Fuzzy Simulated Evolution Algorithm For Topology Design Of Campus Networks

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Abstract- The topology design of campus networks is a hard constrained combinatorial optimization problem. It consists of deciding the number, type, and location of the active network elements (nodes) and links. This choice is dictated by physical and technological constraints and must optimize several objectives. Example of objectives are monetary cost, network delay, and hop count between communicating pairs. Furthermore, due to the nondeterministic nature of network traffic and other design parameters, the objective criteria are imprecise. Fuzzy Logic provides a suitable mathematical framework in such a situation. In this paper, we present an approach based on Simulated Evolution algorithm for the design of campus network topology. The two main phases of the algorithm, namely, *evaluation* and *allocation*, have been fuzzified. To diversify the search, we have also incorporated Tabu Search-based characteristics in the allocation phase of the SE algorithm. This approach is then compared with Simulated Annealing algorithm, which is another well-known heuristic. Results show that on all test cases, Simulated Evolution algorithm exhibits more intelligent search of the solution subspace and was able to find better solutions than Simulated Annealing.

Keywords: Structured Networks, Network Topology, Fuzzy Logic, Campus Networks, Simulated Evolution, Tabu Search, Combinatorial Optimization.

1 Introduction

A typical campus network consists of a large number of components, such as mainframe computers, mini systems, workstations, PCs, printers, etc. [1]. Various devices such as bridges, routers, hubs, multiplexers, are used to interconnect these computers and peripherals. The network topology is governed by several constraints. Geographical constraints dictate the breakdown of such internetworks into smaller parts or groups of nodes, where each group makes up what is called a LAN. Thus, we can define a campus network as a collection of interconnected LANs. Further, the nodes of a LAN may be subdivided into smaller parts, called *LAN segments*, to satisfy other constraints and objectives, for example, minimization of delay, containment of broadcast traffic, and minimization of cabling and equipment cost [1]. The topology design of LAN itself consists of two main issues: *segmentation*, where LAN segments are found, and *design of actual topology*, which consists of interconnecting the individual segments. Topology design at LAN level requires interconnection of LAN segments via bridges and layer 2 switches [2, 3].

It is recommended to structure the campus/enterprise network into the following layers (see Figure 1):

1. Local Access Layer, which provides workgroup access to the network.
2. Distribution Layer, which provides policy based connectivity among the workgroups. This layer is implemented with layer 3 switches, routers, and gateways. This is where packet manipulation takes place.
3. Backbone Layer, which provides high speed optimal transport of data among local sites.

Thus, the design of such a structured campus network can be approached in four steps:

1. Assignment of users/stations to LAN segments.
2. Assignment of LAN segments to local sites that will make up a single LAN.
3. Design of the internal structure of each local site (i.e., in what topology the LAN segments of a local

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site are connected). This step serves also to select appropriate switching equipment.

4. Backbone design, where the local sites are connected to the backbone. This step also will dictate the required backbone equipment.

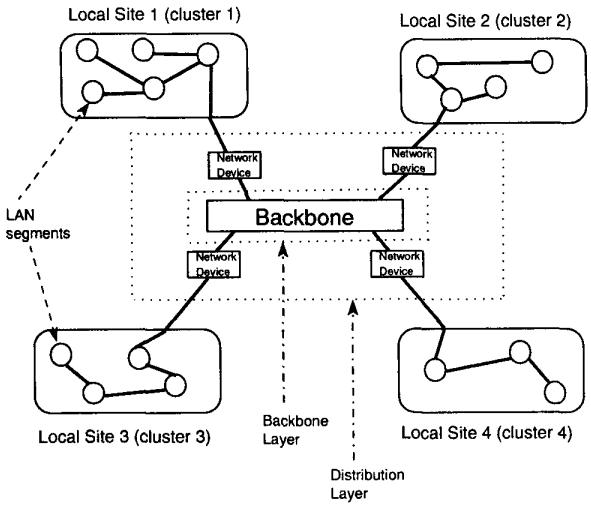


Figure 1: A typical campus network.

Topological design of campus networks is a hard problem [1]. Even the design of a LAN is itself an NP-hard problem [2, 3, 4]. Therefore, we have to use approximation methods known as 'heuristics' to get near optimal solutions in reasonable amount of time.

In this work, we have used simulated evolution (SE) algorithm [5] for topology design of structured campus networks based on several criteria, which are: monetary cost, maximum number of hops between any source-destination pair, and average network delay per packet. For assignment of segments to local sites, Augmenting Path algorithm is used [6]. According to recommended structured cabling standards, the network topology is constrained to be a tree. Hence we target to find a tree topology of desirable quality with respect to the three design objectives.

Since the backbone design problem is a multi-objective combinatorial optimization problem, we resort to fuzzy logic to formulate the various objectives in the form of fuzzy rules that will guide the search toward solutions of desirable quality.

In Section 2, assumptions and notation are given. Section 3 describes computation of objective values and constraints. Section 4 presents the proposed algorithm. Section 5 gives results and discussion. We conclude in Section 6.

2 Assumptions and Notation

- The term "node" is used to refer to different objects at different levels. At the segment level, a node refers to a user, while at the LAN level, a node refers to a segment. At the backbone level, a node refers to a LAN, which is also called a 'cluster'.
- A cluster is constrained to consist of segments of the same technology.
- The "capacity" of a network device is equal to the number of interfaces it has.
- The location of a node within a cluster can be represented by its (x, y) coordinates with respect to some reference point.
- Each node has a LAN network interface card of a particular technology such as 10/100baseT Ethernet or Token Ring type [7].
- The Root node is a switch acting as a collapsed backbone with given required interfaces.
- Between two local sites, only fiber optic cable [8] is used.
- There is a user specified limit on the number of network addresses per local site.
- The number of segments is known a priori i.e., users have already been assigned to segments.
- Hubs, switches, routers and other networking devices cannot be placed in any location. They have designated locations.
- Maximum allowed utilization of any link should not exceed a desired threshold (e.g., 60%).

In the following sections, we shall use the notation given below:

n	number of clusters.
m	number of LAN segments in a cluster.
T^b	$n \times n$ local site topology matrix where ${t^b}_{ij}$ = 1, if local sites i and j are connected and ${t^b}_{ij}$ = 0 otherwise.
ω_i	traffic within cluster i.
λ_i	traffic on link i.
$\lambda_{max,i}$	capacity of link i.
L	number of links of the proposed topology.
D_{nd}	delay due to network devices.
g_i	maximum number of clusters which can be connected to cluster i.
γ_{ij}	external traffic between clusters i and j.
γ	overall external traffic.
S_k	the forwarding speed of network device k.
h_{ij}	number of hops between clusters i and j.

3 Problem Statement

We seek to find a feasible topology of near optimum *overall cost*. A feasible topology is one that satisfies design constraints. Optimality of a topology is measured with respect to three objectives: monetary cost, average network delay per packet (network latency), and maximum number of hops between any source-destination pair.

Three important constraints are considered.

1. The first set of constraints is dictated by bandwidth limitation of the links. A good network would be one in which links are "reasonably" utilized, otherwise this would cause delays, congestion, and packet loss. Thus the traffic flow on any link i must never exceed a threshold value:

$$\lambda_i < \lambda_{max,i} \quad i = 1, 2, ..., s \tag{1}$$

where s is the total number of links present in the topology.

2. The second constraint is that the number of clusters attached to a network device G must not be more than the port capacity of that device.

$$\sum_{j=1}^{n} t_{ij}^{b} < g_i \qquad i = 1, 2, ..., n \qquad \forall i \neq j \tag{2}$$

3. The third set of constraints express the designer's desire to enforce certain hierarchies on the network devices. For example, he might not allow a hub to be the parent of a router or a switch to be the parent of a router.

Below, we describe the objective criteria used to measure the goodness of a given topology.

3.1 Monetary cost

The goal is to find the topology with minimum possible cost, while meeting all the requirements and constraints. The cost of the cable and the cost of the network devices are the two main entities affecting the monetary cost, therefore:

$$cost = (l \times c_{cable}) + (c_{nd}) \tag{3}$$

where l represents the total length of cable, c_{cable} represents the cost per unit of the cable used, and c_{nd} represents the combined costs of all the routers, switches, and hubs used.

3.2 Average Network Delay

The second objective is to minimize the average network delay, while considering the constraints and requirements.

To devise a suitable function for average network delay, we approximate the behavior of a link and network device by an M/M/1 queue [2].

The delay per bit due to network device between local sites i and j is $B_{i,j} = \mu b_{i,j}$, where $b_{i,j}$ is the delay per packet. If γ_{ij} is the total traffic through the network device between local sites i and j, then the average delay due to all network devices is:

$$D_{nd} = \frac{1}{\gamma} \sum_{i=1}^{d} \sum_{j=1}^{d} \gamma_{ij} B_{ij} \tag{4}$$

The, total average network delay is composed of delays of links and network devices and is given by [2]

$$D = \frac{1}{\gamma} \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_{max,i} - \lambda_i} + \frac{1}{\gamma} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} B_{ij} \tag{5}$$

3.3 Maximum number of hops between any source-destination pair

The maximum number of hops between any source-destination pair is also another objective to be optimized. A hop is counted as the packet crosses a network device.

4 Fuzzy Simulated Evolution Algorithm for Network Topology Design

4.1 Simulated Evolution

Simulated Evolution (SE) is a general iterative heuristic proposed in [9]. It falls in the category of algorithms which emphasize the behavioral link between parents and offspring, or between reproductive populations, rather than the genetic link [10]. This scheme combines iterative improvement and constructive perturbation and saves itself from getting trapped in local minima by following a stochastic perturbation approach. It iteratively operates a sequence of evaluation, selection and allocation steps on one solution. The selection and allocation steps constitute a compound move from current solution to another feasible solution of the state space. The SE proceeds as follows (see Figure 2). It starts with a randomly or constructively generated valid initial solution. A solution is seen as a set of movable elements, each with an associated goodness measure in the interval [0,1]. The main loop of the algorithm consists of three steps: **evaluation**, **selection** and **allocation**. These steps are carried out repetitively until some stopping condition is satisfied. In the evaluation step, the goodness of each element is estimated. In the selection step, a subset of elements are selected and removed from current solution. The lower the goddness of a particular element, the higher is its selection probability. A bias parameter B is used to compensate for inaccuracies of goodness measure. Finally, the allocation step tries to assign the selected elements to better locations. Other than these three steps, some input parameters for the algorithm are set in an earlier step known as **initialization**.

Simulated_Evolution($B, \Phi_{initial}$, *StoppingCondition*)
NOTATION
B= Bias Value.
Φ= Complete Solution.
e_i= Individual link in Φ.
O_i= Lower bound on cost of i^{th} link.
C_i= Current cost of i^{th} link in Φ.
g_i= Goodness of i^{th} link in Φ.
S= Queue to store the selected links.
ALLOCATE(e_i, Φ_i)=Function to allocate e_i in partial solution Φ_i
Begin
Repeat

EVALUATION: **ForEach** $e_i \in \Phi$ **DO**
begin
$g_i = \frac{O_i}{C_i}$
end
SELECTION: **ForEach** $e_i \in \Phi$ **DO**
begin
IF *Random* $> Min(g_i + B, 1)$
THEN
begin
$S = S \cup e_i$; Remove e_i from Φ.
end
end
Sort the elements of S
ALLOCATION: **ForEach** $e_i \in S$ **DO**
begin
ALLOCATE(e_i, Φ_i)
end

Until *Stopping Condition is satisfied*
Return Best solution.
End (*Simulated_Evolution*)

Figure 2: Structure of the simulated evolution algorithm.

4.2 Proposed Algorithm and Implementation Details

This section describes our proposals of fuzzification of different stages of the SE algorithm. We confine ourselves to tree design because they are minimal and provide unique path between every pair of local sites.

4.3 Initialization

The initial spanning tree topology is generated randomly, while keeping into account the feasibility constraints mentioned earlier.

4.4 Proposed Fuzzy Evaluation Scheme

The **goodness** of each individual is computed as follows. In our case, an individual is a **link** which interconnects two local sites (at the backbone level) or two network devices (at the local site level). In the *fuzzy evaluation scheme*, monetary cost and optimum depth of a link (with respect to the root) are considered fuzzy variables. Then the goodness of a link is characterized by the following rule.

Rule 1: IF a link is *near optimum cost*
AND *near optimum depth*
THEN it has *high goodness*.

Here, *near optimum cost*, *near optimum depth*, and *high goodness* are linguistic values for the fuzzy variables cost, depth, and goodness. Using and-like compensatory operator [11], Rule 1 translates to the following equation for the fuzzy goodness measure of a link l_i.

$$g_{l_i} = \mu^e(l_i) = \alpha^e \times min(\mu_1^e(l_i), \mu_2^e(l_i)) + (1 - \alpha^e) \times \frac{1}{2} \sum_{i=1}^{2} \mu_i^e(l_i) \quad (6)$$

The superscript e stands for **evaluation** and is used to distinguish similar notation in other fuzzy rules. In Equation 6, $\mu^e(l_i)$ is the fuzzy set of *high goodness links* and α^e is a constant. The $\mu_1^e(l_i)$ and $\mu_2^e(l_i)$ represent memberships in the fuzzy sets *near optimum monetary cost* and *near optimum depth*.

In order to find the membership of a link with respect to *near optimum monetary cost*, we proceed in following manner. From the cost matrix, which gives the costs of each possible link, we find the minimum and maximum costs among all the link costs. We take these minimum and maximum costs as the lower and upper bounds and call them "LCostMin" and "LCostMax" respectively and then find the membership of a link with respect to these bounds. Furthermore, in this work, we have normalized the monetary cost with respect to "LCostMax". The required membership function is represented as depicted in Figure 3, where $x-axis$ represents $\frac{LCost}{LCostMax}$, $y-axis$ represents the membership value, $A = \frac{LCostMin}{LCostMax}$, and $B = \frac{LCostMax}{LCostMax} = 1$.

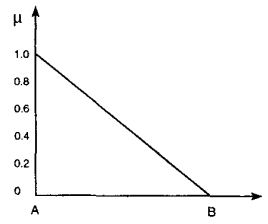


Figure 3: Membership function for the objective to be optimized.

In the same manner, we can find the membership of a link with respect to *near optimum depth*. The lower limit, which we call "LDepthMin" is taken to be a depth of 1 with respect to the root (see Figure 4). The upper bound, which we call "LDepthMax" is taken to be 1.5 times of the maximum depth generated in the initial solution or a maximum of a user specified limit.[1] For example, if in the initial solution, the maximum depth turns out to be 4, then "LDepthMax" for the depth membership function would be 6. This is done to give flexibility

[1]This user specified limit may be a design constraint, e.g., i. each hop represents a router that uses Routing Information Protocol (RIP) then a reasonable limit would be 7, i.e., a branch of the tree should not have more than 7 routers.

to links which may have more depth than the one in the initial solution. If we take the initial solution maximum depth as "LDepthMax", then in the following iterations some links with higher depths will have a membership value of zero (with respect to depth membership function) and thus they will not be able to play any role as far as depth is concerned. However, due to technological limitations, we have limited the maximum possible depth to 7, in the case when "LDepthMax" turns out to be more than 4. The reason for having the maximum depth of 7 is that the hop limit for RIP is 15. This means that if a maximum depth of 7 is taken, then in the worst case we would have a total of 14 hops from a source to a destination. The membership function with respect to *near optimum depth* can be represented as illustrated in Figure 3, where $x - axis$ represents $LDepth$, $y - axis$ represents the membership value, $A = LDepthMin$, and $B = LDepthMax$.

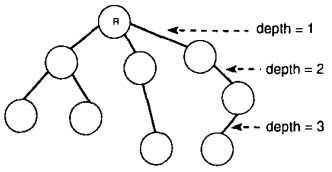


Figure 4: Depths of links with respect to the root.

4.5 Selection

In this stage of the algorithm, for each link l_i in current tree topology, where i = 1,2,..., *n-1*, a random number $RANDOM \in [0,1]$ is generated and compared with $g_{c_i} + B$, where B is the selection bias. If $RANDOM > g_{c_i} + B$, then link l_i is selected for allocation and considered removed from the topology. Bias B is used to control the size of the set of links selected for removal.

A bias methodology called *variable bias* [12] has been used in this paper. The *variable bias* is a function of *quality of current solution.* When the overall solution quality is bad, a high value of bias is used, otherwise a low value is used. Average link goodness is a measure of how many "good" links are present in the topology. The bias value changes from iteration to iteration depending on the quality of solution. The *variable bias* is calculated as follows:

$$B_k = 1 - G_{k-1}$$

where B_k is the bias for k^{th} iteration and G_{k-1} is average goodness of all the links at the end of $(k-1)^{st}$ iteration.

4.6 Proposed Fuzzy Allocation Scheme

During the **allocation** stage of the algorithm, the selected links are removed from the topology one at a time. For each removed link, new links are tried in such a way that they result in overall better solution. Before the allocation step starts, the selected links are sorted according to their goodness values, with the link with the worst goodness being the head-of-line in the queue.

In the *fuzzy allocation scheme*, the three criteria to be optimized are combined using fuzzy logic to characterize a good topology, as depicted in Figure 5.

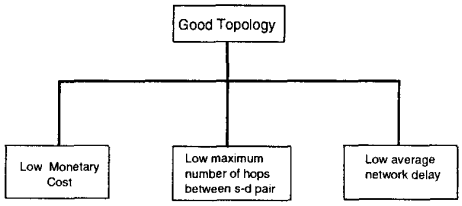


Figure 5: Basic components for a good topology.

The reason for using fuzzy logic is that the characterization of a good topology with respect to several criteria is usually based on heuristic knowledge which is acquired through experience. Such knowledge is most conveniently expressed in linguistic terms, which constitute the basis of fuzzy logic. For the problem addressed in this paper, a good topology is one that is characterized by a low monetary cost, low average network delay, and a small maximum number of hops. In fuzzy logic, this can easily be stated by the following fuzzy rule:

> Rule 2: **IF** a solution X has *low monetary cost*
> AND *low average network delay*
> AND *low maximum number of hops between any source-destination pair*
> **THEN** it is a *good topology.*

The words "low monetary cost", "low average network delay", "low maximum number of hops", and "good topology" are linguistic values, each defining a fuzzy subset of solutions. For example, "low average network delay" is the fuzzy subset of topologies of low average network delays. Each fuzzy subset is defined by a membership function μ. The membership function returns a value in the interval [0,1] which describes the degree of satisfaction with the particular objective criterion. Using the and-like ordered weighted averaging operator [11], the above fuzzy rule reduces to the following equation.

$$\mu^a(x) = \beta^a \times min(\mu_1^a(x), \mu_2^a(x), \mu_3^a(x)) + (1-\beta^a) \times \frac{1}{3}\sum_{i=1}^{3} \mu_i^a(x) \qquad (7)$$

where $\mu^a(x)$ is the membership value for solution x in the fuzzy set *good topology* and β^a is a constant in the range [0,1]. The superscript a stands for allocation. Here, μ_i^a

for $i = \{1,2,3\}$ represents the membership values of solution x in the fuzzy sets *low monetary cost*, *low average network delay*, and *low maximum number of hops between any source-destination pair* respectively. The solution which results in the maximum value for Equation 7 is reported as the best solution found by the SE algorithm.

Below we will see how to get the membership functions for the three criteria we have mentioned above.

4.6.1 Membership Function for Monetary Cost

First, we determine two extreme values for monetary cost, i.e., the minimum and maximum values. The minimum value, "TCostMin", is found by using the Esau-Williams algorithm [13], with all the constraints completely relaxed. This will surely give us the minimum possible monetary cost of the topology. The maximum value of monetary cost,"TCostMax", is taken to be the monetary cost generated in the initial solution. The monetary cost is normalized with respect to "TCostMax". The corresponding membership function is shown in Figure 3, where $x-axis$ represents $\frac{TCost}{TCostMax}$, $y-axis$ represents the membership value, $A = \frac{TCostMin}{TCostMax}$, and $B = \frac{TCostMax}{TCostMax} = 1$.

4.6.2 Membership Function For Average Network Delay

We determine two extreme values for average network delay. The minimum value, "TDelayMin", is found by connecting all the nodes to the root directly, ignoring all the constraints and then calculating the average network delay using Equation 5. The maximum value of average delay,"TDelayMax", is taken to be the average delay generated in the initial solution. The average delay is normalized with respect to "TDelayMax". The membership function is shown in Figure 3, where $x - axis$ represents $\frac{TDelay}{TDelayMax}$, $y - axis$ represents the membership value, $A = \frac{TDelayMin}{TDelayMax}$, and $B = \frac{TDelayMax}{TDelayMax} = 1$.

4.6.3 Membership Function For Maximum Number of Hops

Again, two extreme values are determined. The minimum value, "THopsMin", is taken to be 1 hop, which will be the minimum possible in any tree. The maximum value,"THopsMax", is taken to be the maximum number of hops between any source-destination pair generated in the initial solution. The membership function is shown in Figure 3, where $x - axis$ represents $THops$, $y - axis$ represents the membership value, $A = THopsMin$, and $B = THopsMax$.

In the proposed allocation scheme, all the selected links are removed one at a time and trial links are placed for each removed link. We start with the head-of-line link, i.e. the link with the worst goodness. We remove this link from the topology. This divides the topology into two disjoint topologies, as depicted in Figure 6.

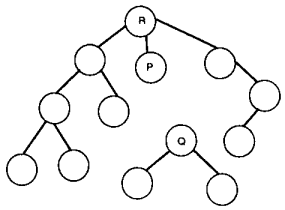


Figure 6: Two disjoint trees containing nodes P and Q.

Now the placing of trial links begins. In this work, the approach to place trial links is as follows. At most ten trial moves (i.e., trial links) are evaluated for each removed link. One point to mention is that for the ten moves, some moves may be invalid. However, we search for only four "valid" moves. Whenever we find four valid moves, we stop, otherwise we continue until a total of ten moves are evaluated (whether valid or invalid). The removal of a link involves two nodes P and Q, of which node P belongs to the subtree which contains the root node and node Q belongs to the other subtree, as shown in Figure 6. For the ten moves we make, five of them are greedy and five are random. For the greedy moves, we start with node Q and five *nearest* nodes in the other subtree are tried. For the random moves, we select any two nodes in the two subtrees and connect them.

It may so happen that all the ten moves are invalid, in which case the original link is placed back in its position. The valid moves are evaluated based on Equation 7 and the best move among the ten moves is made permanent. This procedure is repeated for all the links that are present in the set of selected links. In the allocation phase, we have used tabu search characteristics. As mentioned above, in the allocation phase certain number of moves are made for each link in the selection set and the best move is accepted, making the move (i.e., link) permanent. This newly accepted link is also saved in the *tabu list*. Thus our *attribute* is the link itself. The *aspiration criterion* adopted is that if the link that had been made tabu produces a higher membership value than the current one in the membership function "good topology", then we will override the tabu status of the link and make it permanent. This strategy prevents the selection and allocation of a tree from repetitvely removing the same link and replacing it with a link of equal or worse goodness. For details of tabu search, refer to [5].

4.7 Stopping Criterion

In our experiments, we have used a fixed number of iterations as a stopping criterion. We experimented with different values of iterations and found that for all the

Name	# of Local Sites	LCostMin	LCostMax	TCostMin	TDelayMin	Traffic
n15	15	1100	9400	325400	2.14296	24.63
n25	25	530	8655	469790	2.15059	74.12
n33	33	600	10925	624180	2.15444	117.81
n40	40	600	11560	754445	2.08757	144.76
n50	50	600	13840	928105	2.08965	164.12

Table 1: Characteristics of test cases used in our experiments. LCostMin, LCostMax, and TCostMin are in US$. TDelayMin is in milliseconds. Traffic is in Mbps.

Case	SA				SE					% Gain		
	C	D	H	T	TL	C	D	H	T	C	D	H
n15	318000	3.469	6	1.17	2	297100	2.78	4	2.25	6.57	19.86	33.3
n25	511320	3.725	6	3	5	483210	3.537	6	4	5.497	5.047	0
n33	708135	5.189	9	5.5	6	682465	4.19	6	8	2.76	19.25	33.3
n40	903735	5.213	8	27.5	7	783970	4.441	9	26	13.25	14.81	-11.1
n50	1124720	5.943	10	57	7	983020	5.245	11	65	12.6	11.74	-9.09

Table 2: Comparison of SA and SE. C = Cost in US $, D = Delay in milli seconds per packet, H = hops, T = execution time in minutes, TL= Tabu list size. The percentage gain shows the improvement achieved by SE compared to SA.

test cases, the SE algorithm converges within 4000 iterations or less.

5 Results and Discussion

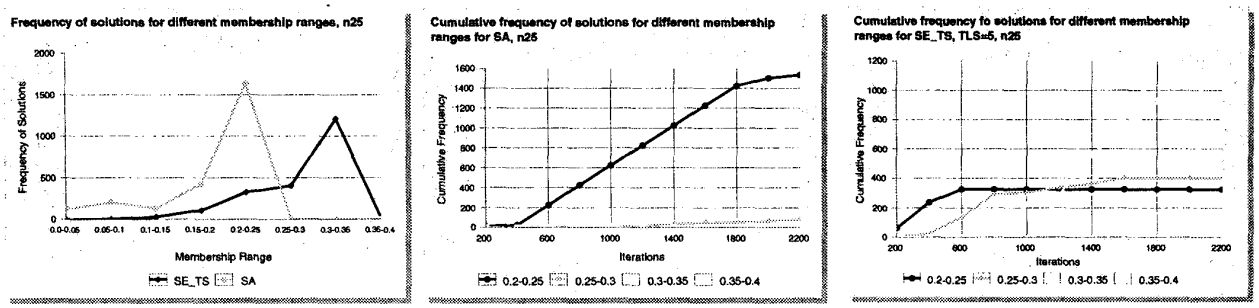
The SE algorithm described in this paper has been tested on several randomly generated networks. For each test case, the traffic generated by each local site was collected from real sites. Other characteristics, such as the number of ports on a network device, its type, etc. were assumed. However, the costs of the network devices and links were collected from vendors. The characteristics of test cases are listed in Table 1. The smallest test network has 15 local sites and the largest has 50 local sites.

We compare the proposed SE with simulated Annealing (SA) algorithm [5]. SA has four important parameters which need to be tuned very carefully. These are: cooling rate α, constant β, initial temperature T_0, and M which represents the time until next parameter update. After trial runs, appropriate values of these parameters were found to be α=0.9, β=1.0, T_0=10, and M=10.

Table 2 presents the results for SA and SE. From this table, it is observed that SE performs better than SA as far as monetary cost objective is concerned. In all the test cases, a gain is achieved by SE. For example, a gain of 12.6 % is achieved in case of **n50**. A similar behavior is seen for average network delay metric, where SE achieves gain in all the cases, e.g. in case of **n40**, where a gain of 14.81% is observed. Similarly, for maximum number of hops metric, a gain is achieved for small (**n15**) and medium (**n33**) size test cases, with a loss of one hop for **n40** and **n50**. However, the loss in maximum hops for **n40** and **n50** is compensated by the improvement in the monetary cost and average network delay metrics. As far as the execution time is concerned, SE has a slightly higher execution time than SA in most of the cases. It is due to the fact that SA performs one move per iteration while SE performs multiple moves in a single iteration.

In order to compare the quality of search space of SA and SE, frequency of solutions for different membership ranges is plotted against the membership value in Figure 7(a) for **n25**. In SA, only one individual (link) is selected at a time, and only one move is allowed for that selected link. If the new link is not a feasible one or does not pass the Metropolis criterion [5], then the original link is placed back in its position. This implies that there may be iterations where original links are placed back and no alteration takes place to the currently existing solution. Therefore, such iterations are not included as giving a new solution for SA. This in turn gives a total of 2200 iterations (out of 4000 iterations) where an alteration took place in the solution. Thus, only these 2200 iterations (solutions) are plotted in Figure 7(a). In this figure, it is observed that SE has more solutions falling in higher membership ranges than SA, suggesting that SE has investigated a better solution subspace. For example, SA has most of the solutions in the membership range 0.2-0.25, whereas SE has most of the solutions in the range 0.3-0.35.

Figures 7(b) and (c) illustrate very interesting and desirable behavior of SE. The figures plot the cumulative frequency of solutions for different membership ranges after each 200 iterations for **n25**. In Figure 7(b), the plot for SA shows that most of the solutions are falling in membership range of 0.2-0.25 where the solutions in this range are few initially but with the passage of iterations, the cumulative frequency of solutions increases. This figure also shows that there are no solutions at all in higher membership ranges. On the other hand, the cumulative distribution of solutions in different ranges for SE in Figure 7(c) shows a pattern where solutions with higher membership ranges are initially less. As more iterations are executed, the cumulative frequency of so-



(a) (b) (c)

Figure 7: Comparison of SE algorithm with SA for different membership ranges in fuzzy set "good topology". (a), (b) & (c) respectively compare the frequency of solutions, cumulative frequency of solutions for SA, and cumulative frequency of solutions for SE.

lutions with higher membership ranges increases, while the cumulative frequency of solution with lower memberhsip ranges remains the same, suggesting that with time, the algortihm is evolving towards better solution subspaces.

6 Conclusion

In this paper we have presented a fuzzy SE for backbone topology design of campus networks. The proposed SE algorithm was always able to find feasible topologies with desirable qualities. Comparison with SA showed that the search performed by SE is more intelligent, that is, the solution subspace investigated by SE is of superior quality than that of SA. Further, as time elapsed, SE progressively evolved toward better solutions, a desirable characteristic of evolutionary heuristics.

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