Multi-Objective Evolutionary Algorithm for Routing in Wireless Mesh Networks

P. Saraswathi, M. Prabha

Abstract: Wireless Mesh Networks are an attractive technology for providing broadband connectivity to mobile clients who are just on the edge of wired networks, and also for building self organized networks in places where wired infrastructures are not available. Routing in Wireless Mesh Networks has multiobjective nonlinear optimization problem with some constraints. This problem has been addressed by considering Quality of Service parameters such as bandwidth, packet loss rates, delay, path capacity and power consumption. Multi-objective evolutionary algorithms can find multiple Pareto optimal solutions in one single run. This paper uses multi-objective evolutionary algorithm based on the Non-dominated Sorting Genetic Algorithm (NSGA), for solving the dynamic shortest path routing problem. Simulation results show that our proposed algorithm can generate well-distributed Pareto optimal solutions.

Multi-objective Optimization, Evolutionary Kevwords: Algorithm, NSGA and Routing.

I. INTRODUCTION

Wireless Mesh Networks are the network in which each node can communicate directly with one or more peer nodes. Wireless mesh networks often consist of mesh clients, mesh routers and gateways. The mesh clients are often laptops, cell phones and other wireless devices while the mesh routers forward traffic to and from the gateways which may but need not connect to the Internet. WMN is dynamically self-organized and self-configured, with the nodes in the network automatically establishing and maintaining mesh connectivity among themselves. WMNs have many advantages over conventional wired networks, such as low installation cost, wide coverage, and robustness, etc. Because of these advantages, WMNs have been rapidly penetrating into the market with various applications, for example, public Internet Access, Intelligent Transportation System (ITS), and public safety. One of the main research issues related to WMNs is to develop the routing algorithm optimized for the WMN. The ability of multi-objective evolutionary algorithms to find multiple Pareto-optimal solutions in one single run have made them attractive for solving problems with multiple and conflicting objectives. Routing is one of the most important issues that have a significant impact on the network's performance. An ideal routing algorithm should strive to find an optimum path for packet transmission within a specified time so as to satisfy the Quality of Service (QoS). Current routing protocols use a simple metric and shortest path algorithm so as to work out the routes.

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In QoS routing, routes must be determined by requirements based on features of the data flows, such as cost, delay, bandwidth, throughput etc. There are two main goals that need to be achieved by the QoS routing algorithm. The first goal is to find a path that satisfies the QoS requirements. The second goal is to optimize the global network resource utilization. Many applications, such as audio, video conferencing or collaborative environments and distributed interactive simulations have multiple QoS requirements such as bandwidth, packet delay, packet loss, cost etc. In this paper, NSGA based approach is proposed for solving the dynamic routing optimization problem. The problem is formulated as a nonlinear constrained multi-objective optimization problem where throughput and delay are treated as competing objectives.

II. PROBLEM FORMULATION

The routing problem is formulated as a multi-objective mathematical programming problem which attempts to minimize delay and to maximize throughput simultaneously, while satisfying the constraints. The topology of a wireless mesh network is specified by an undirected graph, where the set of nodes is V, and the set of its link is E. It describes the design of the ETX metric. The metric's overall goal is to choose routes with high end-to-end throughput. End-to-end delay is another potential metric, but changes with network load as interface queue lengths vary; this can cause routes to oscillate away from a good path once the path is used. The ETX of a link is the predicted number of data transmissions required to send a packet over that link, including retransmissions. The ETX of a route is the sum of the ETX for each link in the route. For example, the ETX of a threehop route with perfect links is three; the ETX of a one-hop route with a 50% delivery ratio is two. The ETX of a link is calculated using the forward and reverse delivery ratios of the link. The forward delivery ratio, df, is the measured probability that a data packet successfully arrives at the recipient; the reverse delivery ratio, dr, is the probability that the ACK packet is successfully received. These delivery ratios can be measured as described below. The expected probability that a transmission is successfully received and acknowledged is (df * dr). A sender will retransmit a packet that is not successfully acknowledged. Because each attempt to transmit a packet can be considered a Bernoulli trial, the expected number of transmissions is:

$ETX = 1/(df^*dr)$

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ETX has several important characteristics:

• ETX is based on delivery ratios, which directly affect throughput.



• ETX detects and appropriately handles asymmetry by incorporating loss ratios in each direction.

• ETX can use precise link loss ratio measurements to make fine-grained decisions between routes.

• ETX penalizes routes with more hops, which have lower throughput due to interference between different hops of the same path.

• ETX tends to minimize spectrum use, which should maximize overall system capacity.

The ETX of a route is the sum of the link metrics.

Multi-Objective Optimization

real-world problems Most involve simultaneous optimization of several objective functions. Generally, these functions are often competing and conflicting objectives. Multi-objective optimization having such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. Here no solution can be considered to be better than any other with respect to all objectives. These optimal solutions are known as Paretooptimal solutions. Classical optimization methods can at the best find one solution in one simulation run. Therefore these methods are inconvenient to solve multi-objective optimization problems. Evolutionary Algorithms, on the other hand, can find multiple optimal solutions in one single simulation run due to their population based approach.

III. IMPLEMENTATION OF NSGA

Non-Dominated Sorting Genetic Algorithm (NSGA) has been described. NSGA uses ranking selection method to emphasize current Non-dominated solutions and a Niching method to maintain diversity in the population. Two main steps are followed in the algorithm (i) fitness assignment which prefers Non-dominated solutions and (ii) fitness sharing strategy which preserves diversity among solutions of each Non-dominated front. In general, the goal of a multi-objective optimization is to find the Pareto-optimal front and also maintain population diversity in the set of the Non-dominated solutions.

A. Initialization

A routing path is encoded by a string of positive integers that represent the IDs of nodes through which the path passes. Each locus of the string represents an order of a node that is indicated by the gene of the locus. The gene of the first locus is for the source node and the one at the last locus is for the destination node. The length of a routing path should not exceed the maximum length n, where n is the number of nodes in the network. Random-based encoding is used for population initialization.

Random Based Encoding: A chromosome or an individual consists of integer node IDs that form a path from the source node to a destination node. The chromosome is essentially a list of nodes along the constructed path, $(S \rightarrow N_1 \rightarrow N_{k-1} \rightarrow N_k \rightarrow D)$. A random path is searched starting from source node S to destination node D by randomly selecting a node N from the list of n nodes that is the neighborhood of S. Then another node N_k is randomly selected from the list of nodes. This process is repeated until the destination D is reached. Since the path should be loop-free, the nodes that

are already included in the current path are excluded, thereby avoiding re-entry of the same node. The initial population can be generated by using the following steps:

Step 1: Set the counter value i as 0.

Step 2: Generate chromosome Chi: select a

path randomly P(S, D).

Step 3: i = i + 1. If i < q, go to Step 2,

Otherwise, stop. Here q = 20.

B. Fitness Assignment

Fitness Assignment is to find a set of solutions in the population that are Non-dominated by the rest of the population. It describes the procedure for finding the non-dominated solution among the population P of size N.

Step 1: Set solution counter, i=1 and create an empty non-dominated set P'.

Step 2: For a solution $j \in P$, j!=i, check if solution j dominates i. If yes, go to Step 4.

Step 3: If more solutions are left in P, j=j+1 and go to Step 2; otherwise, set P'=P' $\in \{i\}$.

Step 4: i=i+1. If i<=N, go to Step 2; otherwise stop and P' is the non-dominated set.

These solutions represent the first front P1 and are eliminated from further contention. This process continues until the population is properly ranked. After classification has been completed, all solutions in the first set are said to belong to the best non-dominated set in the population. The second best solutions in the population are those that belong to the second set, and so on.

C. Fitness Sharing (Niching Method)

The more individuals are located in the neighborhood of a certain individual, the more its fitness value is degraded. The neighborhood is defined in terms of a distance measure d and specified by the niche radius σ share. Given a set of n_k solutions in the k^{th} front each having a dummy fitness value f_k , the sharing procedure is performed in the following way for each solution $i=1,\ldots,n_k$:

Step 1: Niche count can be calculated by using sharing function value which depends on the Euclidean distance from one solution to another solution.

$$\begin{array}{c} n_k \\ nC_i = \sum Sh \; (d_{ij}) \\ j = 1 \end{array}$$

Step 2: Sharing function value can be calculated by

 $1-(d_{ij} / \sigma_{Share})^2$, if d $\leq \sigma_{Share}$

Sh $(d_{ij}) = 0$, otherwise

Step 3: Euclidean distance can be calculated by

$$p_{ij} = Sqrt(\sum_{k=1}^{p_{ij}} ((X_k^{(i)} - X_k^{(j)}) / (X_k^{max} - X_k^{min}))^2)$$

$$k=1$$

39

Published By: Blue Eyes Intelligence Engineering & Sciences Publication Pvt. Ltd. Step 4: Shared fitness value can be calculated by

$$F_i = f_i / nC_i$$

D. Selection

Selection plays an important role in improving the average quality of the population by passing the higher quality chromosomes to the next generation. The individual with the lowest front number is selected if the two individuals are from different fronts. The individual with the highest crowding distance is selected if they are from the same front. A higher fitness is assigned to individuals located on a sparsely populated part of the front. In each iteration, the N existing individual parents generate N new individual offspring. Both parents and offspring compete with each other for inclusion in the next iteration.

E. Crossover and Mutation

Crossover is the first genetic operation that has been done to the chromosomes in the mating pool. It can be used to create an information exchange between two chromosomes. By doing this, it will generate new path and able to find better path in the process. Partially mapped crossover method has been implemented and it is used to avoid the repetition of nodes by using mapping function. It finds many new paths without increasing hop count.

For example:

Parents for PMX

Parent 1: N1 \rightarrow N2 \rightarrow N3 \rightarrow N4 \rightarrow N5 \rightarrow N10

Parent2: $N1 \rightarrow N5 \rightarrow N2 \rightarrow N6 \rightarrow N3 \rightarrow N10$

Offspring After Mapping Section Crossed

Offspring 1: $X \rightarrow X \rightarrow N2 \rightarrow N6 \rightarrow X \rightarrow X$

Offspring 2: $X \rightarrow X \rightarrow N3 \rightarrow N4 \rightarrow X \rightarrow X$

Offspring After Crossover

Offspring 1: N1 \rightarrow N3 \rightarrow N2 \rightarrow N6 \rightarrow N5 \rightarrow

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N10
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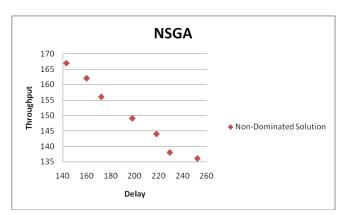
Offspring 2: N1 \rightarrow N5 \rightarrow N3 \rightarrow N4 \rightarrow N2 \rightarrow

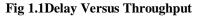
The objective of **mutation** is to create diversity in the population.

IV. RESULTS AND DISCUSSIONS

In order to test the capability of NSGA algorithm for the shortest path routing problem, an undirected network with randomly generated 25 nodes was considered. Each of the links in the network is associated with two additive Quality of Service parameters, throughput and delay. The range of delay varies from 10 to 250 and the range of throughput varies from 5 to 200. The simulation was carried out on an IBM PC with Intel core processor and the coding was developed using NS2 version 2.33, software package. The simulation intends to show the behavior of a multi-objective evolutionary algorithm in terms of optimality of solutions and computational complexity. The algorithm was implemented and a series of simulation runs were conducted to test the effectiveness of the routing algorithm. For all the

runs, the sender is always the first node and the receiver is the twenty fifth node since that would give the largest number of possible paths in the network. The population size and maximum number of generations have been selected as 25 and 15 respectively. The probability for crossover, *Pc* and mutation, *Pm* are 0.8 and 0.1 respectively. The Pareto-optimal front discovered by the proposed approach is shown in Fig. 1.1.





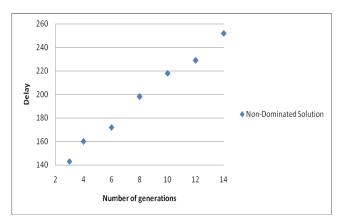


Fig 1.2 No of Generations Versus Delay

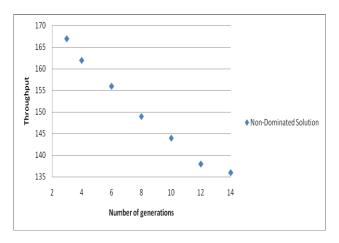


Fig 1.3 No of Generations Versus Throughput

V. CONCLUSION

In this paper, a feasible multi-objective evolutionary algorithm, NSGA,



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was proposed and simulated to solve the routing problem in communication networks. This paper described the implementation of NSGA algorithm. The results obtained show that NSGA may be an efficient approach for multiobjective shortest path problem. The experimental results obtained from the multi-objective solution revealed that the number of Pareto points increase with the number of generations. The results show that the NSGA algorithm is efficient for solving multi-objective routing problem where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the non-dominated solutions obtained are well distributed and have satisfactory diversity characteristics. The approach is quite flexible so that other formulations using different objectives and/or a larger number of objectives are possible. Simulation experiments demonstrate the quality of solutions and computational efficiency of NSGA. Various combinations of encoding and cross over methods were used for the demonstration of the algorithm.

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AUTHORS PROFILE



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