in MANETs. A DSPRP model is built up in this paper. A specialized ABC is designed for the SP problem in MANETs. Several parameters that have been developed and compared for ABCs for general DOPs are adapted and integrated into the ABC to solve the DSPRP in MANETs. Then, extensive simulation experiments are conducted based on a large-scale MANET constructed in this paper to evaluate various aspects of ABC variants for the DSPRP.

References

[1] C. W. Ahn, R. S. Ramakrishna, C. G. Kang, and I. C. Choi, “Shortest path routing algorithm using Hopfield neural network,” Electron. Lett., vol. 37, no. 19, pp. 1176–1178, Sep. 2001.

[2] C. W. Ahn and R. S. Ramakrishna,“A genetic algorithm for shortest path routing problem and the sizing of populations,” IEEE Trans. Evol.Comput., vol. 6, no. 6, pp. 566–579, Dec. 2002.

[3] M. K. Ali and F. Kamoun, “Neural networks for shortest path computation and routing in computer networks,” IEEE Trans. Neural Netw., vol. 4,no. 6, pp. 941–954, Nov. 1993.

[4] J. Branke, “Memory enhanced evolutionary algorithms for changing optimization problems,” in Proc. 1999 Congr. Evol.Comput., pp. 1875–1882.

[5] J. Branke, Evolutionary Optimization in Dynamic Environments. Norwell, MA: Kluwer, 2002.

[6] J. Branke, T. Kaußler, C. Schmidt, and H. Schmeck,"A multi-population approach to dynamic optimization problems," in Proc. 4th Int. Conf. Adaptive Comput.Des. Manuf., 2000, pp. 299–308.

[7] H. G. Cobb and J. J. Grefenstette, "Genetic algorithms for tracking changing environments," in Proc. 5th Int. Conf. Genet. Algorithms, 1993,pp. 523–530.

[8] J. J. Grefenstette, "Genetic algorithms for changing environments," in Proc. 2nd Int. Conf. Parallel Problem Solving Nature, 1992, pp. 137–144.

[9] S S. Yang, "Genetic algorithms with elitism-based immigrants forchanging optimization problems," in Proc. EvoWorkshops 2007: Appl. Evol. Comput. (Lecture Notes in Computer Science), vol. 4448, pp. 627–636.

[10] D. Karaboga and B. Basturk, On the performance of artificial bee colony (ABC) algorithm, Applied Soft Computing 8 (2008), pp.687-697, 2008.

[11] D. Karaboga, An Idea Based On Honey Bee Swarm For Numerical Optimization, Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.

[12] A. W. Mohemmed, N. C. Sahoo, and T. K. Geok, "Solving shortest path problem using particle swarm optimization," Appl. Soft Comput., vol. 8, no. 4, pp. 1643–1653, Sep. 2008.

[13] S. Oh, C. Ahn, and R. Ramakrishna, "A genetic-inspired multicast routing optimization algorithm with bandwidth and end-to-end delay constraints," in Proc. 13th Int. Conf. Neural Inf. Process.(Lecture Notes in Computer Science), 2006, vol. 4234, pp. 807–816.

[14] M. Parsa, Q. Zhu, and J. Garcia-Luna Aceves,"An iterative algorithm for delay-constrained minimum-cost multicasting," IEEE/ACMTrans.Netw., vol. 6, no. 4, pp. 461–474, Aug. 1998.

[15] C. E.Perkins Ed., Ad Hoc Networking. London, U.K.: Addison-Wesley, 2001.

[16] C. S. R. Murthy and B. S. Manoj, Ad HocWireless Networks: Architectures and Protocols. Englewood Cliffs, NJ: Prentice-Hall, 2004.

[17] C.-K. Toh, Ad Hoc Mobile Wireless Networks: Protocols and Systems. Englewood Cliffs, NJ: Prentice-Hall, 2002.

[18] S. Yang, "Memory-based immigrants for genetic algorithms in dynamic environments," in Proc. 2005 Genet. Evol.Comput. Conf., vol. 2,pp. 1115–1122.