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Bio Inspired and Evolutionary Approaches to Optimize MANET Routing

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Abstract

Mobile Ad Hoc Network (MANET) is a dynamic multihop wireless network which is established by a set of mobile nodes on a shared wireless channel. One of the major issues in MANET is routing due to the mobility of the nodes. Routing means the act of moving information across an internet work from a source to a destination. When it comes to MANET, the complexity increases due to various characteristics like dynamic topology, time varying QoS requirements, limited resources and energy. There are various bio inspired and evolutionary approaches including Genetic Algorithm (GA), Neural Network, Evolutionary programming (EP) exploited for routing optimization in MANETs. The Swarm Intelligence based algorithmic approaches; Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are more promising in providing loop free, energy-aware, and multi-path routing in mobile ad hoc. In this paper we study some PSO and GA algorithms to optimize the MANET routing.

Keywords: PSO, GA, MANET, Optimization, Routing

Introduction

A mobile ad hoc network (MANET) is a decentralized group of mobile nodes which exchange information temporarily by means of wireless transmission [1]. Since the nodes are mobile, the network topology may change rapidly and unpredictably over time. The network topology is unstructured and nodes may enter or leave at their will. A node can communicate to other nodes which are within its transmission range. This kind of network promises many advantages in terms of cost and flexibility compared to network with infrastructures. MANETs are very suitable for a great variety of applications such as data collection, seismic activities, and medical applications. Due to the frequently changes in topology and infrastructure less nature, Ad hoc networks require a highly adaptive routing algebraic approaches. In ad hoc networks, component failure is caused by the multicast routing protocols. Multicast and the multipath structure for the routing have the redundancy. In mobile and ad hoc networks, power is constrained and topology changes repeatedly.

The focus of this study is the collection of Genetic Algorithm and Swarm Intelligence based routing algorithms proposed for the routing optimization in Ad Hoc Networks by considering various constraints i.e. mobility, energy awareness, overhead, end to end delay etc. The biological inspired routing protocols are more promising for routing optimization, with consideration of specific issues, due to the nature of Mobile Ad hoc Networks (MANETs) than early approaches like AODV[1], DSR[2], OLSR[3] and ZRP[4]. There are various protocol suits given in[5], used in computer networks. Some routing algorithms are more efficient at ad hoc & sensor networks while some are more promising on fixed infrastructure. There are various evolutionary based (GA,, EP .etc) approaches are used in the wired networks as well as MANETs for the routing optimization and Quality of Service but the survey study concluded that Swarm Intelligence based heuristic approaches Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Honeybees are more promising for the ad hoc and wireless networks due to the nature of their working and design systems. Swarm Intelligence inspired, routing algorithms are more capable to tackle various issues associated with the routing in MANETs and WSNs due to their mobility and non infrastructure nature. It is desired very fast and exact location search of destination in ad hoc networks. For the optimum utilization of resources like, power consumptions, bandwidth and routing overhead reduction; in ad hoc sensor networks, routing approaches exploits the natural warm behavior mimicked in Swarm Intelligence.

Swarm Intelligence. Swarm Intelligence (SI) is that the property of a system whereby the collective behaviours of unsophisticated agents interacting domestically with their surroundings cause coherent practical world patterns to emerge. SI provides a base with that it's doable to explore collective (or distributed) drawback solving while not centralized management or the availability of a world model. SI evolution 1st searches the surroundings for smart regions ,and when finding an honest region of the search space, appearance for the most effective purpose in that region.

Genetic Algorithm. Genetic Algorithm (GA) is an exploratory search and optimisation methodology that was devised based mostly on the principles of natural biological evolution and population genetics [9]. As mentioned within the introduction, GA could be a metaheuristic approach that doesn't need mathematical descriptions of the optimisation drawback, however instead depends on the value perform so as to assess the fitness of a particular resolution to the matter in question. GA, as such, is capable of providing a sturdy and efficient search during a complicated area. The powerful ability of GA optimisation led to interest in its performance for world optimisation on an outsized scale. The flowchart shown in Figure seven.1 illustrates the most operations of a GA in sequence.

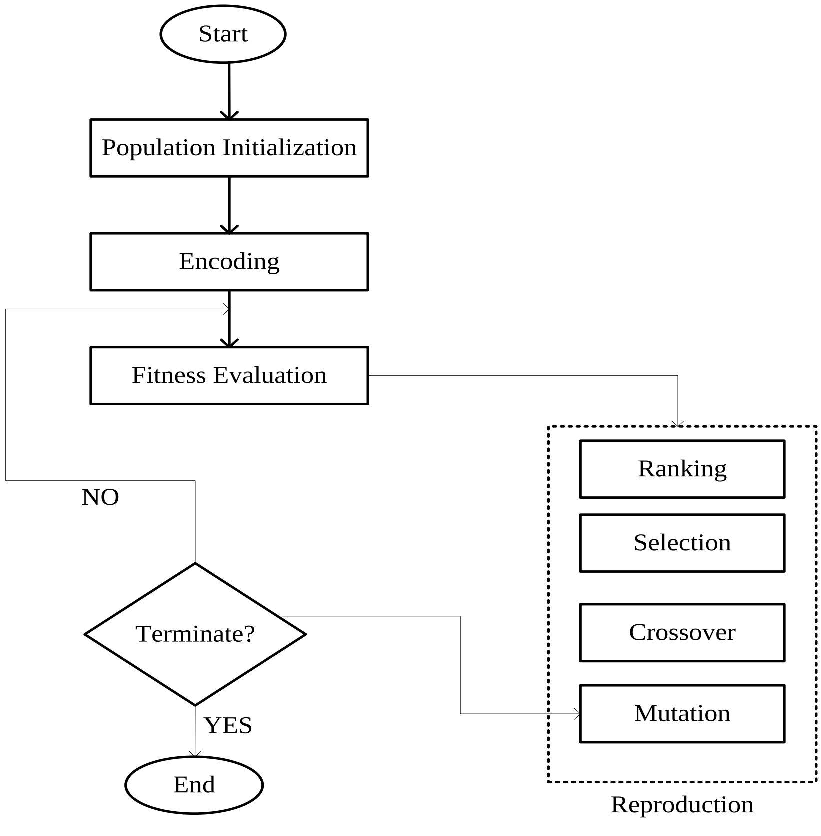


Figure 1: Typical Genetic Algorithm flowchart

A. Population initialization: potential resolution candidates are initialized by randomly generating a population of individual chromosomes, with every representing a distinct resolution to the matter. The population in every generation is set by the amount of chromosomes. the primary column in Table 1 represents the chromosome population.

B. Encoding: In laptop science, the matter is encoded into a group of strings (chromosomes) and each individual encoded into binary string that contains a well-defined range of bits (1's and 0's). An example of this can be shown in Figure 2 (a), whereas a chromosome that's an array of genes converted into either 0s or 1s is shown in Figure 2 (b).

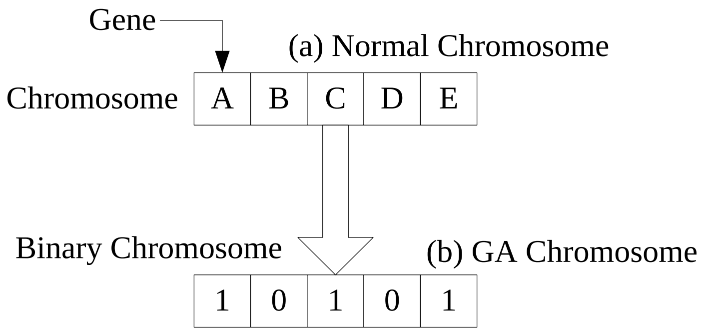


Figure 2: Chromosome presentation.

C. Evaluation: This method contains a predefined fitness perform that evaluates every member of the population. A fitness worth is assigned to work out how "good" every string is, as every string represent an answer. the upper the fitness worth of a private string, the upper its probability of survival and replica. The second column in Table seven.1 shows an example of fitness perform results for a chromosome population, where the worth for every perform was selected randomly in order to elucidate the GA analysis method. The third column within the figure represents the chromosome fitness analysis level from (1-10), with the foremost work chromosome scoring ten and also the least scoring one.

Chromosome population	Fitness function	Ranking	Evaluation level
Chromosome 1	f(Chromosome 1) = 0.5	Chromosome 10	5
Chromosome 2	f(Chromosome 2)	Chromosome 4	3
Chromosome 3	f(Chromosome 3)	Chromosome 7	4
Chromosome 4	f(Chromosome 4)	Chromosome 6	8
Chromosome 5	f(Chromosome 5)	Chromosome 1	1
Chromosome 6	f(Chromosome 6)	Chromosome 3	6
Chromosome 7	f(Chromosome 7)	Chromosome 2	7
Chromosome 8	f(Chromosome 8)	Chromosome 8	2
Chromosome 9	f(Chromosome 9)	Chromosome 5	10
Chromosome 10	f(Chromosome 10)	Chromosome	9

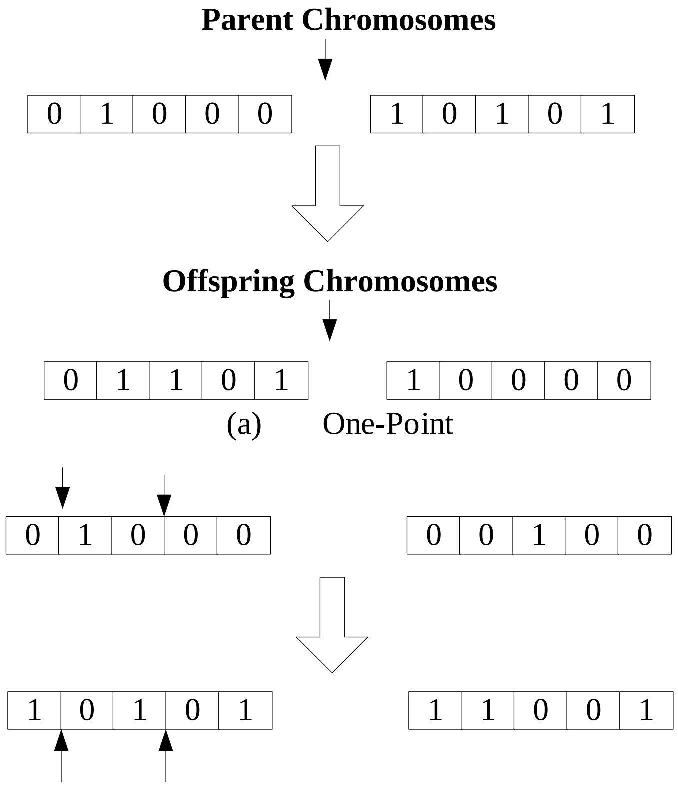
Table 1: GA chromosome population, evaluation function and ranking processes.

In the copy method, new offspring are created through random variation; the copy consists of ranking, selection, crossover, and mutation.

D. Ranking: The fittest people are ranked in line with their analysis level, as shown within the fourth column in Table 1. This operation models the natural mechanism "survival of the fittest." Fitter solutions (individuals with a highest fitness value) survive and are copied into future generation whereas the weak ones perish.

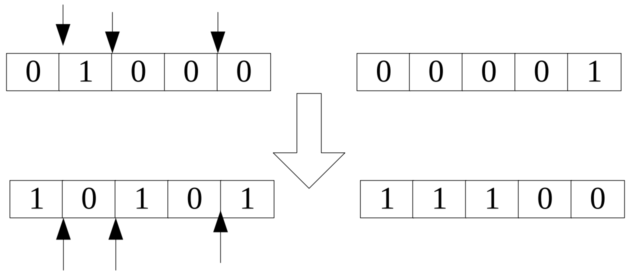
E. Selection: This method decides the chromosomes that may be forwarded to future operation, or the crossover (see below). the 2 preferred choice strategies are the roulette wheel and tournament choice strategies. In the roulette wheel technique, a chromosome is chosen randomly from the vary (0 - 1). The roulette wheel contains the chromosome population (as shown in Figure 2), as every chromosome is represented by a slot. The slot width varies reckoning on the chromosome fitness operate (the second column in Table 1), where the slot width will increase with a rise within the chromosome fitness function. Therefore, the likelihood of "dropping the ball" for the chromosome with the best fitness will, during this manner, even be increased. This technique was adopted during this chapter through implementing GA with MANET. In the tournament technique, variety of chromosomes are picked randomly from the population to form a "tournament" pool. the 2 chromosomes with the best fitness functions are then selected from this tournament pool as folks.

F. Crossover: so as to form a higher population than the initial one, a mating method is carried out among the fittest people within the previous generation, since the relative fitness of every individual is employed as a criterion for alternative. Hence, the chosen people are randomly combined in pairs to provide 2 offspring by crossing over components of their chromosomes at a randomly chosen position of the string. These new offspring are purported to gift a higher resolution to the matter. The 3 known crossover sorts, one-point, two-point, and uniform, are presented in Figure 2. In the one-point crossover (Figure 2 (a)), 2 parent strings are cut at identical purpose and offspring are fashioned by combining complementary genes from the fogeys. In two-point crossover (Figure 2 (b)), oldsters are cut at two points and offspring are fashioned by inserting a central sequence from the primary parent into the second parent, and vice versa. different forms of crossover are doable, such as uniform crossover (Figure 2 (c)), within which offspring are generated by taking a particular variety of genes from every parent, with no restriction on where these genes occur within the string.



(a) One-Point

(b) Two-Point



(c) Uniform

Figure 3: Genetic Algorithm crossover types: (a) One-point, (b) Two-point, and (c) Uniform.

G. Mutation: so as to supply further excitation to the generation method, randomly chosen bits in the strings are inverted (0's to 1's and 1's to 0's), as shown in Figure 3. This mechanism is thought as mutation and helps to hurry up convergence by preventing the population from being dominated by the same people. A compromise, however, ought to be reached between an excessive amount of or too very little excitation by selecting atiny low likelihood of mutation.

Figure 4: GA mutation.

The generational method is repeated till a termination condition has been reached. Common terminating conditions are listed below:

- an answer is found that satisfies the minimum criteria;
- a set variety of generations is reached;
- The allotted budget (computation time/money) is reached;
- the very best ranking solution's fitness has reached, or is reaching, a plateau such that successive iterations not manufacture higher results;
- A manual inspection is performed; and
- Any combination of the on top of.

All in all, this ensures that the answer set isn't empty. In MANET, GA are involve in solving route issues by choosing the shortest path] and developing optimised routing protocols like [6] and [7]. Also, GA was combined with ANN, as in paper [8], for fast route rebuilding.

PSO Algorithm

Particle Swarm Optimisation (PSO) may be a international optimisation technique that finds the simplest resolution for the downside, presented as some extent and a velocity. based mostly on bound metrics, every particle assigns a value to the position it's and additionally remembers the simplest position it's seen. The particle then communicates the simplest position to the opposite swarm members. Therefore, the particles can regulate their own positions and velocity based mostly on this info. The communication may be common to the whole swarm, or be divided into native neighbourhoods of particles [9].

The general characteristics of particle swarm algorithm are as follows [10]: One, PSO employs a population of particles. Two, PSO has the “traditional” topology gbest and pbest to explain the interconnections among the particles. The gbest topology is taken into account the totally interconnected population as each member of the population may be influenced by each different member. In another words, the particles may be affected by the person who has found the simplest resolution to date. Therefore, the responsibility of gbest is ultimately to trace the simplest resolution found. The pbest topology is taken into account as a partially interconnected population within which each particle is connected to the neighbouring particles within the population array. Putting the previous characteristics in follow, Clerc and Kennedy [11] presented a simplified deterministic version of the particle swarm. As shown in Figure 5 and also the flowchart in Figure 6 the particle's population is initialized with random positions x(t) and velocities v(t), and a value perform is evaluated using the particle's positional coordinates as input values. Positions and velocities [12] are adjusted with the perform that evaluated the new coordinates at every time step.

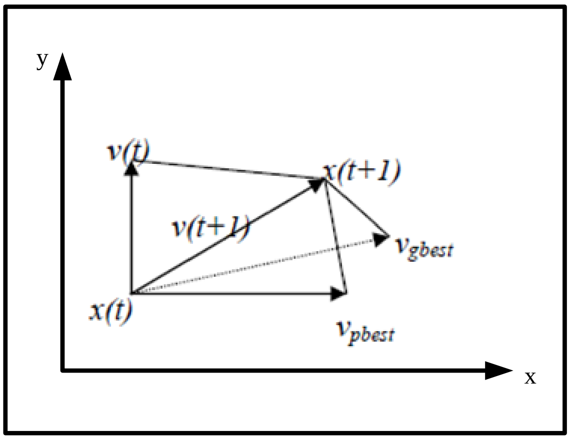


Figure 4: Concept of modification of a searching point by PSO.

When a particle discovers a pattern that's higher than any it had previously found, it stores the coordinates in pbest(t). The distinction between pbest (the best purpose found thus far) and therefore the individual's current position is stochastically added to this velocity, inflicting the trajectory to oscillate around that time. Further, every particle is outlined inside the context of a topological neighbourhood comprising itself and some other particles in the population. The stochastically weighted distinction between the neighbourhood's best position gbest(t) and therefore the individual's current position is additionally added to its velocity, adjusting it for ensuing time step.

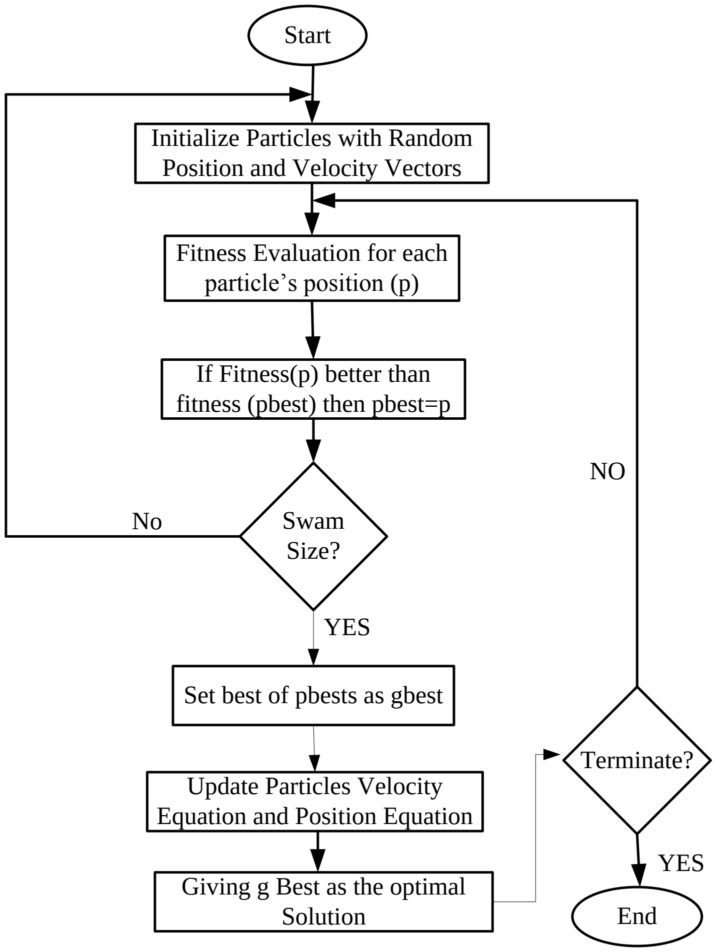


Figure 6: Typical flowchart for Particle Swarm Optimisation.

These changes to the particle's movement through area cause it to go looking round the 2best positions, as shown within the equation below:

$$v(t+1) = wv(t) + \phi_1 r_1 (pbest)(t) - x(t)\ ) + \phi_2 r_2 (gbest(t) - x(t)) \tag{1}$$

where w is that the inertia weight which will be either a relentless or a worth that changes linearly with the time; φ1 and φ2 are known as "cognitive" and "social" parameters, respectively, and are random positive constants that weight the influence of the 2 totally different swarm memories; and r1 and r2 are random numbers between zero and one. After the speed vector had been calculated, the positions of the particles were updated in keeping with the equation below:

$$x(t+1) = x(t) + v(t+1) \tag{2}$$

PSO was utilised within the impromptu network to satisfy some network needs and develop routing protocol, as exemplified by papers [13] and [14]. Also, the PSO algorithm was concerned in sensor networks to form energy-efficient networks, as in papers [15] and [16].

Comparison between GA and PSO

In this section, the most variations between the 2 investigated algorithms, GA and PSO, will be presented. whereas each algorithms use the fitness concept, they differ in alternative ideas that are listed in the table below.

Table 2 GA and PSO Comparison

GA	PSO

1	Implements the Servival of the Fittest	All its particles kept as members of the population through the course of the run
2	Has Selection Operation	Has no Selection Operation
3	Has CrossOver Algorithm	The Adjuustment toward the best p(t) and g(t)
4	Has Mutation Algorithm	Balance is achieved through the inertial weight factor(w)

The Optimisers Configurations

The two algorithms GA and PSO were utilized as MANET Optimisers to seek out and choose the optimum routing protocol primarily based on the output performance. each GA and PSO Optimisers were programmed in MATLABTM.

The NF models were equipped to each Optimisers; where every output parameter was modelled separately against the input parameters, every Optimiser normalizes the 5 performance parameters then merges them into one equation (cost function), and performs calculations for this equation in each Optimisers. There are several strategies [17] to implement a parameter's normalization; the chosen method depends on the out there and known information. Thus, for the normalization during this thesis, the parameters rely upon the equation below, because the most and therefore the minimum values are known for each parameter:

$$NormalizedPerformanc\,eParameter = \frac{parameter - paramete_{\min}}{parameter_{\max} - parameter_{\min}} \qquad (3)$$

The cost function is the Mean Square (MS) of the normalized performance parameter, as shown below:

$$CostFunction\,\frac{(RA)^2 + (Datadrop)^2 + (Load)^2 + (Delay)^2 + (1 - Throughput)^2}{5} \qquad (4)$$

From the Optimiser's call it may be concluded that, looking on the price perform, it'll choose the routing protocol with the minimum MS to be the optimum routing protocol for that iteration. For each iteration (or generation) this choice method are going to be repeated. The GA and therefore the PSO optimisation method can end in variety of solutions equal to the iteration or the generation range. the chosen resolution, that's the optimum routing protocol, are going to be the one with the simplest objective (the minimum MS).

MANET Optimisation

Each Optimiser has to be provided with 2 inputs; the network size and therefore the nodes average mobility to start its computing. 9 cases were studied based mostly on Table 3, as in every case the inputs selected depended on the second rows of Tables 4 and 5.

GA MANET Optimiser. The GA Optimiser can base its call on the outputs of the neuro-fuzzy models to seek out the optimum protocol that has to be adopted. The GA was set with three bits of chromosome length for the 3 parameters (network size, average mobility, and protocol's name), with the chromosome worth randomly selected between zero and 250 and then converted to binary. The population size was ten with average ranking, the mutation was zero.06, and therefore the crossover likelihood was zero.95. Finally, the GA went through twelve generations to seek out the optimal answer. Table 6 shows the GA's optimum routing protocol answer for every case, the answer best objective amplitude, and therefore the generation range for that answer.

Table 6 Genetic Algorithm Module Results

Case No.	GA Inputs	GA		GA Outputs	
	Network Size	Average Mobility (m/s)	Routing Protocol	Best Objective	Generation No.
Case1	62	18	AODV	0.5288	10
Case2	62	11	OLSR	0.4874	11
Case3	62	3	OLSR	0.9596	10
Case 4	20	18	AODV	0.976	1
Case 5	20	11	DSR	1.0959	1
Case 6	20	3	DSR	1.0035	1
Case 7	8	18	AODV	0.9983	8
Case 8	8	11	AODV	1.0718	1
Case 9	8	3	DSR	0.9981	10

PSO MANET Optimiser. The PSO Optimiser was set with three-dimension swarm; the scale represent the inputs (network size, average mobility, and protocol's name). the scale of the swarm was ten, which was iterated ten times; the error accepted was set to be but 1×10-10. The PSO Optimiser used the practical swarm optimisation for the rate and therefore the position equations, as in Equations (1) and (2).

The optimum routing protocol selected by PSO with its best objective and its iteration number is shown in Table 7.

Table 7 Practical Swarm Optimization Module Results

	PSO Inputs			PSO Outputs	
Case Number	Network Size	Average Mobility (m/s)	Routing Protocol	Best Objective	Iteration No.
Case1	62	18	AODV	0.324004	7
Case2	62	11	OLSR	0.323958	1
Case3	62	3	OLSR	0.323958	5
Case 4	20	18	AODV	0.324002	8
Case 5	20	11	DSR	0.323958	9
Case 6	20	3	DSR	0.323962	1
Case 7	8	18	AODV	0.518332	5
Case 8	8	11	AODV	0.570085	6
Case 9	8	3	DSR	0.323977	7

MANET Optimisers choice. The GA Optimiser characteristic are going to be compared with the PSO Optimiser characteristic, based on Clerc and Kennedy statement concerning PSO [10] that says, "Particle swarm optimisation contains a very straightforward concept and paradigms; it may be implemented during a few lines of pc code. It needs only primitive mathematical operators, and is computationally cheap in terms of each memory requirements and speed [11]."

a. GA is additional sophisticated than PSO and includes several algorithms for encoding, ranking, cross over, and mutation. PSO is way easier than GA as PSO computation depends on 2 basic equations.

b. GA needs longer within the computation method thanks to the amount of algorithms to be processed. As such, few PSO pc codes will build the PSO Optimiser faster than the GA Optimiser at finding the solutions.

Comparing the potency of the 2 techniques quantitatively, the simplest objective in every of the fifth column of Tables 6 and 7 were studied. once examining the 2 columns, it shows that, in general, the GA best objective was continually higher in worth than the PSO best objective. for instance,in Case 9, when network size was eight nodes with average mobility three m/s, the routing protocol selected was DSR with GA best objective = 0.9981 and PSO best objective = 0.323977. This clearly shows that PSO have the minimum MS.

These comparison results evaluate every Optimiser; on this basis, a call created to implement PSO techniques as an Optimiser within the AHORS-MANET routing protocols optimisation system.

Conclusion

In this paper, the need of utilising the synthetic Intelligence (AI) algorithms for optimizing MANET has been highlighted as a result of the AI's ability to adapt to changes within the atmosphere and its algorithms' quick convergence. Here, the sequence operations for every GA and PSO technique were conjointly explained intimately. Furthermore, 2 MANET Optimisers were created: one with GA and therefore the second with PSO. The results show that each Optimisers selected a similar routing protocols for a similar specified context. Having evaluated the 2 Optimisers, it had been concluded that the PSO optimisation technique are going to be the optimisation technique employed in the AHORS-MANET routing protocols optimisation system.

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