A Multi-objective Optimization Strategy based on GSO for the Multicast Routing Problem

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Abstract— In this paper a nature inspired multi-objective optimization based on new improved Group search optimizer algorithm has been modelled to solve the NP-complete, multicast routing problem. This proposed algorithm will use an effective objective function which ensures quick convergence and finds the optimized path between the single source and multiple destination nodes based on the objective QoS metrics that include delay, delay jitter, bandwidth and packet loss. It uses an adaptive and iterative path search approach and takes the advantage of multi-group structure of GSO to quick convergence of global optimum. The performance of the proposed multi-objective group search optimizer (MOGSO) is evaluated by simulations. The simulation results show that the proposed routing algorithm can provide best performance with an acceptable complexity and can reduce processing time which provides better network utilization than the competing algorithms.

Keywords— Dynamic multicast routing, multi-objective, Combinatorial optimization problem, Group Search optimizer.

I. INTRODUCTION

Nowadays there is a phenomenal incipient ultimatum in the numerous real time applications such as Videoconferencing, VoIP (Voice over Internet Protocol), Online gaming, Community storage solutions, E-commerce transactions, Chatting , E- learning and IM's(Instant messaging) which has led to the enhancement of efficient QoS routing scheme. These real world multimedia applications must satisfy its QoS parameters such as delay, delay jitter, bandwidth and packet loss for effective and dynamic communication between source and the destination nodes. Different applications might impose varied QoS constraints and depending on the type of the application their sensitivity is measured. Multicast routing is a NP complete problem for finding the best route for transfer of information from source to multiple destination nodes. Many heuristic algorithms (Vijayalakshmi K. and Radhakrishnan, 2007; Changbing Li et al., 2007; WeiFanga et al., 2011; Y. del Valle et al., 2008; Krithiga R and Sathya M, 2012; T. Ray and K. M. Liew, 2003) such as Genetic algorithm, Particle Swarm Optimization algorithm, Ant colony optimization algorithm, Self Organizing Migrating Algorithm have been employed to solve the QoS-aware constrained stochastic optimization problems in various domains such as web service computing, e-learning and Digital libraries (Sathya M., et al., 2006; Sathya M., et al., 2008, Sathya M., et al., 2010; M.Swarnamugi and M.Sathya, 2010).

The aim of the paper is to develop an efficient heuristic algorithm that can solve the dynamic routing problem. Group search optimizer algorithm is a stochastic Evolutionary optimization algorithm that mimics the foraging behavior of animals. Group search optimizer algorithm (GSO) is a random search approach to solve large-scale optimization problems and combinatorial problems. When tested against benchmark functions, in low and high dimensions, the GSO algorithm has competitive performance to other EAs in terms of accuracy and convergence speed, especially on high-dimensional multimodal problems (S.He et al., 2009). In order to accomplish the foraging task in GSO algorithm the producer-scrounger strategy (C.J.Barnard and R.M.Sibly, 1981) is employed. Producing refers to the activity of searching for food and scrounging means joining the group for foraging. Many evolutionary algorithms have been employed for dynamic routing but the convergence speed is not satisfactory. But GSO algorithm is found to be efficient and produces better convergence speeds.

The rest of the paper is organized as follows: In Section2 we briefly confer the various QoS parameters that are mandatory for resourceful routing in networks. We give a meticulous explanation of the Group search optimizer algorithm in Section 3. Section 4 elucidates GSO based algorithm for dynamic routing in networks. Section 5 demonstrates the experimental setup with the simulation results and finally Section 6 concludes the paper.

II. RELATED WORKS

QoS based dynamic routing has been a fascinated research issue in the recent years. Many researchers have worked on different heuristic algorithms for QoS based dynamic routing in networks. Genetic Algorithm (GA) is a directed random search technique to solve large-scale optimization problems and combinatorial problems. It works based on the principle of evolution and uses payoff function to guide the random search (T.N.Bui and B.R.Moon, 1996; L.Davis, 1991).

Various researchers proposed the construction of static least cost multicast tree which satisfy either single or multiple constraints using simple GA(W.Zhengying et al., 2001; Q. Sunand L. Li, 2004; G.Bao et al., 2006; A.T.Haghighat et al.,2003; C.F.Tsai et al., 2004; C.P.Ravikumar and R.Bajpai, 2004). But the above algorithms produce the static multicast tree and sometimes converged to local optimum. In genetic algorithm heuristic local search function has been devised and embedded with normal genetic operation to increase the speed and to get the optimized tree. Genetic Algorithm (GA) has the chance of attaining global optimum values but it has some problems like premature and slow convergence speed (Vijayalakshmi K. and Radhakrishnan, 2007). PSO is powerful, easy to understand, easy to implement, and computationally efficient. An improved version of Particle Swarm optimization termed as the modified quantum-behaved particle swarm optimization (QPSO) method for QoS based routing. In the proposed method, QoS multicast routing is converted into an integer programming problem with QoS constraints and is solved by the QPSO algorithm combined with loop deletion operation .Xi-Hong et al. (Xi-Hong C., 2010)proposed an ACO-PSO algorithm to solve the NP -complete problem. The solution generated by ACO is regulated by position update strategy of PSO, which extends the search scope efficiently and avoids premature convergence to local optima. (Changbing Li et al., 2007) described a new evolutionary scheme for the optimization of QoS routing based on the hybrid of GA and PSO, called HGAPSO. In HGAPSO, the upper-half of the best-performing individuals in a population are considered as elites. Instead of being reproduced exactly in the next generation, these elites are improved first. The group constituted by the elites is regarded as a swarm, and each elite corresponds to a particle within it.

All of mentioned efforts are dedicated to the QoS based dynamic routing algorithms in high speed communication networks. To the best of our knowledge, this is the first work in which Group search optimizer algorithm (GSO) has been applied to dynamic routing problem. In this paper we have employed clustered mechanism to the GSO algorithm termed as the multi-cluster GSO (MOGSO) to increase the convergence speed and avoid getting struck at the local optima.

III. MULTICAST NETWORK ROUTING PROBLEM FORMULATION

A. Network Path Modelling

In reality the entire network can be represented as weighted graph G(V, E), where V(vertices) denotes the nodes of the network and E (edges) denotes the connection link between the nodes. In Fig.1 we have presented a scenario network model consisting of 60 nodes. In this figure red node indicates the source node, black nodes indicate the multiple destination nodes and violet nodes indicate the intermediate nodes. The nodes of the network are randomly distributed and the path between each node consists of several factors such as delay, delay jitter, bandwidth and packet loss. When the source and the intended destinations have been set, the main problem that arises is to choose an optimal path from the source to the destination nodes and when the search scope is inefficient we get struck at the local optima. In order to overcome this issue we split the entire network into 'clusters'. This multicast routing is an NP-complete problem because there are several nodes that are available in a particular zone and the main problem is picking the suitable node that satisfies all our QoS constraints.
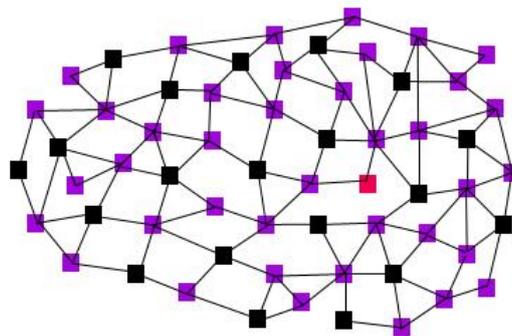

Fig. 1 Scenario network model consisting of 60 nodes

Hence there are different paths that are available from the source to the destination. This clearly depicts that routing is an NP-complete problem and we need some mechanism to choose an optimal path. One such mechanism that we have suggested in our paper is routing based on the various QoS parameters. Thus an optimal path from the source to the intended destination can be chosen based on the QoS constraints.

2.2 Quality of Service (QoS) attributes

Bandwidth- Bandwidth (*B*) represents the rate at which an application's traffic must be carried by the network. When the capacity of the bandwidth increases it is assured that the performance will be better.

$$B(p_t(s, d_m)) = \min\{bandwidth(e), e \in r_t(s, d_m)\} \tag{1}$$

Delay - The delay (*D*) of a network is the time taken by a bit of data to be transferred from source to sink node measured in fractions of seconds. Delay can be split into several categories namely : i) Processing delay, ii) Queuing delay and iii) Transmission delay.

$$D(p_t(s, d_m)) = \sum_{e \in r_t(s,d_m)} delay(e) + \sum_{n \in r_t(s,d_m)} delay(n) \tag{2}$$

Jitter - The jitter (*J*) is the variation in the time between packets arriving, caused by network congestion, timing drift, or route changes.

$$J(p_t(s, d_m)) = \sum_{e \in r_t(s,d_m)} jitter(e) + \sum_{n \in r_t(s,d_m)} jitter(n) \tag{3}$$

Packet Loss- Packet loss (PL) is generally said to occur when or more number of data packets transmitted over a network fails to reach the intended destination due to several issues such as channel congestion, hardware fault in the network or problem with network drivers.

$$PL(p_t(s, d_m)) = 1 - \prod_{e \in p_t(s,d_m),}(1 - PL(e)) \tag{4}$$

IV. GROUP SEARCH OPTIMIZER ALGORITHM

Group search optimization (GSO) is a novel stochastic optimization algorithm that was developed by (S. He et al., 2009). This algorithm is inspired by the foraging behaviour of animals. The entire population of the GSO algorithm is termed a group and each individual in the population is called a member. There are three types of members namely: producers, scroungers and rangers. In order to achieve this foraging task the producer-scrounger strategy is engaged. Producing signifies to the action of searching for food and scrounging means joining the group for foraging. Rangers perform random walks in the search space. According to the GSO algorithm only one member is chosen to be the producer and the remaining members are scroungers and rangers. The producer constantly looks and finds the resources and the scroungers just join the producer. During iterations, the member that is found to have the best fitness value is chosen as the producer. The producer scans the environment to look for its resources. Scanning is a vital factor of search orientation. In the GSO algorithm, at the kth iteration the producer $\mathbf{X}_p$ behaves as follows. The producer will first scan at zero degree and then choose three random points i).A point at zero degree ii) A point crosswise at the right hand side of the producer iii)A point crosswise at the left hand side of the producer.

$$X_z = X_p{}^k + r_1 l_{max} D_p{}^k(\phi^k) \tag{5}$$
$$X_r = X_p{}^k + r_1 l_{max} D_p{}^k(\phi^k + r_2 \theta_{max}/2) \text{ one point in the right hand side} \tag{6}$$
$$X_l = X_p{}^k + r_1 l_{max} D_p{}^k(\phi^k - r_2 \theta_{max}/2) \text{ one point in the left hand side} \tag{7}$$

where r_1 is where $r_1 \in R^1$ is a normally distributed random number with mean 0 and standard deviation 1 and $\mathbf{r}_2 \in R^{n-1}$ is a uniformly distributed random sequence in the range *(0, 1)* and θ_{max} is the maximum pursuit angle and $\theta_{max} \in R1$ and maximum pursuit distance $l_{max} \in R^1$.

If the producer finds a better position than its current position then it will move to that point otherwise it will stay in its current position and turn its head angle using the formula,

$$\phi^{k+1} = \phi^k + r_2 \alpha_{max} \tag{8}$$

where $\alpha_{max} \in R^1$ is the maximum turning angle.

In case the producer cannot find a better position after *a* iterations, then it will turn its head back to zero degree

$$\phi^{k+a} = \phi^k \tag{9}$$

where $a \in R^1$ is a constant.

During iterations a number of group members are selected as scroungers. The scroungers will keep searching for opportunities to join the resources found by the producer. At the kth iteration, the area copying behaviour of the ith scrounger can be modelled as a random walk toward the producer

$$x_i^{k+1} = x_i^k + r_3 \cdot (x_p^k - x_i^k) \tag{10}$$

where $r_3 \in R^n$ is a uniform random sequence in the range *(0, 1)*.

In case the scroungers or the rangers finds a better position than the producer then in the next iteration the one that has better position switches its role and becomes the producer. This mechanism helps the entire group to escape from being struck at local minima. Random walks, which are thought to be the most efficient searching method for randomly distributed resources are employed by the rangers. At the kth iteration, it generates a random head angle ϕ_i using (5); and then it chooses a random distance

$$l_i^{k+1} = a \cdot r_1 l_{max} \tag{11}$$

and move to the new point

$$x_i^{k+1} = x_i^k + l_i D_i^k(\phi^{k+1}) \tag{12}$$

Different strategies were adopted by the animals to restrict their searches. GSO algorithm uses a strategy called as bounded search space. According to this strategy if any member is outside the search space it will turn back into the search space by setting the variables that violated the boundary criteria.

V. MULTI-CLUSTER BASED GSO ROUTING SCHEME

The GSO algorithm has been redefined to solve the multicast routing that dynamically handles the changes that occur in the network due to the varied network configurations and node failures. Our objective is to improve the stochastic GSO algorithm in order to provide a diversified co-operative searching approach that significantly speeds up the individual members to converge to global optimum which is achieved in MOGSO algorithm using clustered mechanism.

The pseudo code of MOGSO based routing scheme is provided in Fig.2. The algorithmic input values are set for the source address, destination addresses, maximum iterations, delay constraint (QD), delay jitter constraint (QDJ), packet loss constraint (QP) and bandwidth constraint (QB). Based on the type of application the QoS constraints are chosen and the nodes are evaluated according to their fitness value. The fitness function can be formulated as,

$$f(Xi) = Minimize\ (Q_B.w_1 + Q_D.w_2 + Q_J.w_3 + Q_P) \tag{13}$$

$$\text{Constraints}\begin{cases} B\left(p_t(s, d_m)\right) \geq C_B \\ D\left(p_t(s, d_m)\right) \leq C_D \\ J\left(p_t(s, d_m)\right) \leq C_J \\ P\left(p_t(s, d_m)\right) \leq C_P \end{cases}$$

where w_1, w_2 and w_3 denotes the weights of bandwidth, delay and delay-jitter. The functions Q_B, Q_D, Q_J and Q_P are defined by

$$Q_B = \sum_{t \epsilon M} max\{C_B - B\left(p_t(s, d_m)\right), 0\}$$
$$Q_D = \sum_{t \epsilon M} max\{D\left(p_t(s, d_m)\right) - C_D, 0\}$$
$$Q_J = \sum_{t \epsilon M} max\{C_J - J\left(p_t(s, d_m)\right), 0\}$$

$$Q_P = \sum_{t \epsilon M} max\{C_P - P\left(p_t(s, d_m)\right), 0\}$$

where w1, w2, w3 and w4 denotes the weights of bandwidth, delay, delay-jitter and packet loss respectively. The best path will get the best fitness value. Initially the nodes of the network are divided into clusters that lead to diversified search. The paths are established with the constraints by choosing a node from each zone. The fitness value of each established solution tree (T) is calculated based on QoS constraints that each application requires using equation (13), and the paths are ranked accordingly. The path that has the highest value is noted as the GBest value is termed as the producer. After producing, the paths are re-evaluated once their position changes. This is mainly done to find the optimum solution (i.e.) to find the best optimal path between the source and the destinations. Once the scrounging and ranging tasks has been performed the fitness values of the individuals and GBest is updated .In case if the obtained GBest value is better than the current producer then this corresponds to the global optimal route between the source and the destination nodes which is repeated in each iteration. The algorithm will get terminated when the total number of iterations exceeds the maximum number of iterations. When the algorithm convergences to an optimal solution, the Global best position should be displayed. This value will contain the nodes that constitute the optimal routes which satisfy the QoS parameters according to the type of application from the source node to the destination nodes.

Set the values for the source and destination address
Randomly initialize members X_i of all clusters;
Calculate the fitness values of initial members: f (X_i) using (13)
For each zone compute X_i in the group:
    Find the producer X_p of the group
        a. *The producer tries to find a better path than its current path by giving a small drift in its position using (5) to (7).*
        b. *If the producer finds a better path than its current path, then producer moves to this new path. Otherwise it will stay in its current path and change its head angle using (8).*
        c. *If the producer cannot find a better solution after a iterations, it will turn its*
        Head back to zero degree using (9)
    80% of the rest of the members perform scrounging
    a. *The remaining members perform searching by doing random walks*
        Generate a random head angle using (8)
    b. *Choose a random distance l_i from the Gauss distribution using (11) and move to the new point using (12);*
    Calculate the fitness value of current path: f (X_i);
    Set k := k + 1
Until the termination conditions are met repeat steps 6-10

Fig. 2 Pseudo-Code of the Proposed MOGSO algorithm

VI. SIMULATION RESULTS

A. Experimental Setup

In order to compare the performances of MOGSO with that of GA and PSO we have considered the network topology consisting of 60 nodes as shown in Fig. 1. The experimental settings were set as follows. The initial population of MOGSO was randomly generated and the population size was set as 100 for all the algorithms considered for study. The initial head angle φ^0 of each individual is set as $(\frac{\pi}{4}, ..., \frac{\pi}{4})$ in the search space. The maximum pursuit angle θ_{max} is calculated using the formula $\frac{\pi}{a^2}$, where 'a' is a constant which in turn is computed using the formula $round(\sqrt{n} + 1)$.

The maximum pursuit distance l_{max} is calculated by $\sqrt{\sum_{i=1}^{n}(U_i - L_i)^2}$ and maximum turning angle α_{max} by $\theta_{max}/2$, where n is the dimension of the search space and L_i and U_i are the lower and upper bounds for the i th dimension. The performance of MOGSO was compared with other EA's namely GA and PSO. The actual code of GA is run using the GAOT toolbox with heuristic cross over and uniform mutation. The other parameters like mutation and crossover probability are set as default. The PSO algorithm incorporated here is a standard one with acceleration constants c1 and c2 of 2.0 and inertia weight ω starts at 0.9 and ends at 0.4. The initial population for both GA and PSO was set to 100. For evaluating the performance of the proposed MOGSO algorithm each of these algorithms were executed on a network topology which consists of 60 nodes. Simulation experiments were carried out in two different constraints set. All the experiments were carried out on a Personal computer with 2 GHZ Intel Processor and 4 GB RAM. The programs were written executed using MATLAB 6.5, and the relevant graphs were generated using Microsoft Excel. The operating system used is Windows7 and the system type is a 32 bit operating system.

VII. EXPERIMENTAL RESULT ANALYSIS

In this section we consider the network topology consisting of 60 nodes with two sets of constraints. The contents of Table I depicts the results obtained by GA, PSO and MOGSO algorithms for calculating the success hit ratio and mean best tree cost respectively in the case of 60 nodes. In constraint set 1 the delay, delay jitter, bandwidth and packet loss were set to 80ms, 15ms, 35 Mbps, 1% respectively. The results obtained by three algorithms over constraint set 1 were as follows. The hit ratios of the three algorithms used for comparison are considered. The results obtained by GA=86.7% <PSO=95.3% <MOGSO=98.7. Hence it is evident MOGSO produces higher hit ratio than GA and PSO. The mean best tree cost over constraint set 1 for GA, PSO and MOGSO was 497.8, 470.6 and 415.9. It is evident from the results that MOGSO has least mean best tree cost which guarantees to the high performance of the algorithm. The results obtained by same network topology over constraint 2 were as follows. The delay, delay jitter, bandwidth and packet loss were set

to 75ms, 13ms, 40 Mbps, 0.8% respectively. The hit ratio were as follows, GA=76.5% <PSO=91.2% <MOGSO=96.1%. MOGSO produces higher hit ratio than GA and PSO. The mean best tree cost over constraint set 1 for GA, PSO and MOGSO was 590.8, 567.4 and 530.8. It is observed that results obtained by constraint set 2 has less performance than constraint set 1 due to its additional QoS constraints.

TABLE I
NETWORK TOPOLOGY CONSISTING OF 60 NODES WITH TWO QOS CONSTRAINTS

Algorithm	Network Topology consisting of 60 nodes			
	Constraint set 1		Constraint set 2	
	D=80ms,Dj=15ms,B=35Mbps,PL=1%		D=75ms,Dj=13ms,B=40Mbps,PL=0.8%	
	Multicast Hit ratio	Mean best tree cost	Multicast Hit ratio	Mean best tree cost
GA	86.7%	497.8	76.5%	590.8
PSO	95.3%	470.6	91.2%	567.4
MOGSO	98.7%	415.9	96.1%	530.8

Fig. 3 clearly illustrates the convergence properties of all the three algorithms considered for study. Based on the unique QoS constraints imposed as depicted in Table 1 relevant graphs were generated. It is evident from the results that MOGSO has quicker convergence with better searching ability than GA and PSO because MOGSO employs clustered based approach in order to enhance the diversity in the searching process and to achieve quick convergence. Fig. 4 represents the best multicast tree achieved in the case of two different QoS constraints imposed.

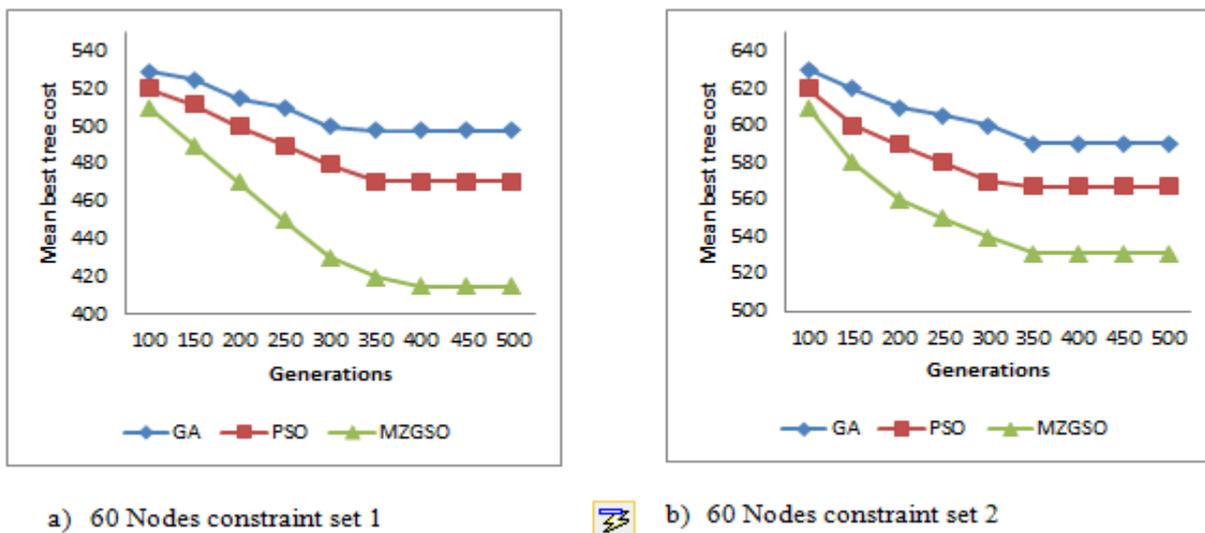a) 60 Nodes constraint set 1   b) 60 Nodes constraint set 2

Fig. 3 Performance evaluation of GA, PSO, MOGSO over scenario network topology consisting of 60 nodes considering Generations .vs. Mean best tree cost

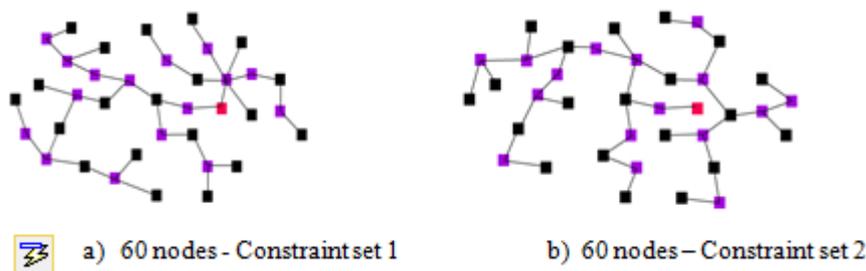a) 60 nodes - Constraint set 1   b) 60 nodes – Constraint set 2

Fig. 4 Best multicast tree achieved over a scenario network model

VIII.   CONCLUSION

In this paper, we have presented a multi-objective routing algorithm based on different QoS constraints. We have considered a network topology consisting of 60 nodes and the proposed algorithm has been in two different set of QoS constraints. The algorithm provides QoS sensitive paths in a scalable and flexible multicast tree in the network environment. To obtain the feasible solution, multi-clustered approach was proposed which enables inter and intra cluster communication. The MOGSO based routing algorithm was tested and evaluated and the results have been compared with standard GA and PSO algorithms. The simulation results showed that the MOGSO based algorithm can yield better multicast trees with quick convergence speed than PSO- based and GA- based routing algorithm.

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