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PERFORMANCE ANALYSIS OF MULTI OBJECTIVE HYBRID SELF ORGANIZED PSO-DGSA BASED ROUTING IN WIRELESS MESH NETWORKS

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ABSTRACT

Wireless Mesh Networks (WMNs), is a type of Wireless Sensor network with topology various from simple star network to multi-hop wireless mesh networks. Connectivity, Stability and Quality of Service (QoS) are the important parameters to be consider in forming the network. In this work, a novel hybrid self-organized Particle Swarm Optimization– Differential Gravitational Search Algorithm is developed to determine an optimal route in WMN. The optimization problem is formulated using bi-objective optimization for the mesh router nodes placement, measuring network connectivity and that of user coverage. Computational results are discussed for the Hybrid SOPSO method, it is optimizing the packet delivery ratio, throughput and delay for effective routing and the results proves it is an effective search method.

Keywords: *Mesh, Optimization, Routing, Gravitational Search, Self Organized.*

1. INTRODUCTION

A Wireless Mesh Network (WMN) is a multi hop network where the node in each the network can communicate with any other node going through multi hop and leveraging other nodes.In an unstructured WMN, the nodes communicate with others nodes within the range in omni-directional mode. In structured WMN, the nodes communicates multiple directional modes. Considering Communication link, storage and computational constraints and limited energy, Implementing WMN is a challenging task. The nodes in WMNs are organised in Mesh topology and make the infrastructure reliable using Multi-hop communication. Hybrid computational intelligence (HCI) have been applied to address issues like data aggregation, energy aware routing, task scheduling, security, optimal deployment. HCI provides adaptive mechanisms that exhibit intelligent behaviour in complex and dynamic environments.The routing mechanism is a challenging task in these WMN. Hybrid Computational Intelligence is applied in finding the efficient routing to solving nonlinear optimization problems is a challenging task and computational intelligence finds application in solving these problem with reduces search space ,complexity and time.A novel hybrid self-organized Particle Swarm Optimization– Differential Gravitational Search Algorithm is developed to determine an optimal route in WMN.Also the paper discuss about how to maximize the Packet Delivery Ratio and throughput,to minimize the delay with increased energy level. The developed Self-Organized Particle Swarm Optimization approach(SOPSO) possess better global diversity based on its social behaviour of flocking and self-organizing principle; This approach is hybridized with the conventional methods in WMN.

Elsayed et.al [1] solved the economic dispatch problem using an improved version of the random drift particle swarm optimization algorithm. Sajedi et.al [2] introduces a discrete version of the GSA (DGSA) for solving 0–1 knapsack problem and introduced a novel method for discretely updating the position of each agent and proposed a unique fitness function. Li et al. [3] applied a multi mutation strategy including single , full mutation operator and proposed a novel binary particle swarm optimization based on the QBPSO algorithm. Susheel Joshi et.al [12] discussed the exploration and exploitation capability of GSA and Chandrashekar Jatoth et.al [13] studied and confirms that new meta-heuristic algorithms for solving QoS-aware web services composition.

Rashedi et al [14] developed a population based stochastic search algorithm named Gravitational Search Algorithm (GSA). This algorithm is inspired by the gravitational forces. Memory is included in the GSA [15]. To improve the exploitation ability of GSA, disruption operator is introduced [16] .Doraghinejad et al. [17] proposed a new operator to prevent from premature convergence. Gupta et.al [18] proposed a fitness based GSA where the performance is compared swarm intelligence based algorithm, namely biogeography based optimization (BBO) algorithm over 16 different benchmark functions and proved that Fitness based GSA is competitive variant of the algorithm.GSA is based on the Newton law of gravity which says "Every particle in the universe attract every other particle with a force that is directly proportional to the product of their masses and inversely proportional to square of the distance between them" [19].Doraghinejad et.al [20] compared the Black hole GSA with standard and real Genetic Algorithm and Particle Swarm Optimisation. Their results prove that GSA provides fruitful result in continuous space problem. Hn et.al[21], proposed a self-organizing radial basis function using the adaptive particle swarm optimization to avoid trapping.

T.y. Chiang et el [22], it proved that results confirm the better performance of the proposed method in solving various nonlinear functions. W. Ding et el [23] , compared the new GSA based on Chaos with other optimization methods, it proved that new algorithm gives high performance results in solving global optimazation problems. H. Mittal et el [24], developed novel Chaotic Kbest Gravitational Search Algorithm (CKGSA), it keeps exploration and exploitation non-linearly. It proved that convergence rates are better at later iterations with high precision and does not trap into local optima.P. Rawal at el [25], proposed Local Exploitation Based Gravitational search algorithm(LEGBSA)over 16 different benchmark functions and proved that more advantages compared to traditional GSA and BBO algorithm.
J. ji at el [26], discussed the Self-Adaptive Gravitional Search Algorithm with a modified Chaotic local search, it ellaborated the aspects of gravitional parameters in GSA optimization. This algorithm adjusts the gravitional parameters automatically to keep the balance of exploration and exploitation.

The proposed hSOPSO-DGSA performs an effective search process based on the self-organized clustering mechanism merged with the local capability of the Differential GSA approach. The developed hSOPSO-DGSA is applied to the Adhoc On demand Distance Vector routing protocol (AODV) and the simulation is carried out in Network Simulator – 2 platform. The developed population based algorithm is validated for its effectiveness with respect to the earlier methods proposed in the literature and the performance comparison is presented. Further, a statistical parameter called as spread is employed to depict the effectiveness of the proposed hSOPSO-DGSA technique in comparison with the earlier methods. The objective of this work is to optimise the packet delivery ratio, throughput and delay for effective routing using a novel hybrid optimisation algorithm named, the future work is to find novel hybrid optimisation algorithm and find the optimal solution.

2.PROPOSED HSOPSO-DGSA ALGORITHMS

The proposed hybrid Self-Organized Particle Swarm Optimization and Differential Gravitational Search Algorithm (hSOPSO – DGSA). The most prominent features of SOPSO &DGSA algorithms are brought out and hybridized to form the proposed hybrid SOPSO-DGSA approach. The modelled hSOPSO – DGSA approach is employed in this work for optimizing the performance metrics to determine the optimal routing of the wireless mesh networks.

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3.PARTICLE SWARM OPTIMIZATION

A stochastic population based optimization approach is the PSO by Kennedy & Eberhard [4] which is inspired by the social behaviour of fish schooling or bird flocking. PSO approach falls into the broad category of swarm intelligence approaches. Initially in the PSO process, the system is initialized with a random population of solution sets and the search goes towards optima as the generation gets updated. During the flow of PSO, the potential solutions called particles are noted to fly through the problem domain by succeeding the current optimal particles. These particles are the metaphor of birds in the flocks. The search space is multi-dimensional and the particles that are randomly initialized are noted to freely fly through the search space. At the time of flight, each particle is noted to update its own velocity and position

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based on its self-experience and that of the entire population.
The process of updating make the particle to fly towards the region with the set objective function value met and henceforth, all the particles will tend to move around the point with the set objective value.

In this PSO algorithm, individual particles get updated by following two "best" values. The first and second best solution are present best (pbest) and global best (gbest).Once the two values are obtained, the particles update its velocity and positions. The PSO algorithmic is shown in Table 1

1: Initialize the number of particles and randomly generate the particles.
2: Compute the fitness value. If the fitness value is better than the pbest value, then current value is set as the new pbest.

Step 3: To attain global best (gbest) value. Select the particle with the best fitness value of all the particles as the gbest.
Step 4: Perform velocity and position updation. For each particle, calculate particle velocity
By equation 1

$$v_i = v_i + c_1R_1(P_{ibest} - P_i) + c_2R_2(g_{ibest} - P_i) \qquad (1)$$

Where, v_i – velocity of particle i,
P_i – position of particle i
P_{ibest} - position with the 'best' fitness value found so far by particle i.
g_{ibest} - best fitness value obtained so far by any particle in the entire population
R_1, R_2 - random variables in the range [0, 1]
c_1, c_2 - learning factors controlling the related weighting of corresponding terms.

Now update particle positions by using equation 2

$$P_i = p_i + v_i \qquad (2)$$

Step 5: Repeat steps 2 to 4 until it reaches the set maximum generations or until the set objective being met. On termination, the algorithm returns the values of gbest and the fitness value corresponding to the 'gbest' value. The flowchart depicting the process of PSO algorithm is as shown in Figure.1.

The proposed SOPSO is developed based on the principle of self-organizing capability of the particles within the search space. The search process is based on the specified constraints and the particles are generated within the limits. Self-organizing of the particles refers to the clustering phenomenon of the particles based on a common index value. The particles possessing the same index value tend to remain in the same self-organized clusters and for each of the self-organized cluster 'pbest' value is attained and then the 'gbest' value among all the clusters are noted and returned.

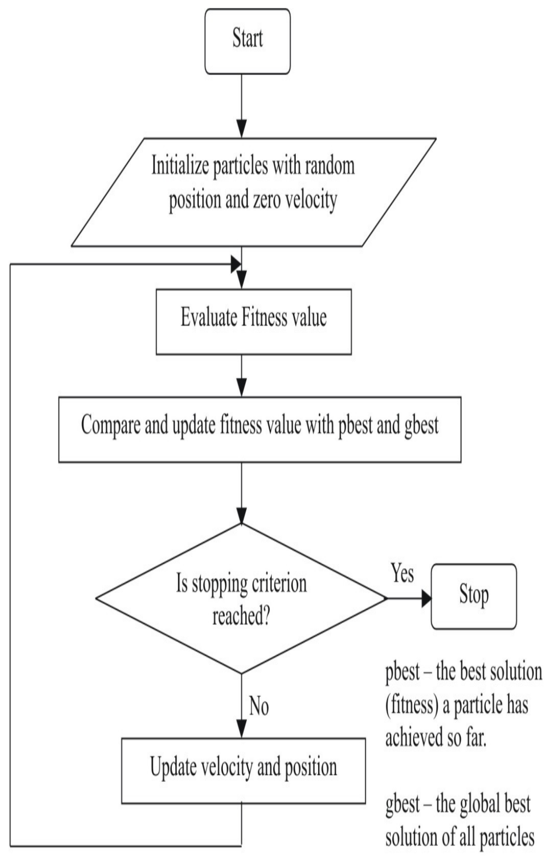

Figure 1: Flowchart for PSO algorithmic Process

Self-organization of the particles leads to better exploration and exploitation of the search process. In this case, p_k^{global} is the global best in the current iteration. This p_k^{global} is the position of the particle that contributes to the best fitness value in the current iteration. A replacement is carried out in p_k^{global} to p_k^{SO}, where p_k^{SO} will assume values from both global best position p_k^{global} and that from the worst position p_k^{worst} during the clustering process. Hence, each component in P_k^{SO} will be formulated based on a Self-Organization principle. The self-organized PSO achieves faster convergence in comparison with that of conventional PSO due to the fact that the global best point will take values from both p_k^{global} and p_k^{worst} each component gets updated based on a Self-Organization condition. Thus the process is noted to establish exploration in the initial iterations and establishes exploitation when it proceeds towards final iterations.

The velocity of particle is updated by equation 3

$$v_{k+1}^i = (w_{k+1})v_k^i + c_1 r_{1,k}^i \left(p_k^i - x_k^i\right) + c_2 r_{2,k}^i \left(P_k^{SO} - x_k^i\right) \quad (3)$$

$$P_k^{SO} = \left[P_k^{i,1}\ P_k^{i,2}\ \ldots P_k^{i,s}\right] \quad (4)$$

The identification of each component in P_k^{SO} is the main contribution in this research work and it is given by equation 5,

$$P_k^{i,1} = \begin{cases} p_k^{global}, & \text{if } cluster_{index} < 0.5 \\ p_k^{worst}, & \text{otherwise} \end{cases} \quad (5)$$

Where p_k^{worst} is the position of the particle that will assume values that contribute the worst fitness value in the current iteration. '$cluster_{index}$' specifies the cluster count in the current generation. This self-organized mechanism is proved to be a best diversifier as it is noted to be a global mechanism for thoroughly exploring the solution space.

3.2. Proposed hybrid SOPSO-DGSA Algorithm

The proposed hybrid SOPSO − DGSA is based on the clustering phenomenon of SOPSO and that of the difference vector added to the acceleration part of DGSA exhibiting the effective local search capability. The velocity and position equations of the proposed hSOPSO− DGSA is given by equation 6 and 7,

$$v_{k+1}^i = (w_{k+1})v_k^i + c_1 r_{1,k}^i \left(p_k^i - x_k^i\right) + c_2 r_{2,k}^i \left(P_k^{SO} - x_k^i\right) + a_i^d(t) \quad (6)$$

$$p_i(t+1) = p_i(t) + v_{k+1}^i \quad (7)$$

Where, $a_i^d(t)$ is the acceleration part of the DGSA included in the velocity equation of the self-organized PSO. The algorithmic steps adopted for the proposed hSOPSO– DGSA are as follows:

Step 1: Identify and locate the search space.
Step 2: Randomly generate initial population of 'N' particles including positions and velocities employing uniform distribution.
Step 3: Compute the objective function for each particles for all the multi-objectives defined for the WMN problem under consideration.

$$f = max(f_{pdr}) + \max(f_{thro}) + \min(f_{delay}) \quad (8)$$

Under the constraints of flow reservation and energy bound being met.
Step 4: Compute G (t) of DGSA process.
Step 5: Calculate the total force in different directions.
Step 6: Calculate acceleration $a_i^d(t)$ with difference vector included in it.
Step 7: Invoke SOPSO: Compute the velocity component as given by equation (3.6).
Step 8: For each mass *i*, do:

Evaluate $Fitness_i$, $Mass_i$, *Force of* $Mass_i$, *Acceleration with difference vector of* $Mass_i$, *Update Velocity of* $Mass_i$ *(which includes self-organizing content) and find new Position of* $Particle_i$.

Step 9: Repeat steps (2) to (8) until the stopping condition with respect to the number of objective function being met.
Step 10: Output the best fitness computed at final iteration as a global fitness and the positions of the corresponding particle at specified dimensions as the global solution of the WMN problem under consideration.

The proposed hybrid SOPSO − DGSA combines the best characteristics of the self-organized particle swarm optimization and differential gravitational search algorithm, so as to perform effective optimal routing of the WMN model. The hybridization of this population based stochastic optimization approach tends to increase the exploration and exploitation rate avoiding premature convergence of the algorithmic process by their social behaviour of clustering and local search capability. The algorithms is limited to number of nodes, as the number of nodes is increased there is limitation in Optimisation parameters.

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4. RESULTS AND DISCUSSION

The performance of the proposed hSOPSO – DGSA algorithm is analyzed for the Adhoc On demand Distance Vector routing protocol (AODV) and the simulation process is carried out in Network Simulator – 2 (NS – 2) platform. The performance metrics considered in this research work for WMN model is the packet delivery ratio, throughput and delay for effective routing. The proposed hSOPSO – DGSA algorithm is simulated and run for 25 trials for obtaining the average performance metric values. Table 3.1 shows the algorithmic parameters of the proposed hSOPSO–DGSA approach finalized after performing the experiments.

The performance of the proposed hSOPSO – DGSA algorithm is validated for its effectiveness by comparing it with the earlier methods proposed in the literature – Genetic Algorithm (GA) approach as proposed for WMN by Oda et al [5], Discrete Multi-Objective Differential Evolution (DMODE) Algorithm as proposed by Murugeswari & Radhakrishnan [6] and individually with PSO algorithm, ACO algorithm and GSA algorithm with respect to PDR, throughput and delay maintaining the flow reserve constraints and energy constraints.

Figure.2 shows the average delay obtained for the AODV routing protocol for 20 nodes and with 6 mesh routers and 14 mesh clients. The developed hSOPSO – DGSA approach is noted to perform in a better manner in case of both low node and high node mobility cases.

Table 1: Simulation parameters of proposed hSOPSO-DGSA.

Parameters	SOPSO
Particle Size	40
Acceleration constants c_1 and c_2	2.0
W_{min} and W_{max}	0.4 and 1.0
Maximum Iteration	100
G_o	100
α	20

It is to be noted that when the mobility of the node increases, the paths between the communications end points tend to break. At the search process, the proposed hSOPSO – DGSA avoids the node redundancy, due to its clustering of the particles based on the index values and the evolution of the difference vector in gravitational search eliminating the redundancy. From Figure .2,it is well inferred that the proposed hSOPSO – DGSA approach achieved lesser delay than other methods considered for comparison including the hACO – DGSA.

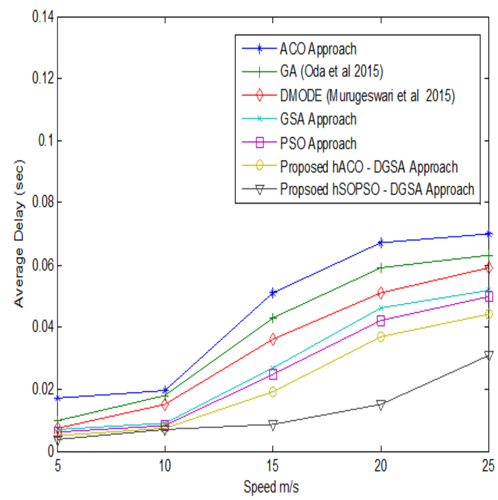

Figure 2: Average delay Vs Speed

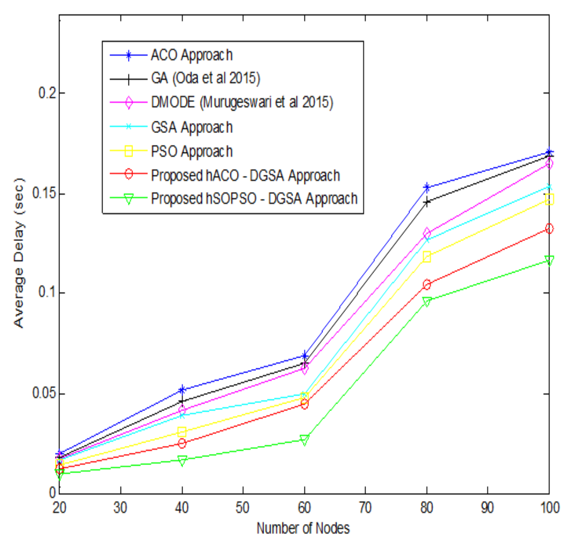

Figure 3: Average delay Vs Number of Nodes

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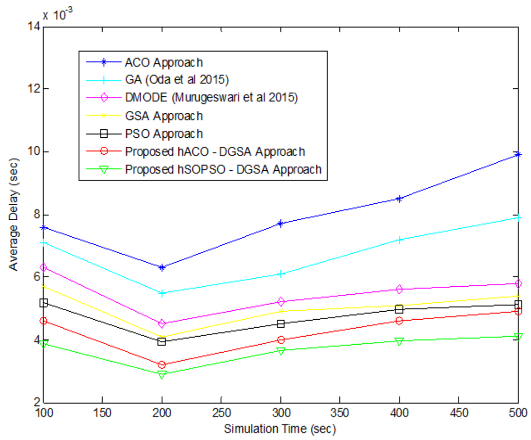

Figure 4: Average delay Vs Simulation Time

The simulation results for the average delay with respect to variations in number of nodes are as shown in Figure 3. The average delay is obtained when the mesh client speed is 5 m/s. The redundancy in this case also is avoided based on the difference vector added in the acceleration component of the DGSA and due to the further hybridization with self-organized PSO. In comparison with the other methods, the proposed hSOPSO - DGSA yielded minimal average delay for increased number of nodes and is well inferred in Figure.3 and Figure.4 shows the comparison of the average delay computed with respect to that of the simulation time employing the proposed approach. It is to be observed from the obtained plot that the delay is increasing with the increase of simulation time. Hence, it is very clear from Figure .4 that the proposed hSOPSO– DGSA performs in a better way than the other methods in this work.

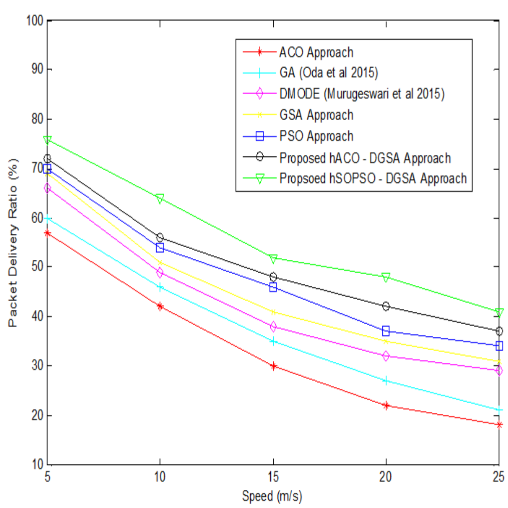

Figure 5: PDR Vs Node Mobility

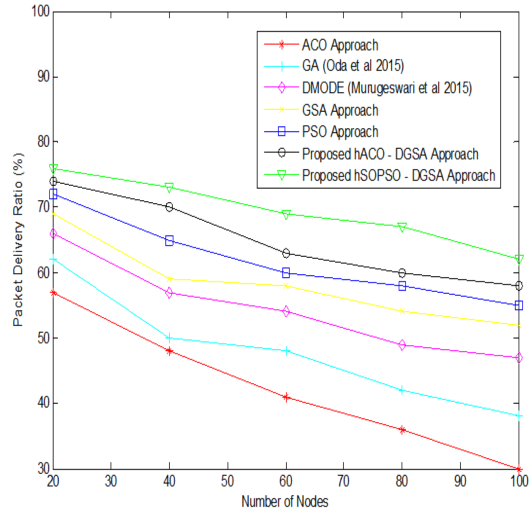

Figure 5: PDR Vs Number of nodes

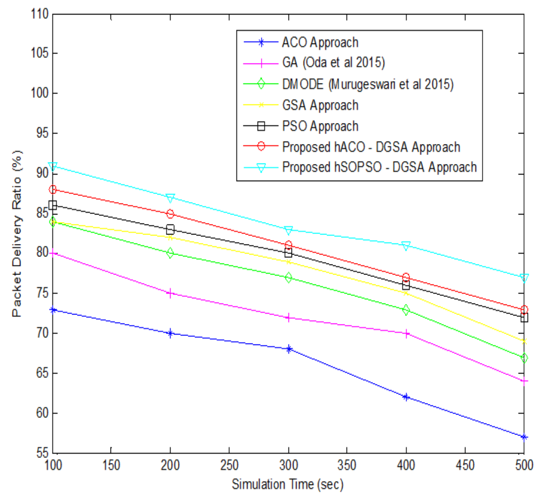

Figure 6: PDR Vs Simulation Time

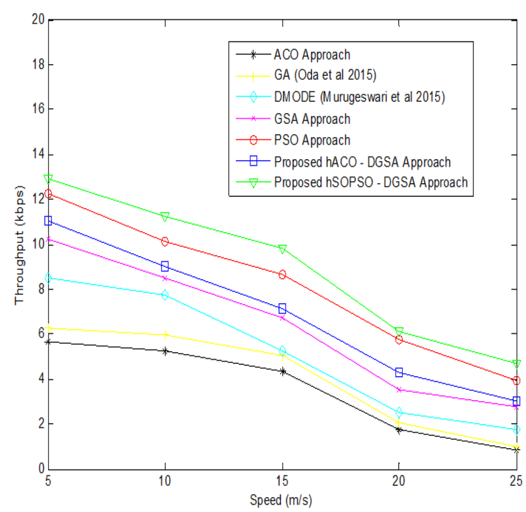

Figure 7: Throughput Vs Node Mobility

Figure .5 shows the Packet Delivery Ratio (PDR) with respect to the considered 20 nodes on varying the node mobility. In this case also, the speed of the mesh client is 5m/s. Individually ACO approach gets 57% of PDR, GSA achieves 69% PDR, PSO achieves 70% PDR and the existing methods from literature are noted to possess 60% in case of GA approach Oda et al [5] and 66% in case of DMODE [7]. The developed hSOPSO – DGSA approach achieved 76% of PDR. Figure .6 shows the obtained simulation results of the PDR with respect to the increase in number of nodes. The maximum speed of mesh client here is 5 m/s. The social and self-organizing behaviour of the proposed hSOPSO– DGSA explores towards a global solution and it is noted that due to this feature it holds the individual particle that reaches the better solution point. Figure.7 shows the calculated packet delivery ratio for increased simulation time and in this case also, the mesh client speed is 5m/s.

The PDR percentage is observed to be higher than the other methods considered for comparison in the literature. The number of possible solution is increased based on the clustering behavior of the particles in the search process of the proposed algorithm. The local behavior is enhanced by the inclusion of difference vector in the acceleration coefficient of differential gravitational algorithm and the social behavior is taken care by the clustering operation within the particles by the self-organized particle swarm optimization thereby performing an effective exploitation and exploration respectively.

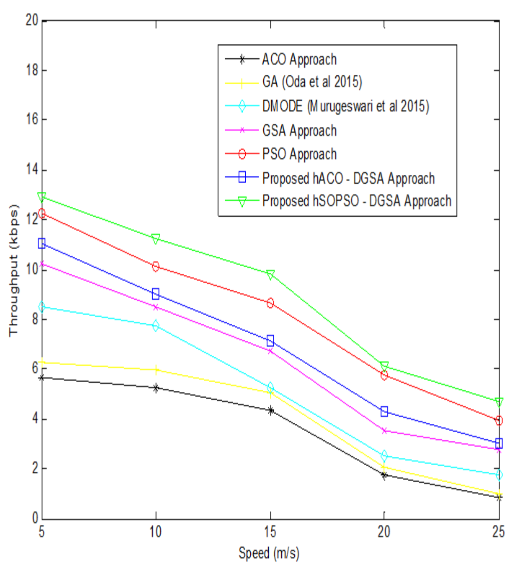

Figure 8: Throughput Vs Node Mobility

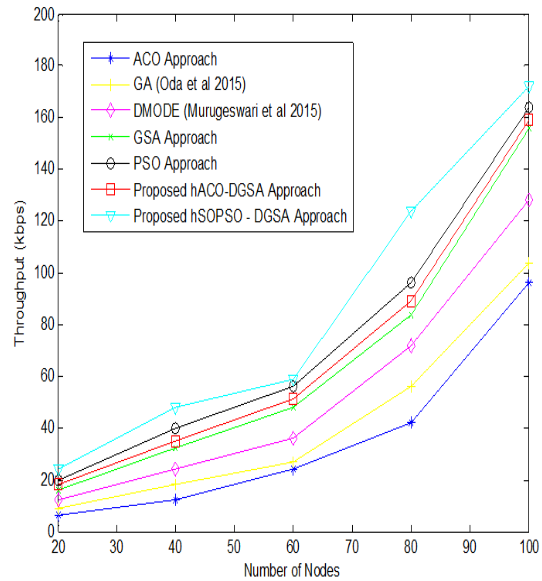

Figure 9: Throughput Vs Node size

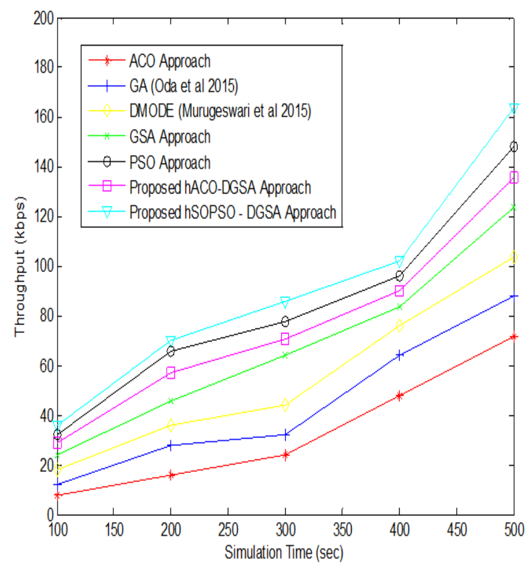

Figure 10: Throughput Vs Simulation Time

Figure.8 shows the throughput computed for 20 nodes by varying the node mobility in the considered AODV protocol .Employing the proposed hSOPSO–DGSA technique, the exploration and exploitation is improved by the enhancement of social and local capability of the algorithm and due to this, better particles gets retained during the search process. Thus the throughput of the proposed algorithm is better than the other methods considered for comparison.

The throughput comparison of the proposed algorithm with respect to the other methods with increase in the node size is simulated and is shown in Figure.9. As the number of nodes gets increased, it minimizes the expected number of transmissions and due to which the throughput gets increased. The proposed cluster based hSOPSO– DGSA achieves higher throughput than the existing GA, DMODE, ACO, PSO and GSA algorithms. From Figure.10, the simulation results prove that better and higher throughput is achieved as the simulation time increases for the proposed approach due to their converging ability, with the speed of the mesh client is set to 5 m/s.

5. DISCUSSION AND VALIDATION OF THE PROPOSED ALOGRITHM

From the simulation results and the graphical plots computed, it is well proven that the proposed hSOPSO - DGSA approach evolved better solutions with respect to the multi-objectives considered for effective QoS routing in WMN model. The modeled algorithm is an evolutionary stochastic based population algorithm.
Hence, the algorithm will have randomness and thus the WMN is a multi-objective problem, it is essential to determine better solutions for all the objectives, wherein pareto-optimal solution is obtained. In this 25 trial runs are carried out to obtain the best pareto-optimal value. The premature convergence of the proposed algorithm is avoided by determining the pareto-optimal front. For a multi-objective algorithm to be working satisfactorily or either in a better way, the user is intended to determine solutions to the near close proximity of the true pareto-optimal front and as well the solutions that span the complete pareto-optimal space in a uniform manner. The validation of the proposed hybrid SOPSO – DGSA approach is done by the statistical parameter 'spread' as given by equation (9). For validating the performance of the proposed hACO – DGSA approach, a metric called as spread as proposed by Deb [8] is employed. Based on the value of spread, it is inferred that an algorithm with minimum value of spread is capable of finding a better diversified set consisting of solutions that are non-dominant. The calculation of spread is done as follows [8],

$$Spread = \frac{\sum_{n=1}^{N} d_n^e + \sum_{i=1}^{|Q|} |d_i - \bar{d}|}{\sum_{n=1}^{N} d_n^e + |Q|\bar{d}} \qquad (9)$$

Where, 'd_i' specifies the distance measure between neighbouring solutions, '$\bar{d}$' indicates the mean value of the distance measures and 'd_n^e' indicates the distance between the extreme solutions.

From Table.2, it is noted that the statistical comparison of the metric 'spread' is done for the mean, best, worst and variance values for the proposed algorithm and as well that of the other algorithms considered for comparison from the literatures. It is inferred from the Table .2, that the statistical values for the spread possess minimum values for the proposed algorithm hSOPSO–DGSA in comparison with the other methods considered. Thus, the proposed approach performs the QoS routing for the AODV routing protocol in WMN model in a better manner than the other methods.

Table 2: Statistical comparison of the 'spread' value for the considered algorithms

Performance metric 'Spread'	ACO	GA	DMODE	GSA	PSO	Proposed hACO – DGSA	Proposed hSOPSO – DGSA
Mean	0.5962	0.4965	0.4223	0.4016	0.3753	0.3619	0.2013
Best	0.4601	0.3876	0.2340	0.2087	0.1938	0.1887	0.1572
Worst	0.7659	0.6928	0.6856	0.6372	0.6111	0.5927	0.3347
Variance	0.01572	0.00961	0.00823	0.00803	0.00776	0.00754	0.00310

6. CONCLUSION

In this paper, a novel hybrid Self-Organized Particle Swarm Optimization along With Differential Gravitational Search Algorithm is proposed to solve the QoS routing problem in the wireless mesh network models. The proposed hSOPSO – DGSA approach aimed to optimize the performance metrics – PDR, throughput and delay with the specified constraints being met.
The key feature of clustering in the self-organized PSO is brought out to retain the better particles belonging to the optimal cluster, thereby increasing the exploration rate of the proposed population based algorithm. The acceleration part of the differential GSA is included in the velocity equation of the proposed SOPSO, thereby enhancing the exploitation rate of the developed algorithm. Thus, the hybrid form of the algorithm has the most prominent social and local behavior, and thereby effectively optimized the multi-objective optimization problem.

Simulation studies were carried out in NS -2 platform and the solutions prove the effectiveness of the proposed hSOPSO – DGSA algorithm over the earlier other methods available in the literature on comparisons. The pareto-optimal front is evaluated in order to validate the performance of proposed hSOPSO– DGSA approach and is done employing the performance metric; spread. This also further substantiates that the proposed approach performs the QoS routing for the AODV routing protocol in WMN model in a better manner than the other methods available in the literature as considered for comparison.

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