Adaptive Shifting of Auxiliary Strategies over Three Formulations of Multicast Routing Problem

Marcos Luiz de Paula Bueno
Faculty of Computer Science
Federal University of Uberlândia
Av. João Naves de Ávila 2160, Bloco B.
Uberlândia MG, Brazil
marcos@facom.ufu.br

Gina Maira Barbosa de Oliveira
Faculty of Computer Science
Federal University of Uberlândia
Av. João Naves de Ávila 2160, Bloco B.
Uberlândia MG, Brazil
gina@facom.ufu.br

ABSTRACT

Multicast routing algorithms have recently been intensively investigated due to the increment over the last years in the use of new point-to-multipoint applications. In this work, three formulations for the routing problem are investigated, considering 3, 4 and 5 objectives related to Quality of Service and Traffic Engineering requirements. A multiobjective evolutionary model is proposed to tackle this problem, using the well-known SPEA2 scheme as the underlying search. The key investigation performed here is about the incorporation of two strategies to help SPEA2 convergence to Pareto solutions, namely, filtering to reduce repeated individuals, and a mating selection based on neighborhood crossover. Results indicate that the adequacy of the strategies depends on the dynamics of currently non-dominated set over the generations. A new adaptive environment is proposed in which this information is considered periodically to decide what kind of strategy will be used in each situation.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods, graph and tree search strategies*; G.2.2 [**Discrete Mathematics**]: Graph Theory—*network problems, graph algorithms*

General Terms

Algorithms

Keywords

multicast routing, genetic algorithm, evolutionary multiobjective optimization, neighborhood

1. INTRODUCTION

In computer networks, a routing algorithm is responsible for calculating paths in which data flows will transit between network links. A multicast transmission corresponds to send data to several destinations, often involving requirements of Quality of Service (QoS) [8] and Traffic Engineering (TE) [1]. Point-to-multipoint applications can have different QoS requirements as maximum delay, minimum total cost and minimum bandwidth. On the other hand, Traffic Engineering (TE) is concerned with optimizing the network utilization aiming to reduce congestion bottlenecks, improve resource use and also to provide adequate QoS for final users.

An instance of Multicast Flow Routing Problem (MFRP) is given by a connected directed graph, with vertices representing hosts, edges representing network links. Also, a tuple of weights defines the features of the network links (as cost and current traffic), and a new traffic demand ϕ is set. In MFRP, we want to calculate a set of Pareto-optimal rooted trees T of G to carry ϕ into G, starting from a source vertex and passing by a subset of vertices called destinations. QoS and TE requirements establish objectives to be minimized or maximized and constraints to be attended, affecting the kind of multicast route we want to produce. Three different formulations of MFRP were considered in this work, simultaneously minimizing 3, 4 and 5 objective functions subject to a link capacity constraint. The following objective functions were considered: maximum link utilization, mean link utilization, total cost, maximum end-to-end delay and hops count.

2. EVOLUTIONARY MODEL

In this work, we tackle MFRP using a multiobjective evolutionary model based on the well-known SPEA2 algorithm [11] to find a set of non-dominated multicast routes. The major steps of this multiobjective model are resultant from several recent works [5], [4], [3] and two strategies are investigated here aiming to improve environment's convergence to Pareto routes, briefly described in the following.

In the proposed genetic algorithm, each individual is represented by a generic rooted tree; the initial population is generated by a random search algorithm for graphs (a randomized breadth-first or depth-first search, e.g.). Each individual is evaluated using the methodology of SPEA2. Regarding the mating selection, it can be done as in SPEA2, or by the means of neighborhood crossover (NC), to be explained later. The crossover operator builds a new tree inheriting common subtrees of its parents, as proposed in [7], [10]; subsequently, these subtrees are connected using heuristics we proposed in [5], [6], to form a valid solution to MFRP. Mutation step, in turn, randomly removes links of an individual, generating a forest of subtrees to be later connected through the same heuristics of crossover. Elitism is used for reinsertion.

Regarding the strategies to improve our model's convergence, the first one is a mechanism to reduce repeated individuals along the population - a kind of forced mutation -

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based on Takahashi-Matsuyama heuristic (f_{tm}) [3]. The second one is the usage of a different mating selection in SPEA2 based on Neighborhood Crossover [4]. These strategies are applied individually and joint to six instances of MFRP extracted from the literature in each formulation (3, 4 and 5 objectives). A detailed exposition of these techniques can be found on references [3] and [4].

3. EXPERIMENTAL RESULTS

To evaluate the adequacy of each auxiliary strategy, six instances of MFRP taken from literatures of Routing and Steiner problems were considered [2], [5]. The methodology of comparison consists on three metrics to assess convergence (*Error Rate* (er) [9], *Generational Distance* (gd) [9] and *Pareto Subset* (ps) [3], [4]), and one metric to assess diversity (*Maximum Spread* ($m3$)). The remaining parameters were set as: mutation probability equal to 10%, node disconnection rate used on mutation equal to 20%, $Np = 90$ and $Ng = 100$, where Np and Ng denote population size and number of generations, respectively.

The first of two series of experiments consisted on evaluating each configuration (SPEA2 basic, SPEA2+f_{tm}, SPEA2+NC, and SPEA2+f_{tm}+NC) over the three formulations (P3, P4 and P5, for short). Observing these results, it was clear that SPEA2+f_{tm} provided the best results on P3 and P4, while the usage of NC deteriorated the performance of the SPEA2 basic, in most instances. Conversely, the application of NC in P5 is an adequate strategy, while f_{tm} had a questionable applicability.

It is better to visualize the behavior described above through the chart on Fig. 1. In this chart, if, for instance, er has decreased from 20.8% (basic SPEA2) to 16.4% (SPEA2+f_{TM}), we compute a gain (reduction) of 21,15% for this scenario (P3, net A). Such chart highlights the observations made previously: considering P3 and P4 instances, the strategy SPEA2+f_{tm} returns the higher gains in convergence while strategy SPEA2+NC returns the higher gains in P5 instances. The composed strategy (SPEA2 + f_{tm} + NC) exhibits the most stable performance over different formulations (P3, P4 and P5); however, the gains using such strategy obtained are not so expressive.

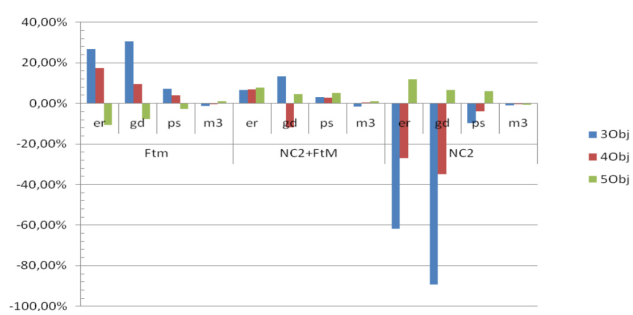

Figure 1: Positive and negative gains obtained due to the application of auxiliary strategies.

Subsequently, we verified that it seems to exist some relation between the size of current P (non-dominated solutions maintained by the GA in a given generation) and Np (size of population). We are looking to use this information of population dynamics to decide when to shift between technique, as long as the generations passes by. Thus, to run a second series of experiments, we defined a rule to alternate between the proposed strategies: from 5 to 5 generations, we compare $|P|$ with Np to decide which strategy to use. After running several combinations of intervals, we set the following rule:

a) if $0 \leq |P| < 50\%Np$: apply SPEA2+f_{tm};

b) else if $50 \leq |P| < 90\%Np$: apply SPEA2+f_{tm}+NC;

c) else apply SPEA2+NC.

This rule intends to work well for most cases of P3, P4 and P5. It will select the configuration SPEA2+f_{tm} on most cases of P3 and P4. It also will work for P5, since in this case $|P|$ quickly achieve Np, so it is necessary that NC comes into action in earlier generations to refine the large number of non-dominated solutions.

The results for the adaptive environment indicated that it overcomes the basic SPEA2 on all three formulations considered in this work. It also reach closer values to best configuration obtained on each formulation, which we can consider as a successfully implementation of our designed rule to periodically check out the current $|P|$ and decide which strategy to use.

4. FINAL REMARKS

This work tackled three formulations of MFRP with 3, 4 and 5 objectives related to Quality of Service and Traffic Engineering requirements. Our main focus here was to verify experimentally if two auxiliary strategies to increase intelligence to MFRP, namely, a filter to reduce repeated individuals and a mating selection based on neighborhood crossover, were able to improve GA's convergence and diversity. Since the filter reached the best results on formulations with 3 and 4 objectives, while neighborhood crossover reached best results on formulation with 5 objectives, our general conclusion is that it was not possible to specify a unique strategy to be used in all formulations, considering the application of the techniques here investigated, because a strong instability was observed when we migrate from 3 to 5 objectives.

A new adaptive environment was proposed as an attempt to handle these questions, in which the population dynamics was considered as an indicative of when to shift between techniques. Thus, we designed a rule to decide when to change the GA configuration based on the growth of the size of the currently non-dominated set. Although we specified the inferior and superior bounds for changing techniques, this task could be done using, for instance, a neural network or a utility function, requiring less or no intervention to parameterize this part of the process.

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