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APPLICATION OF SWARM INTELLIGENCE PSO TECHNIQUE FOR ANALYSIS OF MULTIMEDIA TRAFFIC AND QOS PARAMETERS USING OPTIMIZED LINK STATE ROUTING PROTOCOL

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ABSTRACT

Mobile ad hoc network (MANET) nodes include wireless transmitters and receivers. At a given point in time, depending on the positions of the nodes, their transmitter and receiver coverage patterns, communication power levels and co-channel interference levels, a wireless connectivity in the form of a random, multi hop graph or “ad hoc" network exists among the nodes. In this research, it is proposed to modify OLSR using swarm intelligence, Particle Swarm Optimization (PSO), to reduce end to end delay and improve throughput in the network by traffic shaping at the network layer. The PSO algorithm represents each solution as a ‘bird’ in the search space and is referred to as ‘particle’. It uses the objective function to evaluate its candidate solutions, and operates on the resultant fitness values. Candidate solution and its estimated fitness, and velocity give the position of the particle. It also remembers the best fitness value it achieved till then during the algorithm’s operation which is usually referred to as the individual best fitness, and the candidate solution that achieved this fitness, is the individual best position ‘pbest’. The best fitness value attained among all particles in the swarm which is called global best fitness, and the candidate solution that attained this fitness, which is called the global best position or global best candidate solution ‘gbest’. OLSR generates link state information through nodes elected as Multi Point Relays (MPRs). It is proposed to modify OLSR using particle swarm optimization to reduce end to end delay and improve network throughput.

KEYWORDS: Mobile Ad hoc Networks (MANETs), Swarm Intelligence, Particle Swarm Optimization (PSO), Multi Point Relay (MPR), Throughput.

INTRODUCTION

Various studies have been conducted to reduce the control traffic overheads by adapting the existing OLSR routing protocol. Routing performance is improved by traffic shaping based on priority of the data packet. In this research, it is proposed to modify OLSR using swarm intelligence, PSO, to reduce end to end delay and improve throughput in the network by traffic shaping at the network layer. Particle swarm Optimization in short named as PSO which offers a quality solutions converging quickly when compared to other population based optimization algorithms such as GA. PSO is mainly based on the social behavior of birds flocking where the cooperation among entities are efficient in achieving goals. The entities/PSO particles consist of two properties such as position and velocity. Representation of a candidate solution as an objective function is performed on them. Mainly the computation in PSO based on a population and also named as swarm of the processing elements called as particles. Each particle can represent a candidate solution. PSO also shares many similarities with evolutionary computation techniques such as Genetic Algorithm's. By updating the generations, system starts with a population of random solutions and searches for optima. The search process exploits a combination of deterministic and probabilistic rules which depends on the information shared among their population members in order to enhance their search processes. No evolution operators are performed such as crossover and mutation in PSO. Each particle in the search space involves in its candidate solution over time, which makes use of its individual memory and knowledge gained by the swarm. The information sharing mechanism is considerably different in PSO when comparing with GA (Ramadan 2009).

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Particle Swarm Optimization (Gharghory 2011) is another derivative-free and flexible optimizer replicating bird flocking. PSO algorithm is promising for various optimization problems. It is effortless and easy to realize when compared to other computation intelligence techniques. It received attention from the field of evolution and is a research hot spot. Though PSO has high convergence speed, literature reveals that PSO finds it difficult to jump out of local optima, if it falls into minima. In literature, many approaches were introduced to improve PSO performance, by merging it with other evolutionary computation techniques. Hybrid PSO, (HPSO) technique merged a mutation operator and natural selection to solve premature convergence. By introducing roulette wheel selection based Cauchy mutation and evolutionary selection, HPSO greatly reduced probability of being trapped in local optimum.

METHODOLOGY

Particle Swarm Optimization (PSO)

PSO is a searching method and was developed in 1995 based on the sociological behavior of bird flocking. The algorithm based on PSO is trouble-free for implementation and it is successfully applied for solving a wide range of optimization problems in many application fields (Zhang 2012). PSO is a technique for maximizing objectives to find parameters by exploring the search space of given problem. This technique, originated from swarm intelligence and evolutionary computation. The swarm intelligence based on the observation of swarming habits of birds and fishes, and the evolutionary computation to find a local or global maximum.

For each particle
Initialize particle
End For
Do
For each particle
Calculate fitness value of the particle f(p)
/*updating particle's best fitness value so far*/
If f(p)is better than pbest
set current value as the new pbest
End For
/*updating population's best fitness value so far)*/
Set gbest to the best fitness value of all particles
For each particle
Calculate particle velocity according equation

$$v_i^d = wv_i^d + c_1 r_1 \left(p_i^d - x_i^d \right) + c_2 r_2 \left(p_g^d - x_i^d \right)$$

Update particle position according equation

$$x_i^d = x_i^d + v_i^d$$

End For

Figure 1 Pseudo Code for PSO algorithm

The PSO algorithm represents each solution as a 'bird' in the search space and is referred to as 'particle'. It uses the objective function to evaluate its candidate solutions, and operates on the resultant fitness values. Candidate solution and its estimated fitness, and velocity give the position of the particle. It also remembers the best fitness value it achieved till then during the algorithm's operation which is usually referred to as the individual best fitness, and the candidate solution that achieved this fitness, is the individual best position 'pbest'. The best fitness value attained among all particles in the swarm which is called global best fitness, and the candidate solution that attained this fitness, which is called the global best position or global best candidate solution 'gbest'.

Particle positions/velocities are generated randomly at the initial stage. The algorithm proceeds iteratively, updates velocities and positions of all particles as given in equation 1 below:

$$v_i^d = wv_i^d + c_1 r_1 \left(p_i^d - x_i^d \right) + c_2 r_2 \left(p_g^d - x_i^d \right)$$
$$x_i^d = x_i^d + v_i^d \qquad (1)$$

where d is number of dimensions, i the size of the population, w the inertia weight, c1, c2 positive constants called cognitive parameter and social parameter respectively, r1 and r2 random values in range [0, 1]. v_i^d is new velocity of ith particle computed, based on the particle's previous velocity, distance between previous best position and current position and distance between best swarm particle which calculates the particle's new position.

In conventional PSO, when gbest is far from the global optimum then particles get trapped in the gbest region's local optimum. To offset this, particles are moved to a bigger search space to fly, and pbest position of a particle is updated based on pbest position of swarm particles increasing the ability to

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avoid local optimum and improve swarm diversity. The particle's updating velocity is given in Equation (2) below:

$$V_i^d = w * v_i^d + c * rand_i^d * \left(pbest_{fi(d)}^d - x_i^d \right) \quad (2)$$

where $f_i = \left[f_i(1), f_i(2), ..., f_i(d) \right]$ refers to pbest that particle i is used and is the dimension of particles pbests. Two particles are randomly selected, and the particle whose velocity is updated is excluded. The particles pbests fitness values are compared, and the dimension of the better one is chosen to update velocity (Agarwal 2005). At each of iteration of PSO, the behavior of a given particle is gets compromised between three possible choices as follows:
Following its own way

- Going towards its best previous position
- Going towards the best neighbour

The objective function establishes particles fitness value with every iteration along with a position as input. Entity velocities are dynamically adjusted because they flit through the search space. A particle is represented as best position and is computed with the use of own information (pbest) and that of a global best position (gbest) are searched by the swarm. The particles modify the velocity consequently and disembark at its new position (Tamizhselvi 2013).

Parameters of PSO
For Particle Swarm Optimization, some parameters are used as follows:

1. Population size
2. Number of generation cycles
3. The max. change of a particle velocity and
4. Current position

The methods used in PSO are positions and velocity, velocity update, and position update (Garg 2012).

PSO computation based on swarm intelligence
In case of traffic sign recognition, the PSO mechanism is implemented which is a simulation of the behavior of living as a group. The individuals in the population will adjust themselves in two different ways,

- To give the best position for the group and
- To give themselves the best position among members of the group.

Mathematically the PSO method can be represented as follows. The swarm size of the PSO is symbolized as "s". Each particle consists of the following attributes:

- A current position xi in the search space,
- A current velocity vi and
- A personal best position pi in the search space.

During each of iteration, every particle in the swarm can be updated by using Equations (3) and (4) which are given below.

$$v_{i+1} = \varpi v_i + c_1 r_1 (p_i - x_i) + c_2 r_2 (p_g - x_i) \quad (3)$$

Each particle is capable to change its position based on the updated velocity according to the following Equation (4). Figure 2 given below shows the position update of particle in PSO (Eslami 2010).

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (4)$$

The variable ϖ is the inertia weight factor and it can be generally specified as given in Equation (5) below:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{T} . \tau \quad (5)$$

where T means that the maximum number of iterations, Wmax and Wmin are the maximum and the minimum value of the weighting factor respectively (Li 2011) and this value is typically a set to vary with range linearly from 0 to 1 during the course of a training run.

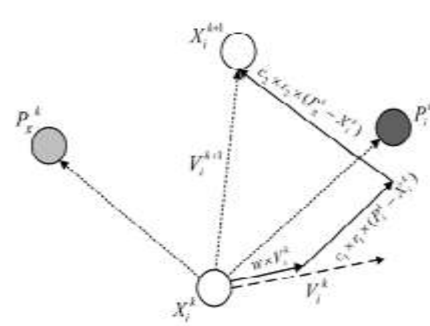

Figure 2 Position update of particle in PSO

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The variables c1 and c2 are the acceleration coefficients, which control how far a particle is moved in a single iteration. The variables r1 and r2 are two random numbers in the range of (0, 1). The variable pg is the global best position which can be found by all particles. The velocity vi of each particle can be clamped to the range of [vmax, vmax] for reducing the likelihood of particles leaving the search space (Surinwarangkoon et al 2012).

Fitness function

A novel fitness function proposed is given below in equation 6:

$$F(t)=\frac{\sqrt{\frac{2J_m}{\lambda_{in}}}e^{-\frac{\lambda_g^2}{2\lambda_{in}}J_m}\int_{\sqrt{\frac{2J_m}{\lambda_{in}}\lambda_g}}^{\sqrt{\frac{2J_m}{\lambda_{in}}(\lambda_g+\frac{\lambda_{in}t}{J_m})}} e^{-s^2}ds}{PDR}$$

(6)

where PDR is the Packet Delivery Ratio,

J_m is the max_jitter,

λ_{in} is the input_package,

λ_g is the Generated_package_in_node,

$\lambda_{out}=\lambda_{in}+\lambda_g$, $t\in[0,J_m]$

Properties of PSO

The properties of PSO are given below:

- Determination of a single particle is done to ensure "how good" is its current position. It restores from its problem space, the exploration knowledge and the knowledge obtained by sharing with the other available particles.
- A stochastic factor in each particle's velocity makes PSO to move through the region of unknown problem space. By combining this property with a good initial distribution of the swarm that enables an extensive exploration of the problem space and gives a very high chance to find the best solutions efficiently.

The standard particle swarm optimization algorithms perform well in case of static environments. Also, it is specified that the original PSO is unable to handle the dynamic environments. Hence the researchers started to introduce a new variation of PSO to overcome its inefficiency. Some of them are compound particle swarm optimization, cellular PSO, etc., (Parvin 2011).

The PSO algorithm includes three steps that are reiterated until some stopping criteria is met (Kennedy & Eberhart 1995):

1. Fitness of each particle is evaluated.
2. Individual and global best fitness and positions are updated
3. Velocity and position of each particle is updated.

If a directed graph G = (V, E) defines a communication graph, where V is a set of n nodes and E set of m edges. Each edge has the parameters of link quality, jitter and packet dropped. These functions can be formulated for a path as follows:

$$\begin{aligned} link\ \text{quality}(p_i) &\geq L & i&=1,....,k \\ jitter(p_i) &\leq J & i&=1,....,k \\ Packet\_dropped(p_i) &\leq PD & i&=1,....,k \end{aligned}$$

Advantages of PSO

- PSO has some advantages over other similar optimization techniques are as follows:
- PSO is easier for implementation and fewer parameters are available to adjust.
- In PSO, every particle remembers its own previous best value as well as the neighbourhood best hence it has a more effective memory capability.
- PSO is more efficient in maintaining the diversity of the swarm since all the particles use the information which is related to the most successful particle in order to improve them (Elseuofi 2012).

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Disadvantages of PSO

- PSO easily suffers from the partial optimism, which may cause the less exact at the regulation on its speed and the direction.
- PSO unable to work out the problems which are caused by the scattering and optimization.

PSO is unable to work out the problems of non-coordinate system, such as the solution to the energy field and the moving rules of the particles in the energy field (Bai 2010).

SIMULATION STUDY AND RESULTS

The simulation is carried out using OPNET Simulator Ver. 14.0 includes 20 nodes spread over 2000 meter by 2000 meter with each node's trajectory being at random. Each node runs a multimedia application over UDP. The data rate of each node is 11 Mbps with a transmit power of 0.005 watts. The simulations are run for 400 sec. The performance of the network is evaluated based on the PDR, end to end delay, jitter and number of TC packets for PSO and compared with gravitational search and local search.

For Multimedia Traffic with FIFO

Multimedia traffic with first in first out queuing model is given below. The packet delivery ratio for multimedia traffic with FIFO is measured for hello intervals 1,2,3,4 and 5 seconds for mobility speeds 0, 5, 10, 15 and 20 m/sec. The data collected for PDR are shown in the Table 1. The data in Table 1 is transformed to a graph and is shown in Figure 3.

Table 1 PDR for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	0.9069	0.9133	0.9263	0.9504
5	0.8999	0.8827	0.8997	0.8749
10	0.8824	0.8401	0.8354	0.814
15	0.8794	0.843	0.8283	0.8091
20	0.8056	0.8035	0.7987	0.7857

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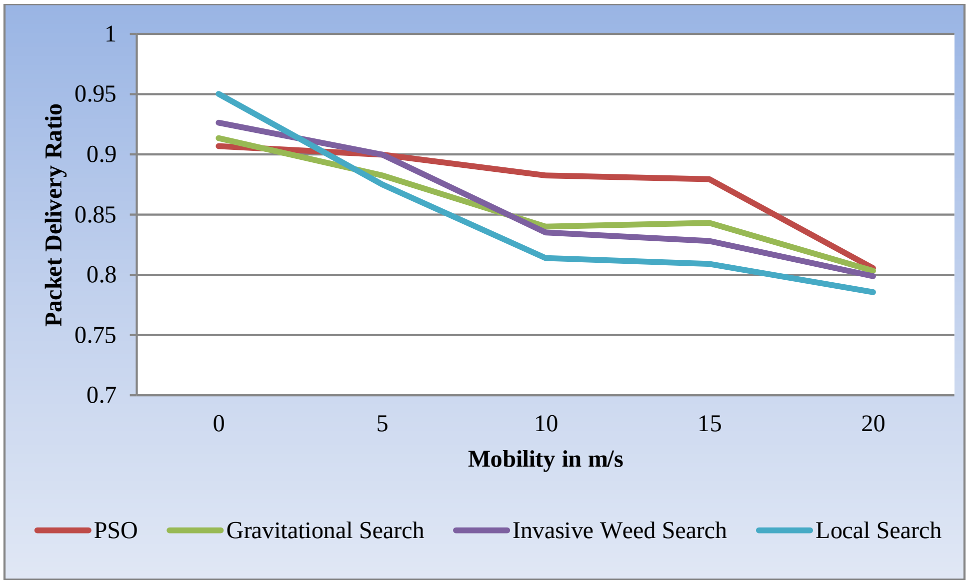

Figure 3 PDR for multimedia traffic

From Figure 3 it is observed that the PDR achieved decreases with increasing mobility. For no mobility, average PDR achieved by PSO is 0.7% lesser than gravitational search. It is 4.58% lesser than invasive weed search and 2.09% lesser than local search. For mobility speed of 20 m/sec, the average PDR achieved is 0.26% greater than gravitational search. It is 2.53 % greater than invasive weed search and 0.86% greater than local search.

For PSO, at hello interval 5 sec, the PDR achieved shows an improvement of 11.61% for mobility speed of 5 m/sec and an improvement of 14.17% for mobility speed of 20 m/sec.

Table 2 End to end delay for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	10.0859	10.3524	10.0803	11.2914
5	11.8537	12.263	13.1805	14.1597
10	13.1886	13.7189	16.1592	16.7574
15	14.1789	15.5155	16.3744	17.5305
20	16.9526	17.835	18.9153	19.3776

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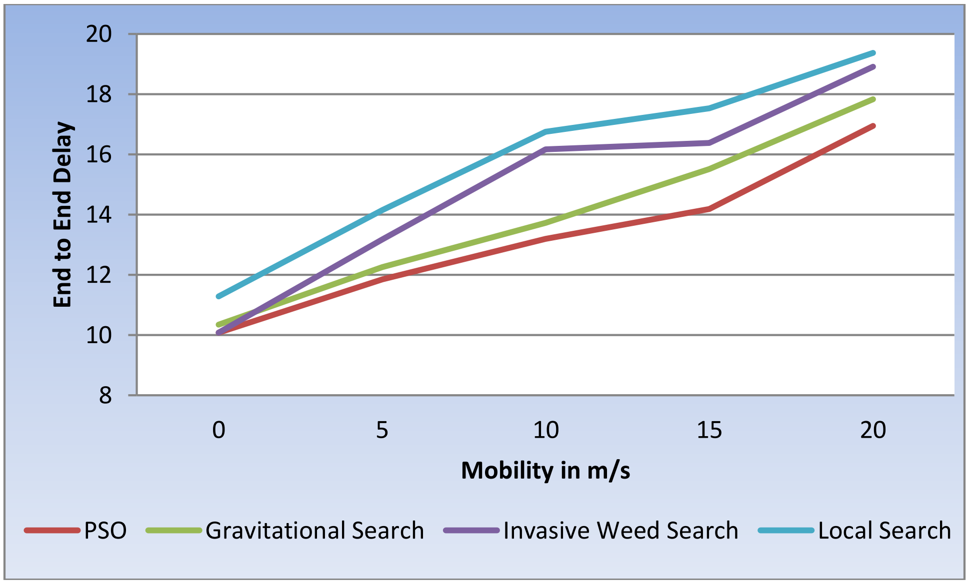

Figure 4 End to end delay for multimedia traffic

The contents of Table 2 are graphically represented and is shown in Figure 4. From Figure 4, it is observed that the end to end delay increases with increasing mobility. For no mobility, the average end to end delay achieved using PSO technique has 2.57 % lower end to end delay compared to gravitational search, 0.06% higher end to end delay compared to invasive weed search and 10.68% lower end to end delay compared to local search. At mobility speed of 20 m/sec, the average end to end delay achieved is 4.95% lower compared to gravitational search, 10.38% lower compared to invasive weed search and 12.51% lower compared to local search. For multimedia traffic with WFQ at hello interval 5 sec, use of PSO technique shows lower the end to end delay of 16.73% at mobility speed of 5 m/sec and lower end to end delay of 19.37% at mobility of 20 m/sec.

Table 3 Jitter for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	1.0796	1.0437	1.1443	1.0368
5	1.2212	1.3924	1.4992	1.0648
10	1.2532	1.222	1.2569	1.2931
15	1.3312	1.0438	1.3553	1.097
20	1.5748	1.2456	1.1582	1.2903

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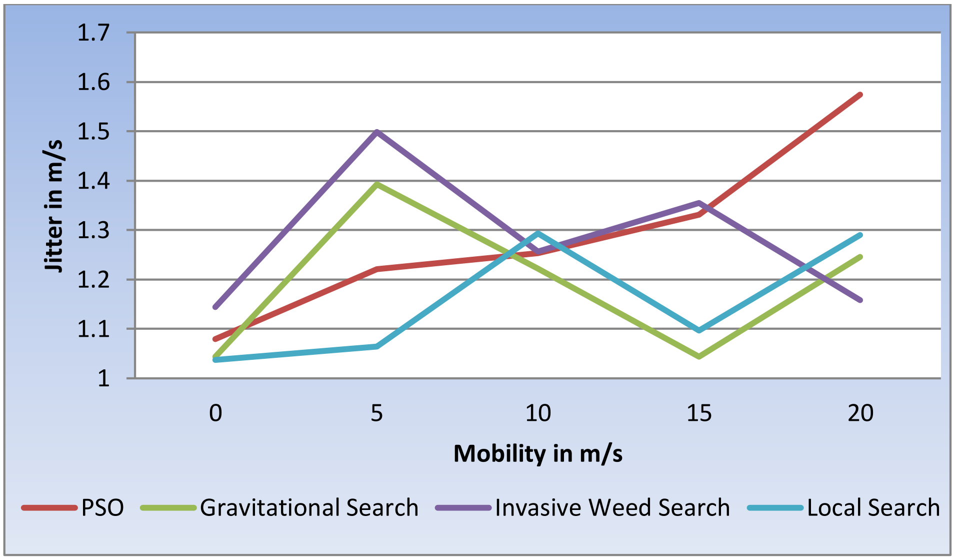

Figure 5 Jitter for multimedia traffic

The contents of Table 3 are graphically represented and is shown in Figure 5. From Figure 5, it is observed that the jitter varies with increasing mobility. For no mobility, the average jitter achieved by PSO is 3.44% higher compared to gravitational search, 5.65% lesser compared to invasive weed search and 4.13% greater compared to local search. At mobility speed of 20 m/sec, the average jitter achieved is 26.43% greater than gravitational search, 35.37% greater than invasive weed search and 22.05% greater than local search. For multimedia traffic with WFQ, using PSO for hello interval 5 sec, with no mobility, the jitter is a decreased by 27.68%. There is a decrease in 11.97% of jitter for mobility speed of 15 m/sec.

Table 4 No. of TC packets for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	357	314	288	290
5	465	452	400	392
10	484	466	449	451
15	495	487	474	483
20	550	510	524	502

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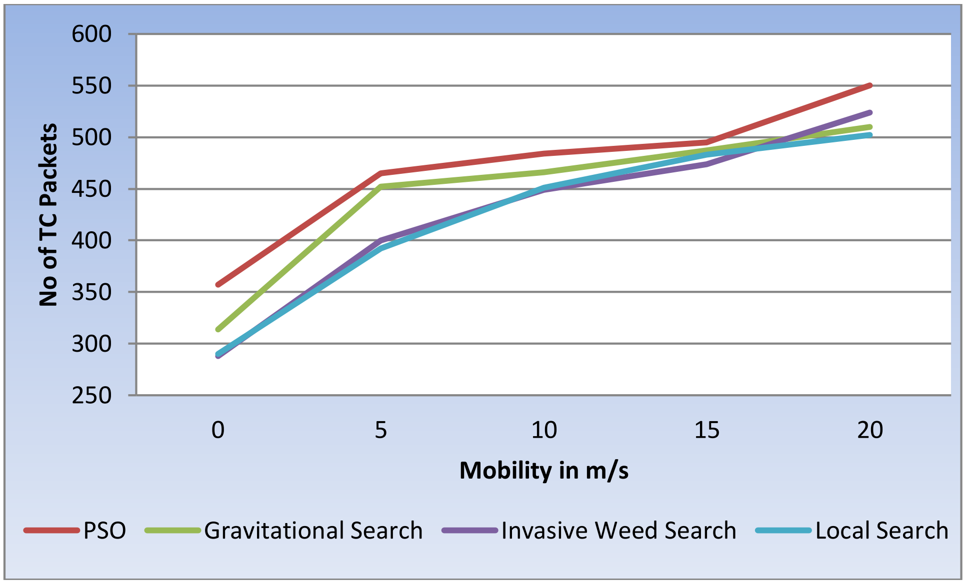

Figure 6 No. of TC packets for multimedia traffic

The contents of Table 4 are graphically represented and is shown in Figure 6. It shows the number of TC packets achieved for PSO, gravitational search, invasive weed search and local search techniques for mobility speeds of 0, 5, 10, 15 and 20 m/sec. The PSO technique at mobility of 5 m/sec has 5.47% higher number of TC packets compared to gravitational search, 10.12% higher number of TC packets compared to invasive weed search and 11% higher number of TC packets compared to local search. For multimedia traffic with WFQ using PSO technique, for hello interval 5, there is 21.84% higher number of TC packets for no mobility. There is 4.96% higher number of TC packets compared to for mobility speed of 20 m/sec.

For Multimedia Traffic with WFQ

Multimedia traffic with WFQ queuing model is given below. The packet delivery ratio for multimedia traffic with WFQ is measured for hello intervals 1,2,3,4 and 5 seconds for mobility speeds 0, 5, 10, 15 and 20 m/sec. The data collected are shown in the Table 5. The data in table 5 is transformed to a graph and is shown in Figure 7

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Table 5 PDR for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	0.8999	0.9056	0.908	0.9232
5	0.8844	0.8671	0.8736	0.8475
10	0.8541	0.818	0.8002	0.7876
15	0.8532	0.8027	0.7792	0.7756
20	0.7829	0.7654	0.7433	0.7386

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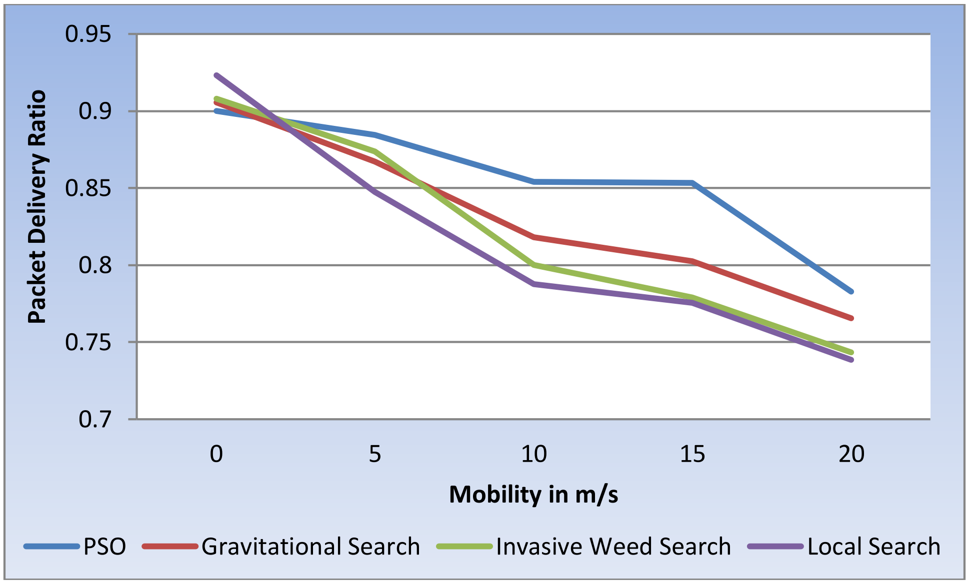

Figure 7 PDR for multimedia traffic

From Figure 7, it is observed that the PDR decreases with increasing mobility. For no mobility, the average PDR achieved by PSO is 0.63% lesser compared to gravitation search, 0.89% lesser compared to invasive weed search and 2.52% lesser compared to local search. For mobility speed of 20 m/sec, the average PDR is 2.29% higher compared to gravitation search, 5.33% higher compared to invasive weed search and 10.01% higher compared to local search. For hello interval 5, the average PDR achieved by PSO is 0.42% lesser for no mobility and 7.81% lesser for mobility speed of 20 m/sec.

Table 6 End to end delay for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	9.7118	10.0049	10.1097	10.9104
5	11.7014	11.7969	13.4738	13.5717
10	13.214	13.7524	16.1777	16.6558
15	14.1896	15.248	15.696	17.2936
20	16.8844	17.8139	18.9472	19.5666

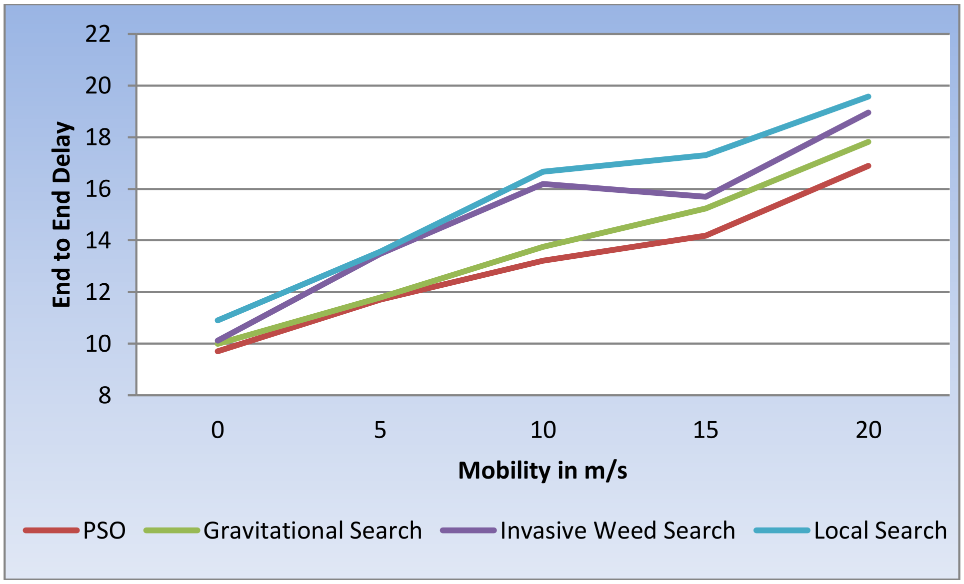

Figure 8 End to end delay for multimedia traffic

The contents of Table 6 are graphically represented and is shown in Figure 8. From Figure 8, it is observed that the end to end delay increases with increasing mobility. For no mobility, the average end to end delay achieved by PSO is 2.93% lesser compared to gravitation search, 3.94% lesser compared to invasive weed search and 10.998% lesser compared to local search. For mobility speed of 20 m/sec, the average end to end delay achieved is 5.22% lesser compared to gravitation search, 10.89% lesser compared to invasive weed search and 13.71% lesser compared to local search. For multimedia traffic with WFQ for hello interval 5, application of PSO technique shows improvement in end to end delay. It is 21.86% lesser for mobility speed of 5m/sec and 17.7% lesser for mobility speed of 20 m/sec.

Table 7 Jitter for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	1.0571	0.9948	1.1078	1.0379
5	1.2081	1.3709	1.4224	1.0493
10	1.2538	1.1833	1.1973	1.2683
15	1.3012	1.0051	1.3271	1.0959
20	1.5355	1.1805	1.1404	1.2276

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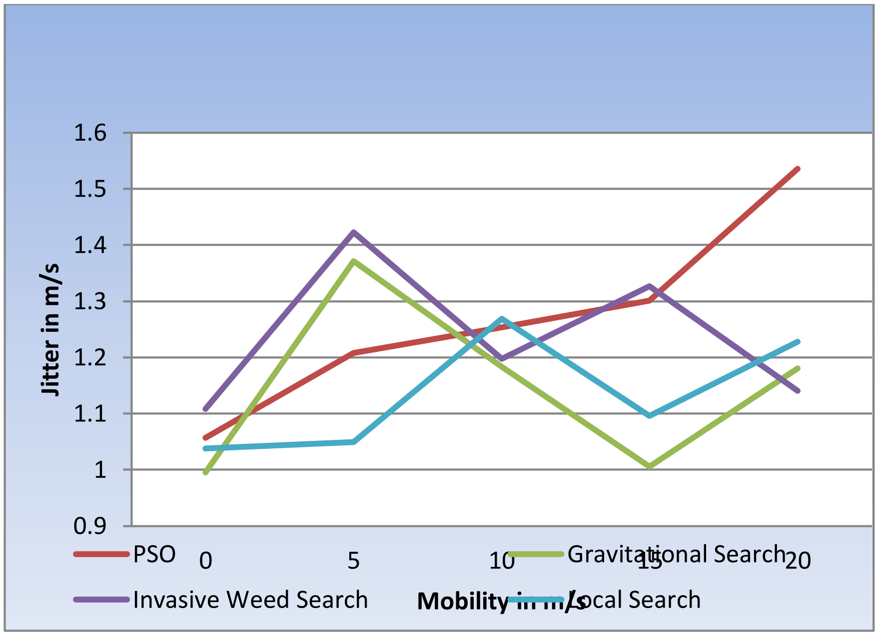

Figure 9 Jitter for multimedia traffic

The contents of Table 7 are graphically represented and is shown in Figure 9. From Figure 9 it is observed that the jitter varies with increasing mobility. For no mobility, the average end to end delay achieved by PSO is 6.26% higher compared to gravitational search, 4.58% lesser compared to invasive weed search and 1.85% higher compared to local search. For mobility speed of 20 m/sec, the average jitter achieved is 30.07% higher compared to gravitation search, 34.65% higher compared to invasive weed search and 25.08% higher compared to local search. For multimedia traffic with WFQ at hello interval 5, application of PSO technique shows lower jitter values. It is 28.29% lower for no mobility and by 12.19% lower for mobility speed of 15 m/sec.

Table 8 No. of TC packets for multimedia traffic

m/s	PSO	Gravitational Search	Invasive Weed Search	Local Search
0	344	315	285	279
5	441	432	402	389
10	462	458	450	435
15	477	468	472	454
20	541	517	505	505

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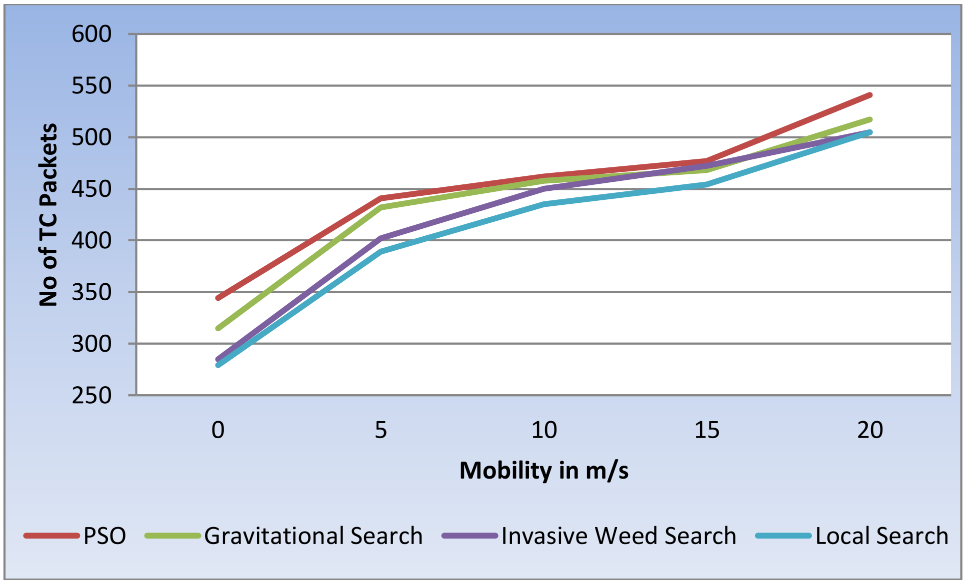

Figure 10 No. of TC packets for multimedia traffic

The contents of Table 8 are graphically represented and is shown in Figure 10. It shows the number of TC packets achieved for PSO, gravitational search, invasive weed search and local search techniques for different mobility. At mobility speed of 5 m/sec it is observed that the number of TC packets achieved is 2.08 % higher compared to gravitational search, 9.7% higher compared to invasive weed search and 13.37 % higher compared to local search. For multimedia traffic with WFQ at hello interval of 5 sec, it is observed that the application of PSO technique gives 19.03 % higher number of TC packets for no mobility and 5.46 % higher number of TC packets at mobility speed of 20 m/sec.

CONCLUSION

1. OLSR generates link state information through nodes elected as MPRs. It is proposed to modify OLSR using particle swarm optimization to reduce end to end delay and improve network throughput.
2. For multimedia traffic with FIFO, the PDR achieved decreases with increasing mobility. For no mobility, average PDR achieved by PSO is 0.7 % lesser than gravitational search. It is 4.58 % lesser than invasive weed search and 2.09 % lesser than local search. For mobility speed of 20m/sec, the average PDR achieved is 0.26 % greater than gravitational search. It is 2.53 % greater than invasive weed search and 0.86 % greater than local search. For PSO, at hello interval 5, the PDR achieved shows an improvement of 11.61 % for mobility speed of 5m/sec and an improvement of 14.17 % for mobility speed of 20 m/sec.
3. For multimedia traffic with WFQ, the PDR decreases with increasing mobility. For no mobility, the average PDR achieved by PSO is 0.63 % lesser compared to gravitational search, 0.89% lesser compared to invasive weed search and 2.52 % lesser compared to local search. For mobility speed of 20 m/sec, the average PDR is 2.29 % higher compared to gravitational search, 5.33% higher compared to invasive weed search and 10.01% higher compared to local search. For hello interval 5 sec, the average PDR achieved by PSO is 0.42 % lesser for no mobility and 7.81 % lesser at mobility speed of 20 m/sec.
4. For multimedia traffic using FIFO, it is observed that the end to end delay increases with increasing mobility. For no mobility, the average end to end delay achieved using PSO technique has 2.57 % lower end to end delay compared to gravitational search, 0.06 % higher end to end delay compared to invasive weed search and 10.68 % lower end to end delay compared to local search. At mobility speed of 20 m/sec, the average end to end delay achieved is 4.95 % lower compared to

gravitational search, 10.38 % lower compared to invasive weed search and 12.51 % lower compared to local search. For multimedia traffic with WFQ at hello interval 5, use of PSO technique shows lower the end to end delay of 16.73 % at mobility speed of 5 m/sec and lower end to end delay of 19.37 % at mobility of 20 m/sec.

5. For multimedia traffic using WFQ the end to end delay increases with increasing mobility. For no mobility, the average end to end delay achieved by PSO 2.93 % lesser compared to gravitation search, 3.94 % lesser compared to invasive weed search and 10.998 % lesser compared to local search. At mobility speed of 20 m/sec, the average end to end delay achieved is 5.22 % lesser compared to gravitational search, 10.89 % lesser compared to invasive weed search and 13.71 % lesser compared to local search. For multimedia traffic with WFQ for hello interval of 5 sec, application of PSO technique shows improvement in end to end delay. It is 21.86 % lesser at mobility speed of 5 m/sec and 17.7 % lesser at mobility speed of 20 m/sec.
6. For multimedia traffic using FIFO, it is observed that the jitter varies with increasing mobility. For no mobility, the average jitter achieved by PSO is 3.44 % higher compared to gravitation search, 5.65 % lesser compared to invasive weed search and 4.13 % greater compared to local search. At mobility speed of 20 m/sec, the average jitter achieved is 26.43 % greater than gravitation search, 35.37% greater than invasive weed search and 22.05 % greater than local search. For multimedia traffic with WFQ, using PSO for hello interval of 5 sec, with no mobility, the jitter is a decreased by 27.68 %. There is a decrease in 11.97 % of jitter at mobility speed of 15 m/sec.
7. For multimedia traffic using WFQ, it is observed that the jitter varies with increasing mobility. For no mobility, the average end to end delay achieved by PSO is 6.26 % higher compared to gravitational search, 4.58 % lesser compared to invasive weed search and 1.85 % higher compared to local search. At mobility speed of 20 m/sec, the average jitter achieved is 30.07 % higher compared to gravitational search, 34.65 % higher compared to invasive weed search and 25.08 % higher compared to local search. For multimedia traffic with WFQ at hello interval of 5 sec, application of PSO technique shows lower jitter values. It is 28.29 % lower for no mobility and is 12.19 % lower at mobility speed of 15 m/sec.
8. For multimedia traffic using FIFO, the number of TC packets achieved using PSO, gravitational search, invasive weed search and local search techniques for various mobility speeds of 0, 5, 10, 15 and 20 m/sec is studied. The PSO technique at mobility of 5 m/sec has 5.4 7 % higher number of TC packets compared to gravitational search, 10.12 % higher number of TC packets compared to invasive weed search and 11 % higher number of TC packets compared to local search. For multimedia traffic with WFQ using PSO technique, for hello interval of 5 sec, there is 21.84 % higher number of TC packets for no mobility. There is 4.96 % higher number of TC packets compared to mobility speed of 20 m/sec.
9. For multimedia traffic using WFQ, the number of TC packets achieved using PSO, gravitational search, invasive weed search and local search techniques for different mobility are studied. At mobility speed of 5 m/sec it is observed that the number of TC packets achieved is 2.08 % higher compared to gravitational search, 9.7 % higher compared to invasive weed search and 13.37 % higher compared to local search. For multimedia traffic with WFQ at hello interval of 5 sec, it is observed that the application of PSO technique gives 19.03 % higher number of TC packets for no mobility and 5.46 % higher number of TC packets at mobility speed of 20 m/sec.
10. The disadvantage of PSO and local search algorithms is that due to the local minima, where the solution to the problem ends up with a sub optimal solution it is difficult to obtain a better solution. This problem can be overcome by applying hybrid algorithms.

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