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Hybrid GA-PSO for Solving Multi-metric Quality of Service Routing Optimization in Mobile Ad Hoc Networks

[1]S.K.Nivetha, [2]Dr.R.Asokan, [2]N.Senthilkumaran and [4]C.K.Brindha

[1]Assistant Professor (Senior Grade), Department of CSE, Kongu Engineering College, Erode – 638052, Tamil Nadu, India.
[2]Principal, Kongunadu College of Engineering and Technology, Tiruchirapalli – 621215, Tamil Nadu, India.
[3]Director, Department of Computer Applications, Vellalar College for Women, Erode – 638112, Tamil Nadu, India.
[4]Software Analyst, Cognizant Technology Solutions, Chennai, Tamil Nadu, India.

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ABSTRACT

Background: In the absence of a dedicated router to perform routing decisions, routing becomes a major task in Mobile Ad hoc NETworks (MANETs). Additionally, dynamic nature of MANET topology makes routing as challenging. While routing packets through this type of network, different applications demand different service requirements. To perform effective routing considering these service requirements, it is required to use multiple Quality of Service (QoS) metrics in addition to hopcount. Usage of a combination of additive, concave and multiplicative metrics requires an optimization technique to effectively solve it as it is proved to be an NP-complete problem. Meta-heuristics are general-purpose algorithms that can be applied to solve almost any optimization problem. **Objective:** In this study, we propose GA-PSO based hybrid meta-heuristic (GPHM) algorithm in order to combine the advantages of both GA and PSO to solve the multi-metric QoS routing problem. **Results: Conclusion:** The study of the proposed scheme shows an effective performance improvement in terms of average end-to-end delay, available bandwidth, remaining node energy and hop count when compared with the pure GA model and pure PSO model.

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INTRODUCTION

MANETs are instantly deployed networks which consist of peer-to-peer wireless mobile nodes that are capable communicating each other. This is an autonomous network as there is no central coordinator to control. There is no fixed infrastructure to be followed and hence it is infrastructureless. Packets forwarded in this network must go through several nodes to reach the destination and thus it uses multihop routing. Nodes in this network can move anywhere anytime, so the topology is dynamic. Due to this dynamic topology, there may be several variations in the link and node capabilities. Nodes in this network are mobile and are operated through battery; therefore, routing (Goldsmith A J, and Wicker S B., 2002) is an energy constrained operation. As there is no dedicated routers present in this network, each node must act as a router.

Due to these characteristics, MANETs need to address unique issues that are not applicable in wired networks. Some of the key issues in MANET (Conti M, and Giordano S., 2014) are, Medium Access Scheme, Dynamic Routing, Security, Scalability, Energy Efficiency and Multicasting. Among these issues routing attracted many researches in the literature as a dominant one. The major challenges (Zhang B, and Mouftah H T., 2005) that a dynamic routing protocol faces are mobility, bandwidth constraints, error-prone and shared channel, resource constraints, loop-free routing, control overhead, scalability, provisioning of Quality of Service (QoS) and security.

The applications of MANET usually include crisis management services, personal area networks, military battlefields, indoor stadiums, classrooms, etc. All such applications require real-time communication (multimedia) like audio and video data transfer. Real-time communications need some knowledge about the resource availability for a particular flow in order to achieve required Quality of Service (Chen.S, 1999). QoS is defined as set of service requirements to be met by the network while transferring the packet from the source to the destination. The major issues (Hanzo L, and Tafazolli R, 2007) are deciding QoS parameters/metrics as demanded by the real-time

Corresponding Author: S.K. Nivetha, Assistant Professor (Senior Grade), Department of CSE, Kongu Engineering College, Erode – 638052, Tamil Nadu, India.

application and designing QoS framework.

QoS metrics (Masip-Bruin X *et al*., 2006) could be defined in terms of any one of the parameters or a set of parameters (mulit-metric) in varied proportions. Most of the research in literature is targeted towards considering either single QoS metric ((Zaki, S. M., Ngadi, M. A., and Razak, S. A., 2009), (Gnana Prakasi O.S., Dr. Varalakshmi P. and Janani J., 2015)) or two QoS metrics (Patil, A. P., Kanth, K. R., and Kumar, M. D., 2011) and very few are considering three metrics (Nivetha S K, and Asokan R., 2014a). But, real time communications require minimum end-to-end delay, maximum available bandwidth, effective utilization of node energy and also minmum hopcount. Among these delay and hopcount are additive metrics whereas bandwidth and energy are concave metrics. QoS routing is NP-complete when a combination of additive, concave and multiplicative metrics is considered. A possible solution to these kinds of problems which cannot be solved using classical methods is the application of stochastic optimization technique. Stochastic optimization techniques are usually categorized in to evolutionary algorithms like Genetic Algorithms (GA) and nature inspired algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithm.

Genetic algorithm is inspired by the Darwinian principles of natural selection and natural genetics which have revealed a number of characteristics particularly useful for routing exploration in MANETs. GA is very easy to understand, easy to transfer to existing simulations/models, solves problems with multiple solutions and it practically does not demand the knowledge of mathematics. GA with its evolving nature, optimizes the shortest path problem by producing better results with the given candidate solutions. This is in agreement with an assortment of schemes proposed based on GA by several authors ((Barolli L, Koyama A, and Shiratori N., 2003), (Tseng S Y, Huang Y M, and Lin C C., 2006), (Brindha C K, Nivetha S K, and Asokan R., 2014)).

GA employs three operators to propagate its population from one generation to another. Namely "Selection" which decides the way parents are selected for offspring production, "Crossover" which propagates features of good surviving designs from the current population into the future population and "Mutation" which promotes diversity in population characteristics and allows for global search of the design space and prevents the algorithm from getting trapped in local minima. Selection operator (Khalid Jebari, and Mohammed Madiafi, 2013) is the most important parameter that may influence the performance of a GA. In the literature there are several selection methods including Roulette wheel selection, stochastic universal sampling, linear rank selection, exponential rank selection, tournament selection, and truncation selection. Each method has its own drawbacks and a non-suitable selection operator can lead to poor performance of GA in terms of both rapidity and reliability. Without selection operator, genetic algorithms are only simple random methods give different values each time. This work proposes hybridization of PSO as a selection operator in GA in order to achieve better results when compared to the traditional models.

PSO (Kennedy, J. and Eberhart, R. C., 1995) is a population based optimization technique inspired by social behavior of bird flock and swarms. It has many similarities (Eberhart, R. C. and Shi, Y. , 1998) with GA. Both involves initializing a population of random solutions and searches for optimal solution by updating generations. Both have fitness values to evaluate the population. However, PSO does not have genetic operators (Rehab F. and Abdul Kader, 2011) like crossover and mutation. Particles (Eberhart, R. C. and Shi, Y. , 2001) update themselves with the internal velocity. They also have memory, which is important to the algorithm. Compared with GA, all the particles tend to converge to the best solution quickly even in the local version in most cases. Additionally, PSO (Nivetha S K, and Asokan R., 2014b) algorithm is simple, easy to implement, robust to control parameters, more accurate, and computationally efficient. Hence, the proposed work combines the strengths of PSO and GA forming an efficient hybrid meta-heuristic to realize the balance between natural selection and the convergence can be attained quickly in order to optimize multi-metric QoS routing problem.

MATERIALS AND METHODS

1.1 Problem Formulation:

In order to achieve effective routing and provisioning of QoS in real-time communications of Mobile ad hoc networks, this work considers average end-to-end delay, available bandwidth, remaining node energy and hopcount as route selection parameters from the multiple paths discovered from source to destination. To find optimal solution it uses GA-PSO based hybrid meta-heuristic as an optimization technique. Meta-heuristics are problem-independent techniques which allows us to explore more thoroughly the solution space and thus to get a hopefully better solution that sometimes will coincide with the global optimum. In GA phase, nodes in MANET are encoded as genes. A path from source to destination is encoded as a chromosome. Set of all possible paths from source to destination are considered as initial population. Fitness function must be defined in terms of required QoS parameters. Fitness values are to be evaluated for each chromosome based on the fitness function. Start PSO phase, for selecting parents from the population. As initializing the population and fitness function evaluation are done at GA phase, PSO directly starts with the steps namely, generating particles' positions and velocities, velocity update, and finally, position update. This results in finding best solutions from the solution space which are considered as parents for the crossover and mutation operation in GA. Finally, when the termination criterion is met it presents the new population as the solution set with optimal paths satisfying the required QoS metrics. The workflow of the GA-PSO based hybrid meta-heuristic is presented Figure 1.

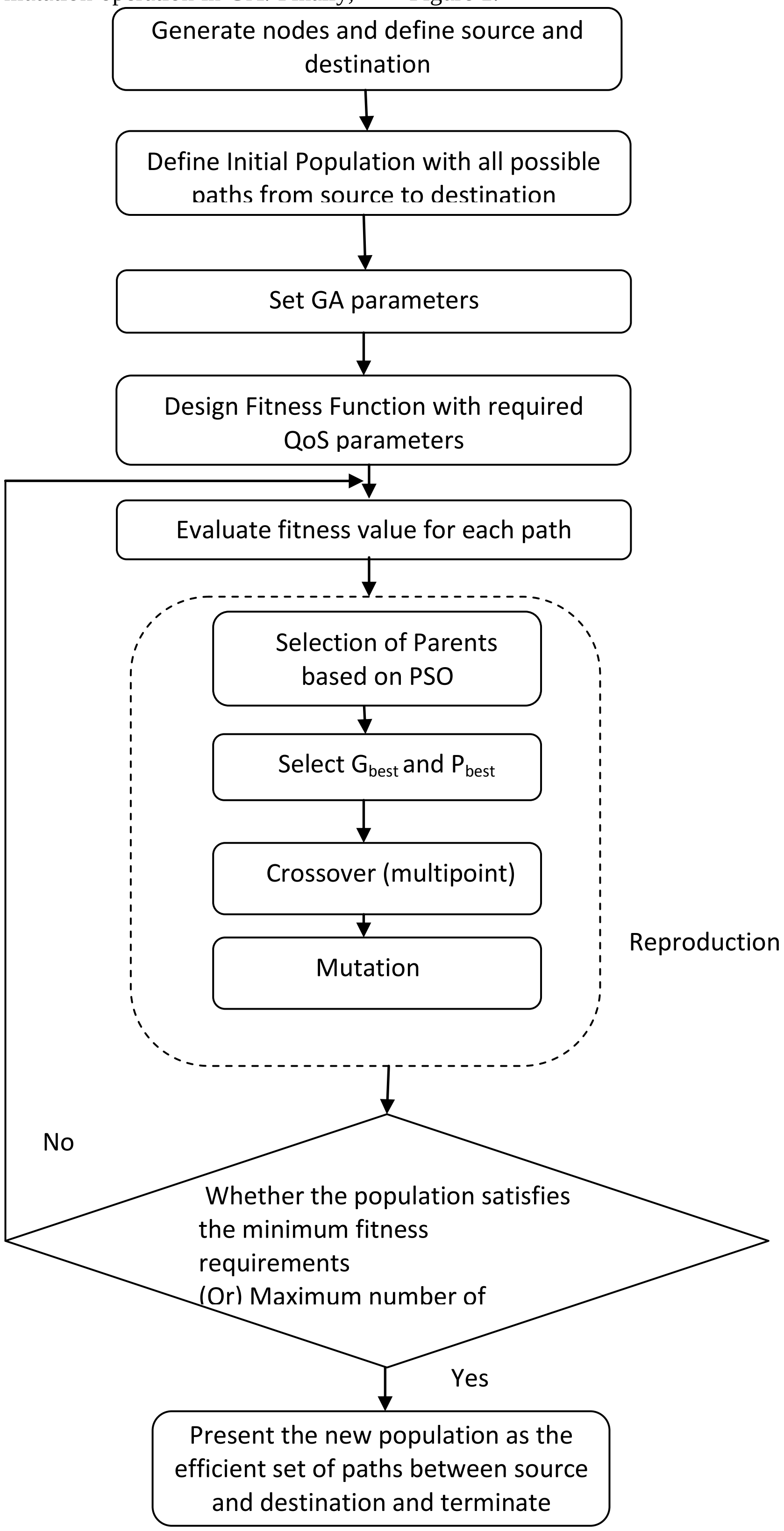

Fig. 1: Workflow of GA-PSO based hybrid meta-heuristic

1.2 Network and Energy Model Implementation:

The models of energy consumption for a link (L.M.Feeney and M.Nilsson , 2001) between two nodes are studied in [ ]. For a transmission of a unit message, the model of the minimum energy needed for a link between nodes *vi* and *vj* is $Pi,j = k1\ (ri,j)^{\beta}+k2$, where *r i,j* Euclidean distance between *vi* and *vj* , *k*1 is a constant dependent on the properties of the antenna, β is the path loss exponent that depends on the propagation losses in the medium, and *k*2 is a constant that accounts for the overheads of electronics and digital processing. We assume that each node in a MANET determines the distance between itself and its neighbor nodes using some distance estimation method [9]. The connectivity of the network depends on the transmission power of each node. Each node can dynamically change its transmission power level. A node can use a different power level for each multicast tree in which it participates. All nodes use Omni-directional antennas. Every node *vi* in the network has two coverage areas: (1) control coverage area (*CRi*); (2) data coverage area (*DRi*), where *DRi Є CRi*. These coverage areas depend on the transmission power selected by node *vi* to transmit its control and data packets, respectively.

According to the control coverage area of each node, a MANET can be modeled as a graph G (V, E), where V = {v1, v2... vn} is a set of nodes (mobile hosts) and E = {(i, j)|vi, vj Є V } is a set of links. (*i*, *j*) *Є E* indicates that *vi* and *vj* are within the control coverage area of each other. Each link (*i, j*) is associated with a delay *di,j* and a distance *li,j* . *di,j* describes the data transmission delay between *vi* and *vj* , which includes queuing delay and propagation delay. *li,j* denotes the Euclidean distance between *vi* and *vj*. Both *di,j* and *li,j* are positive real numbers.

Let *s Є V* be a source and *D* be a destination. A unicast multipath tree *T* (*s,D*) *Є G* is a tree rooted at *s* and reaching the destination *D*. The delay of a path on *T* from *s* to a destination *D*, denoted as *delay*(*pT* (*s, D*)), is *delay* (*pT* (*s,D*)) = ∑ (*i,j*) *Є pT* (*s,D*) *di,j* . Then, the delay-constrained minimum Steiner tree problem is to find a minimum cost unicast multipath tree *T* * (*s,D*) such that *delay* (*PT* Є* (*s, D*)) ≤ δ, where δ is the overall allowable delay from *s* to a destination *D*. Once *T* *(*s,D*) is found, each node on T, adjusts its transmission power properly to transmit data packets along the tree.

1.3GA-PSO model implementation:

1) Initial Population:

Many individual solutions are randomly generated initially to form an initial population. Two issues should be considered in the process of population initialization: (1) population size *Np*; (2) the method of population formation. *Np* is set by the system. In this the initial population represents set of all possible paths from source to destination.

2) Fitness Function:

Fitness function measures the quality of the represented solution and it is always problem dependent. The initial population is evaluated based on the fitness value. The fitness function should reflect the individual performance. The good individual has higher fitness than the bad one. In this the fitness function is designed based on energy cost of the tree (Lu T, Zhu J., 2013), end to end delay, bandwidth utilization and also on hop count. The fitness function is

$$f(\mathrm{T}) = \frac{a}{Cost(\mathrm{T})}(\phi(\mathrm{delay}(P_T(\mathrm{s,D})) - \delta) + \phi(\mathrm{B}(P_T(\mathrm{s,D})) - B_d)) \qquad (1)$$

Where cost(T) is the energy cost of the path,

$$Cost(\mathrm{T}) = \sum_{Vi \in T} C_i^T = \sum_{Vi \in T} b[k_1(r_{i,j})^{\beta} + k_2] \qquad (2)$$

Where a is any positive real weighting co-efficient.

3) Selection of Parents:

Among the individuals, best individuals are selected based on PSO model. In PSO (Qinghai Bai, 2010), each single solution is a "bird" in the search space and it is called as a "particle". All particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles and searches for optima by updating generations. In every iteration, each particle is updated by following two values. The first one is the best solution (fitness)that the particle has achieved so far. This value is called pbest which is also stored. Another value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This is a global best value and called as gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

After finding the two best values, the particle updates its velocity and positions with following equation (a) and (b).

v[] = v[] + c1 * rand() * (pbest[] - present[]) + c2 * rand() * (gbest[] - present[]) (3)
present[] = persent[] + v[] (4)

v[] is the particle velocity, persent[] is the current particle (solution). pbest[] and gbest[] are defined as stated before. rand () is a random number between (0,1). c1, c2 are learning factors. usually c1 = c2 = 2.

The pseudo code of the procedure is as follows
For each particle
Initialize particle
END
Do
For each particle
Calculate fitness value
If the fitness value is better than the best fitness value (pBest) in history set current value as the new pBest
End
Choose the particle with the best fitness value of all the particles as the gBest
For each particle
Calculate particle velocity according equation (3)
Update particle position according equation (4)
End
While maximum iterations or minimum error criteria is not attained

Particles' velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user. Then the velocity on that dimension is limited to Vmax.

Selection of parents is done based on $G_{best\ and}$ P_{best}.PSO stores the best member (G_{best}) of the previous generation. The best member of the previous generation (G_{best}) is stored as last in the array. If the best member of the current generation (P_{best}) is worse then the best member of the previous generation, the latter one would replace the worst member of the current population.

4) Crossover Operation:

Crossover operation is performed between the two paths selected and a child is created. Cross over is a process of taking more than one parent solutions and producing a child solution from them. Based on the PSO selection model, a pair of chromosomes is selected as the parents to produce a single offspring. Let *Ta* and *Tb* be the selected parents. The crossover operator generates a child *Tc* by identifying the same links between *Ta* and *Tb*, and retaining these common links in *Tc*. Thus, the common links between two parents are more likely to represent the "good" traits. However, retaining these common links in *Tc* may generate some separate sub-trees. Therefore, links are needed to be selected to connect these sub-trees. These sub trees are then connected with least delay path which are denoted as dotted lines.

5) Mutation Operation:

Following the crossover operation, mutation operation is performed on the new offspring. The mutation procedure randomly selects a subset of nodes in the multiple paths and breaks the link between the nodes in the paths. Then it reconnects these nodes along the paths with the least delay paths. Thus the new population is created. The newly generated offspring is again evaluated with the fitness value. Then the newly generated efficient unicast multiple paths can be accepted if it gives an optimal solution. Otherwise it is again selected for reproduction. Thus the resulting paths will give optimized multiple unicast paths from source to destination.

6) Analysis of Convergence:

The algorithm could finally converge to the global optimal solution. For a large-scale network, it is time-consuming to obtain the optimal solution to this problem. This can be overcome by setting an appropriate iteration time for the genetic algorithm. Thus a near optimal solution can be obtained within a reasonable time limit.

RESULTS AND DISCUSSION

2.1 Simulation Environment:

In order to analyze the performance of this work, we used the event-driven network simulator NS2 version 2.34. The simulation area is 1500x1500 square meters with 50 nodes placed randomly. The channel transmission rate is 2 Mbps whereas the data flow transmission rate is 10 packets/s. Initial node energy for all the nodes is set as 100 joules. The transmission power of each node is set as 1.5 watts and the receiving power of each node is set as 1.0 watts. The other simulation parameters are shown in Table 1.

Table 1: Parameters for the simulation scenario

Simulation Area(Grid Size)	1500m x 1500m
Number of Nodes	50
Node Communication Range	250 m
Initial node energy	100 J
Node Initial Placement	Random
Medium Access Mechanism	IEEE 802.11b

Traffic Source Model	CBR
Packet Size	512 Bytes
Traffic Load	10 pkts/s
Mobility Model	Random Waypoint
Node speed	10 m/s
Pause time	0 – 480s
Simulation Time	900s
Number of Simulations	15

Average end-to-end delay, bandwidth, node residual energy and hop count were considered as major QoS parameters for route computation. End-to-end delay is the cumulative count of all link delays between source and destination which is taken from the constraint vector of a link. End-to-end delay also includes processing, queuing and transmission delays which assumed as constant for this network. Hop count is defined as the number of links between the source and destination. The available bandwidth from source to destination is determined as the minimum of all link bandwidths between source and destination. Node pause time is considered as the scenario metric which define the environment in which an ad hoc network functions. Average end-to-end delay, average residual node energy, hop count, bandwidth utilisation, packet delivery ratio and routing overhead were used as the performance metrics to investigate the performance with the existing systems. Each simulation result (each reported point on each curve) represents an average of 15 independent trials.

2.2 Simulation Results:

The simulation results are analyzed under different pause times. Pause time is defined as the period of time during which mobile nodes are being static before start moving towards a defined destination axis. Seven different pause times, from 0s to 480s, were modelled to investigate the effect of the algorithm. The number of nodes placed was 50. The speed was set to 10 m/s. Each simulation result for GA-PSO Hybrid Meta-heuristic (GPHM) algorithm was compared to that of a GA based algorithm and a PSO based algorithm.

In Figure 2, the graph for average end-to-end delay has been shown with respect to varying pause times. From the graph it has been seen that the proposed hybrid method results in reduced delay than the pure GA and pure PSO method. When the pause time increases there is a gradual reduction in delay. This is due to the static nature of the scenario when the pause time is high. Particularly when the pause time increases beyond 30 s, delay is getting reduced with high rate. It has also been seen that GA and PSO models do not produce much deviation in delay.

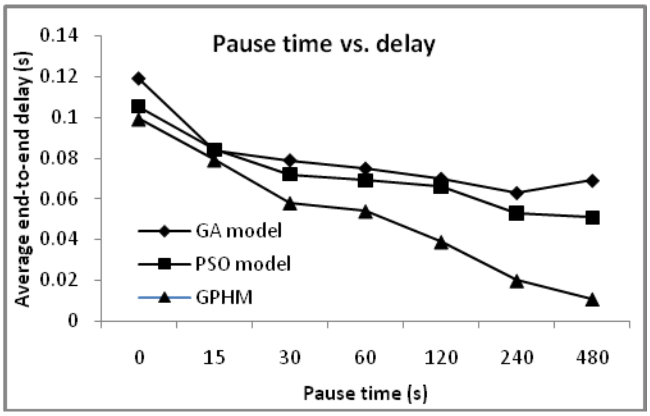

Fig. 2: Pause time (s) vs. Average end-to-end delay (s)

Figure 3 shows the effect of varying pause times in bandwidth utilization. PSO model resulted in better utilization than GA model and GPHM produces even better results than PSO model. Due to the static nature of the scenario when the pause time increases, the bandwidth utilization is also improved gradually.

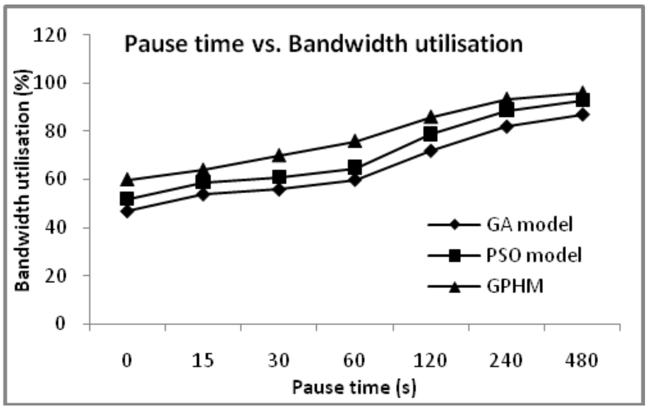

Fig. 3: Pause time (s) vs. Bandwidth utilisation (%)

The graph in Figure 4 shows the average residual node energy after the simulation is over under the three routing models. It shows that GA model and PSO model did not result in much deviation but GPHM results in higher residual node energy. Particularly when pause time is 60 s, all the three models have high residual node energy. This may be due to the simulation scenario resulted during 60s pause time which had effective node positioning as it follows random waypoint model.

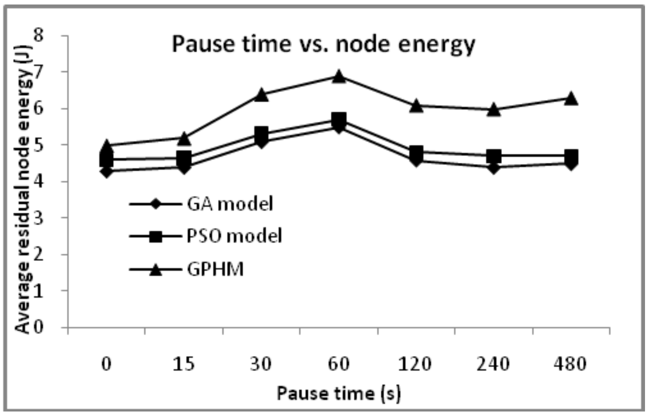

Fig. 4: Pause time (s) vs. Average residual node energy (J)

In Figure 5, the average numbers of hopcounts under different simulations are plotted. The proposed GPHM uses 8 to 10 hops in an average for reaching the destination whereas the other two algorithms use more than 10 hops for reaching the destination.

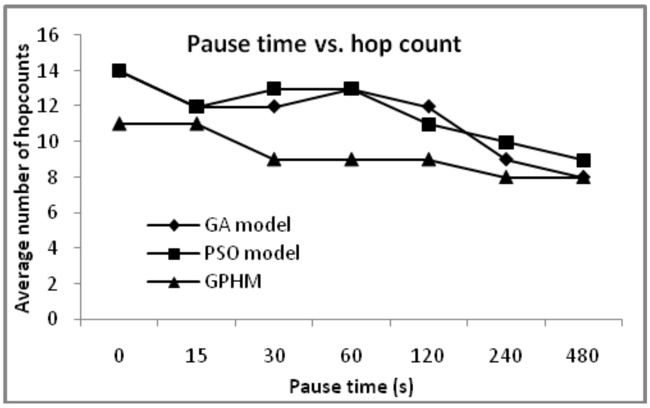

Fig. 5: Pause time (s) vs. Hopcount

From Figure 6 it has been seen that GA and PSO based algorithms have similar effect in packet delivery ratio except under 480s pause time. And GPHM resulted in improved packet delivery ratio.

From the graph it has also been seen that PDR is gradually increasing for GPHM until 60s pause time and reducing after that. This may be due to the random waypoint scenario resulted during that simulation.

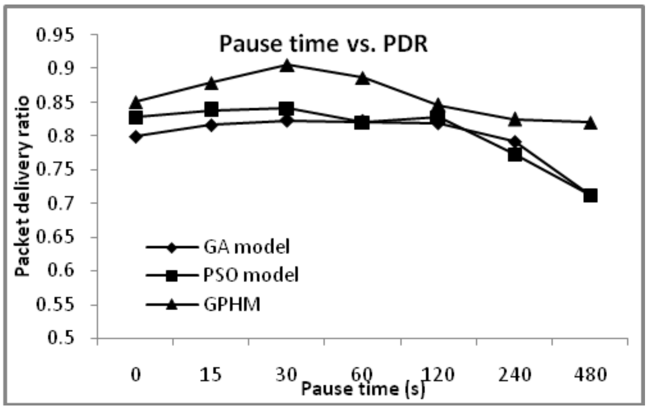

Fig. 6: Pause time (s) vs. Packet delivery ratio

Figure 7 presents the effect of routing overhead under various pause times. From the graph it is identified that GPHM has little higher overhead than the other two protocols but after 60s pause time, it is reduced. For lower pause time values the algorithm results in slightly high overhead due to the introduction of additional control packets of GA and PSO. But for higher pause time values these are compromised and it results in less overhead than the other two. From the investigation, it has been shown that the proposed GPHM approach has improved performance with respect to end-to-end delay, bandwidth utilisation, residual node energy, packet delivery ratio, throughput and hop count.

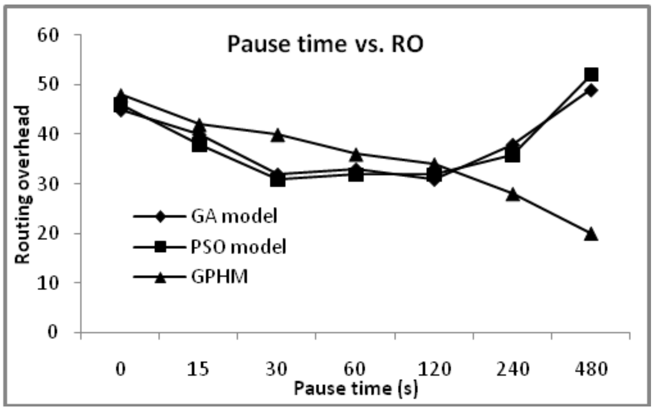

Fig. 7: Pause time (s) vs. Routing overhead

Conclusion:

Provisioning of QoS in MANET routing is a challenging task particularly when more than three metrics are considered for route selection. Meta-heuristics are useful in achieving near optimum solution to these kinds of optimization problems. This work aims at combining two of the popular meta-heuristic algorithms GA and PSO in order to achieve better solutions for the multi-metric QoS routing problem in MANETs. The proposed hybrid algorithm is implemented as a dynamic routing protocol with end-to-end delay, available bandwidth, node energy and hopcount as route selection metrics. The simulation results demonstrate that there is some amelioration when compared with the pure GA model and pure PSO model though it incurs little high routing overhead because of the additional computations involved.

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