National Conference on Synergetic Trends in engineering and Technology (STET-2014)
International Journal of Engineering and Technical Research ISSN: 2321-0869, Special Issue

QoS Multicast Routing using Elitist- Multiobjective Differential Evolution

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Abstract— **In this paper we intend to solve Quality of Service (QoS) multicast routing problem using E-MODE[1] Differential Evolution (E-MODE) a new Multi-objective Optimization algorithm is designed and implemented for the solution of real parameter multi-objective function optimization. E-MODE extends Differential Evolution to deal with multi-objective optimization. Multiple groups were implemented and a number of multicast trees were obtained as part of the solution. The experimental results dealt with relations between the number of nodes in the input graph, number of particles present in the system and the number of iterations required for convergence.**

Index Terms— **QoS, Multicast Routing, Differential Evolution, Optimization, multi-Objective.**

I. Introduction

Multicast is a communication technique over the IP infrastructure in a network for one-to-many communication. The source sends a packet only once, even if it needs to be delivered to a large number of receivers, using the network resources optimally. The intermediate nodes replicate the packets whenever necessary to address a large receiver population[2]. The most common protocol to use multicast addressing is User Datagram Protocol(UDP). Multicast routing is used in various continuous media applications and is employed for streaming media and Internet media applications. The primary function of QoS[3][5][6][7] is to ensure that all applications are getting the necessary bandwidth to function at a desired level. QoS uses resource reservation control mechanisms to allow administrators to set a desired level of service for each traffic type on the network. The goal of QoS is to provide preferential delivery service for the applications that need it by ensuring sufficient bandwidth, controlling latency and jitter, and reducing data loss. QoS is important as it provides the following benefits, Gives administrators control over network resources, ensures that time-sensitive and mission-critical applications have the resources they require, improves user experience, reduces cost by using existing resources efficiently. QoS is important for real time streaming media applications, since these often require fixed bit rate and are delay sensitive.. It is an important design decision as it affects the performance of the entire algorithm [4].

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II. MOTIVATION

Multicast routing is widely used in Internet applications and for live video streaming. Hence we need an efficient implementation of this routing technique which has low computational cost and good performance. Genetic Algorithms(GA)
and Ant Colony Optimization(ACO) techniques have been used to solve this problem.
However, GA has a tendency to converge towards local optima or even arbitrary points rather than the global optimum of the problem. Also, GA cannot effectively solve problems for which the only fitness function is right/wrong, as there is no way to converge on the solution. In these cases, a random search may find a solution as quickly as a GA. For certain
optimization problems, simpler optimization techniques such as Differential Evolution may find better solutions than genetic algorithms Thus, E-MODE can be easily used to solve the Quality of Service Multicast Routing problem and this approach forms the basis of this paper.

III. Differential Evolution

Differential Evolution (DE) is a population-based and directed search method [8], [9]. Like many other evolutionary algorithms, it starts with an initial population vector, which is randomly generated when no a priori knowledge about the solution space is available. Let us assume that $X_{i,G}(i = 1, 2, ...,N_p)$ are candidate solution vectors in the generation G (N_p: population size). Successive populations are generated by adding the weighted difference of two randomly selected vectors to a third randomly selected vector.

Mutation

For each vector $X_{i,G}$ in generation G a mutant vector $V_{i,G}$ is defined by

$V_{i,G} = X_{a,G} + F(X_{b,G} - X_{c,G})$,

where $i = \{1, 2, ...,N_p\}$ and a, b, and c are mutually different random integer indices selected from $\{1, 2, ...,N_p\}$. Further, i, a, b, and c are different so that $N_p >= 4$ is required. $F \in [0, 2]$ is a real constant which determines the amplification of the added differential variation of $(X_{b,G} - X_{c,G})$. Larger values for F result higher diversity in the generated population and lower values cause faster convergence.

Crossover

DE utilizes the crossover operation to increase the diversity of the population. It defines the following trial vector:

$U_{i,G} = (U_{1i},G,U_{2i},G, ...,U_{Di,G})$,

where D is the problem dimension and

$$U_{ji,G} = \begin{cases} V_{ji,G} & \text{if } randj(0, 1) <= Cr, \\ X_{ji,G} & \text{otherwise.} \end{cases}$$

C_r Є (0, 1) is the predefined crossover rate constant, and randj(0, 1) is the jth valuation of uniform random number generator. Most popular values for C_r are in the range of (0.4, 1) [8].

Selection The approach that must decide which vector ($U_{i,G}$ or $X_{i,G}$) should be a member of next (new) generation, G + 1. For a maximization problem, the vector with the higher fitness value is chosen. There are other variants based on different mutation strategies [9].

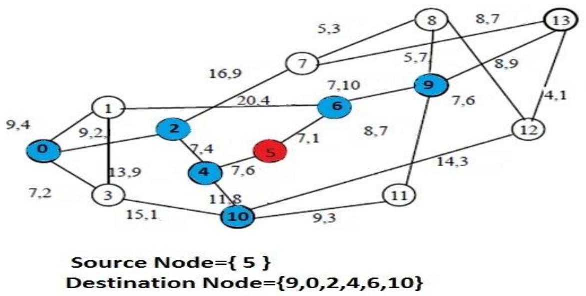
IV. PROPOSED WORK

For a directed network graph, the problem of finding an optimal multicast tree with the least cost is formally defined as follows

GIVEN: A directed network *G* = (*V*, *E*, *c*) consists of a nonempty set *V* of |*V*| vertices and a set *E*, |E| edges connecting pairs of vertices. Each edge is associated with a cost function *c:E* *R*. In addition, a non-empty set $N = \{v_0, u_1, u_2, ..., u_k\}$ of terminals in *G* is given where *N* is the source node, and $D = \{u_1, u_2, ..., u_k\}$ is the set of destination nodes
FIND: A sub network *TG*(*N*) = (*VT*, *ET*, *cT*) of *G* such that:
There is a path from the source node to each destination node;
1) The cost of *TG*(*N*), is minimized.
2) The end-to-end delay of *TG*(*N*), is minimized.

→

Routing Table:
In the network graph, *G* = (*V*, *E*), there are |*V*| (|*V*|- 1) possible source-destination
pairs. A source-destination pair can be connected by a set of links, which is called a “route”. There are usually many possible routes between any source-destination pair. For example, consider the network shown in Fig. the possible routes between *v*5 to *v2* include *v*5- *v*4- *v2*-, *v*5- *v*6- *v*1- *v0-v2*...., and so on



National Science Foundation Graph

PROPOSED ALGORITHM

Routing Table of *v*5- *v2*	
Route No.	Route List
1 . . . R_n	*v*5- *v*4- *v2* *v*5- *v*6- *v*1- *v0-v2* . . and so on

Steps for Generating Routing Table
Findout the Adjancy Matrix of Graph
1. Give the Value of Source Node and Destination Node
2. Do until all the path not found
3. Store the value of source Node in to array A
4. Start Breadth First Search from the source Node
4.1 Visit the adjacent node of the current node
4.2 Store the value of current Node in to Array A
4.3 Do the Step 4.1 to 4.2 until Node is equal to the Destination Node
5. Add the array A as row of Array B

Representation of Chromosome
For the given source V5 and the destination set D = $\{u_1, u_2,..,u_k\}$, a chromosome can be represented by a string of integer with length k. A gene, $G_{i\ ,\ 1\leq I\geq k}$ of the chromosome is an integer in {0, 1, …., R-1} which represents possible routes between V5 and V2 . The relationship between the chromosome, gene, and routing table is explained below.

G_1	G_2	………………	G_i	………………..	G_k

G_i= 1

Routing Table of V5 to V2	
Route No.	Route List
1 . . . R_n	*v*5- *v*4- *v2* *v*5- *v*6- *v*1- *v0-v2* . . and so on

Representation of Chromosome
1. Setting Parameters
Input the required DE parameter Like population size (NP), Crossover rate (CR), Scaling factor (F), Maximum Generation, number of objective function and bounds constraints. NP (Number of Population) = 30
Maxgen (Maximum Generation) = 1000
C_R (Crossover Rate) =0.6
F (Scaling Factor) =0.5
2. Initialization

Initialize all the vectors randomly within boundary constraints. And generate a randomly generated vector

3. Function Evaluation

Evaluate the function with the randomly generated vector and obtain the best front so far using non-dominant sorting.

3. Mutation and Crossover

Perform Mutation and crossover operation as per DE Algorithm on all the population member

- For each parent, select three distinct vectors randomly from the current population. The selected parent must not be the parent vector. These vectors combine to produce an offspring. So in DE three parents that mutate to produce an offspring.
- Calculate new mutation vector.
- Perform crossover using crossover mechanism.

4. Evaluate the objective function from trial population

5. Obtain the best_front_so_far from the combined population of Parent population and trial population.

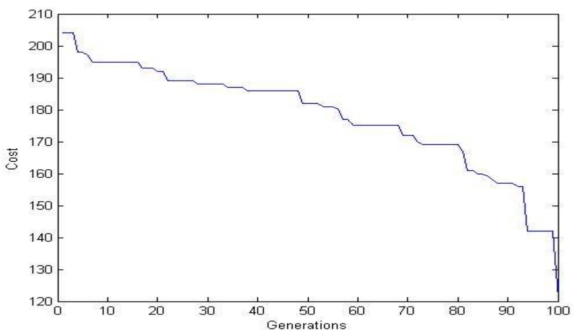
6. Selection

There are three conditions in selection

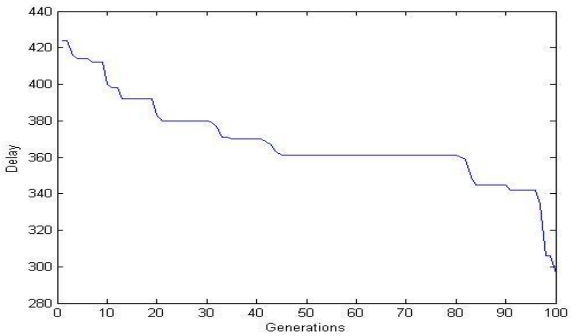
- If the number of solutions in the best_front_so_far is equal to N then put all these solutions in the new population P(t+1).
- If the number of solutions in the best_front_so_far is greater than N then select N solutions from this set using Crowding Distance Metric.
- If the number of solutions in the best_front_so_far is less than N then put all the solutions of this set in the new population P(t+1) and select remaining members of the new population using the following procedure

RESULTS

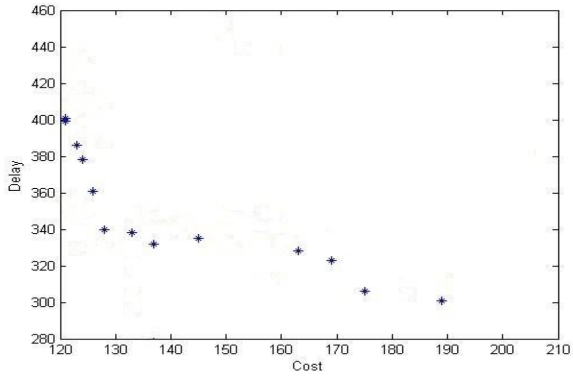
1. Convergence curve for cost



2. Convergence curve for delay



3. Pareto Optimal Front



CONCLUSION AND FUTURE WORK

For the optimization of real-world problems it is important that the applied algorithm is capable of handling multiple objective functions and several constraints. In this work Differentia Evolution algorithm is extended to a new version of Multi-objective Differential Evolution (E-Mode) based on a non-dominant sorting and crowding distance.

In this work, Elitist Multi-objective Differential Evolution (E-MODE) a new Multi-objective Optimization algorithm is implemented for the solution of real parameter multi-objective function optimization. The Performance of EMODE is also tested on Multi-objective Multicasting Routing Problem. The obtained results are quite promising indicating its applicability to the solution of even bigger instances of real-world Multi-Objective Multicast Routing Problem.

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