A Methodology for Topological Design of Computer Communication Networks under Link Reliability Constraints

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This paper describes a method to design a cost effective computer communication network which employs unreliable links. The problem of selecting a capacity value for each link in a computer communication network is considered when different links have different reliabilities. The network topology and the total capacity of the network are given; a set of reliability values for the candidate links and the expected grade of service from the network are also available. The goal is to obtain the least costly feasible design where costs include both the link capacity and the link reliability. We present a general mathematical model for this problem and formulate the relevant constraint equations. The model is an improvement over our earlier work . Next, Lagrangean relaxation and subgradient optimization techniques are used to obtain an optimum solution for the model. The methodology is tested on several topologies, and, in all cases, good feasible solutions as well as tight lower bounds are obtained.

Keywords: Network topology design, link reliability, two-variable optimization, Lagrangean relaxation, subgradient optimization, heuristic.

1. Introduction

A Computer Communication Network (CCN) is a set of geographically distributed autonomus computers which are connected by communication links to exchange inter-computer messages. Both the number and the range of applications, supported by CCNs, have increased significantly over the years. As a result, a variety of wide area networks and a host of local area networks are currently available. The objective of the topological design [1–3] of a CCN is, in general, to achieve a specified performance at a minimal cost. It assigns the links as well as their capacities for connecting the network nodes and has several performance and economic implications.

A variation of topological design with reliability constraints is a problem where, given a finite set of nodes and a finite set of links with nonzero failure probabilities, the objective is a cost-efficient selection of link capacities sufficient to satisfy the node-to-node traffic demands (or, grade of service) in normal and failed conditions. Similar problems have been addressed by a few researchers in recent past [1–10]. A variety of mathematical formulations of the problem with exhaustive and heuristic algorithms to solve it have been developed with partial success. But none of them, except Gavish et. al. [5], has taken the reliability measure explicitly into the design cost. Gavish [5], too, considered the reliability constraint for fibre-optic networks only. The formulation, developed in this paper, involves reliability constraints through grade of service which is a direct function of link reliabilities.

The model followed in this paper is based on the following arguments [9,11,12]. During its operational phase, every CCN passes through a number of states which are characterized by sub-capacity traffic flows through links. The links are forced to operate under below capacity conditions due to several uncontrollable environmental factors like irregular replacement of facilities (i.e., changes in topology), network congestion, cable cut, buffer overflow, packet loss or duplication, inefficient protocol, bad routing strategy, software bugs etc. To take all these factors (leading to degradation in network performance) into account, we specify a new parameter, called link reliability p, which measures the extent to which a link can be utilized to its maximum capacity over a period. The complement of p i.e., $(1-p)$ is called the failure probability q of the link.

This paper deals with the following problem: how to select the link capacities for non-zero link failure probabilities in a CCN so as to ensure an acceptable grade of service (i.e. performance level) at a minimum cost. The topology of the network can accordingly be refined upon the findings of the solution to match the desired link capacities and the traffic requirement characteristics.

2. Background

The problem considered in this paper is faced by a network designer whenever a new network is set up, or when an existing network is expanded. Formal treatment of the backbone network design problem in a general setting [1–3,5–7] exists for a long time and, recently, some of the current research [4, 8–12, 15–17] have dealt with the subproblems independently. But few of them have addressed the capacity assignment problem [12] from the point of view of link failure probability [10–12]. This is often inappropriate, in that the close relationship between the capacity value of a link and the delay (or the congestion incurred by a given flow) on that link makes it difficult to claim that the solution for a given grade of service, expected from the network, is good enough. The literature, focusing on both the issues of link capacity and link failure probability together, is very limited [4,8–10,17]. In Ref [12], authors incorporated the link failure constraints into capacity assignment problem, assuming failure probability for each link as an input parameter. They have also introduced link failure probability concept to the hierarchical design [14] based on the clustering concepts [7]. However, a characteristic common to both afore mentioned attempts, is to consider the link cost as independent of its reliability. This affects the usefulness of those algorithms for real life applications. This is why the capacity assignment problem has been reformulated in this paper as a generalized optimization problem with the design cost being a function of both the link capacity and the link reliability.

3. Mathematical Formulation of the Problem

In this section, we develop a mathematical programming formulation of the network design problem and then solve it by Lagrangean relaxation method [13] in the next section. To develop the mathematical model, the following notations are used throughout the paper.

Notations:

M =Total number of links in the network

C =Total capacity of the network

$\overline{C}$ =Total effective capacity of the network

G =Total cost of the network

c_i =Capacity of link $i, i \in [1, M]$(decision variable)

p_i =Reliability of link $i, i \in [1, M], 0 \leq p_i < 1$

q_i =Failure probability of link $i, q_i = (1 - p_i)$

f_i =Maximum input traffic for link $i, i \in [1, M]$

Γ_i =Variable cost factor of link i (per effective capacity), $i \in [1, M]$

g =Grade of service

γ_i =Fixed cost factor of link $i, i \in [1, M]$

$\alpha_1, \alpha_2, \alpha$ =Computational cost parameters, $(\alpha_1, \alpha_2, \alpha > 1)$

$\vec{\rho}, \vec{\mu}$ =vector of Lagrangean multipliers.

In general, the formulation of a topological design problem corresponds to different choices in design variables, performance measures and constraints. In this paper the following formulation of the problem is selected:

Given (input data):

i) total number of network nodes and links (M)

ii) total capacity of the network (C bits/sec),

iii) coefficient vector (g_i) of fixed cost,

iv) reliability (p_i) of each link

v) grade of service (g)

vi) flow (f_i) on each link

vii) coefficient vector (Γ_i) of variable cost.

Variables (to be solved for):

each link capacity $c_i (i = 1, \ldots, M)$

Performance constraints (to be satisfied):

The grade of service (g) of the network is defined as $g = 1 - (\overline{C}/C)$. Link capacities, which can be supported by the final design, must add up to a value which is within $(1 - g)\%$ of C.

Objective (to optimize):

To optimize the network cost satisfying the given constraints.

Based on the above discussion the problem can be mathematically formulated as a *single variable* nonlinear combinatorial optimization problem:

$$\text{Minimize: } G = \sum_{i=1}^{M} (c_i \gamma_i)^{\alpha}, \tag{1}$$

$$\text{Subject to: } C = \sum_{i=1}^{M} c_i \tag{2}$$

$$\overline{C} = \sum_{i=1}^{M} c_i (1 - q_i) \tag{3}$$

$$g = 1 - (\overline{C}/C) \tag{4}$$

$$\alpha > 1 \tag{5}$$

In equation (1), α is a computational cost parameter which has been used to determine the nature of the cost function G. For instance, if α is set to be less than unity, the cost function becomes concave for which only a near optimal solution can be obtained. If a linear cost function is desired, then α is to be made equal to unity. However, our aim was to formulate the problem as a nonlinear combinatorial optimization problem (in order to fit it into our solution methodology) as well as to obtain an optimal solution at the same time. To achieve this purpose, we have assumed α to be greater than unity. But, if a solution for a linear cost function is still necessary with our formulation, this is also possible by putting a value of α which is very close to but slightly greater than unity (for e.g., $\alpha = 1.0001$) in the solution. This will be exemplified in the next section where we will find out the solution for c_i. More details can be found in Ref [12] or Ref [14].

The way in which the cost function is presented in the above equation (1) is a somewhat weaker formulation of the problem in the sense that it considers only the fixed cost but not the variable cost which will be a function of link reliability. We have solved the above formulation in Ref [12]. The solution methodology was tested on various sets of data to illustrate the applicability of the technique to a number of non-trivial problems. But the solutions obtained from the above formulation differ from the real life solutions quite a bit due to the inherent lack of reliability consideration. This motivates us to refine the model so as to include the link reliability parameter into the cost function. This new model, along with its comparison with the previous model, is a major contribution of this paper.

The formulation to be presented here is a generalization of the one introduced above. The two formulations share some common assumptions, and there are similarities in the solution procedures as well. The reader is referred to our earlier work in Ref [12] for finer details, which are omitted here for the sake of brevity.

Since the model accounts, in an unified way, for both the link failure probability and the capacity assignment issues, the cost function is redefined as follows (in terms of two variables, namely c_i and p_i):

$$G = \sum_{i=1}^{M} (c_i \gamma_i)^{\alpha_1} + (c_i p_i \Gamma_i)^{\alpha_2},$$

where α_1 and α_2 are two cost parameters.

Now we can reformulate the network design problem as the following *two variable* nonlinear optimization problem:

$$\text{Minimize: } \sum_{i=1}^{M} (c_i \gamma_i)^{\alpha_1} + (c_i p_i \Gamma_i)^{\alpha_2} \tag{1}$$

$$\text{Subject to: } C = \sum_{i \in M} c_i \tag{2}$$

$$\overline{C} = \sum_{i \in M} c_i p_i \tag{3}$$

$$g = 1.0 - (\overline{C}/C) \tag{4}$$

$$f_i \leq p_i C_i \tag{5}$$

$$0 \leq p_i < 1 \tag{6}$$

$$\alpha_1, \alpha_2 > 1 \tag{7}$$

The objective function captures the total cost including both the fixed cost of buying the links and the variable cost of using the links (weighted by the probabilities assuming that the failure prone links charge less). This reflects the conjecture that the cost of a link is not only proportional to its capacity but also proportional to its quality (i.e., reliability). The constraint equation (2) assures that the sum of all link capacities is equal to the given capacity bound. The constraint equation (4) ensures that the network will operate under the given grade of service. The constraint equations (5) and (6) are self-explanatory. Following the same logic described for a in case of the previous formulation of G, here also both α_1 and α_2 are assumed to be greater than unity in the last constraint equation (7).

4. Solution Procedure

The following approach is used to find the optimum solution of the problem. First, the constraints equations (2), (3), and (4) are relaxed and the corresponding Lagrangean dual is constructed. Next a subgradient optimization procedure is used in order to improve the quality of the Lagrangean lower bound. The solution to the Lagrangean problem, obtained at each iteration of the subgradient procedure, is used as the basis for generating feasible solution to the problem.

In spite of somewhat increased complexity, the Lagrangean relaxation of the present problem has the same fundamental structure as the one discussed in Ref [12]. We write the Lagrangean relaxation as:

$$L(\rho, \mu) = \sum_{i=1}^{M} (c_i \gamma_i)^{\alpha_1} + (c_i p_i \Gamma_i)^{\alpha_2} + \sum_{i \in M} \rho_i \Big(\sum_{i \in M} c_i p_i - f_i \Big) + \sum_{i \in M} \mu \Big(\sum_{i \in M} c_i - C \Big)$$

subject to the constraint equations (2), and (5). Differentiating the Lagrangean relaxation partially with respect to c and equating the result to zero, the optimum value of c can be established [14]. The solution to this relaxation is given below. Details can be found in Reference [12] or [14].

$$c_i = [(-\rho_i p_i - \mu_i)/(\gamma_i \Gamma_i p_i)^{\alpha}]^{1/(\alpha-1)},$$

where $M \geq i \geq 1$ and we have taken $\alpha_1 = \alpha_2 = a$ for the sake of simplicity. Now we can choose a according to our convenience in computation. For example, if $\alpha = 2$, then the soluton becomes:

$$c_i = [(-\rho_i p_i - \mu_i)/(\gamma_i \Gamma_i p_i)^2]$$

Again, if we choose α to be 1.01, then we obtain a solution for a near linear cost function and it is given by:

$$c_i = [(-\rho_i p_i - \mu_i)/(\gamma_i \Gamma_i p_i)]^{100}.$$

This clearly exhibits the flexibility of our formulation.

Now we describe the subgradient procedure [15] used to estimate $(\vec{\rho}, \vec{\mu})$, the vector of multipliers corresponding to the Lagrangean that provides the tightest lower bounds. The detailed description of the procedure, comprising the subgradient algorithm, can be found in References [14] and [15].

Let $(\vec{\rho}, \vec{\mu}) \geq 0$ be a row vector of dual variables associated with constraints (2) and (5), respectively. Let us consider the following dual function:

$$L(\vec{\rho}, \vec{\mu}) = \operatorname*{Min}_{\delta \geq 0} \sum_{i=1}^{M} (c_i \gamma_i)^{\alpha_1} + (c_i p_i \Gamma_i)^{\alpha_2} + \sum_{i \in M} \rho_i \Big(\sum_{i \in M} c_i p_i - f_i \Big) + \sum_{i \in M} \mu \Big(\sum_{i \in M} c_i - C \Big).$$

We observe that $L(\vec{\rho}, \vec{\mu})$ is a piecewise linear concave function. For any $(\vec{\rho}, \vec{\mu}) \geq 0$, the vectors

$$\sum_{i=1}^{M} (c_i p_i - f_i) \text{ and } \sum_{i=1}^{M} (c_i - C)$$

are subgradient to L at $(\vec{\rho}, \vec{\mu})$.

A good approximate solution of the dual is obtained by applying a subgradient algorithm according to the following procedure:

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step 0: (initialization) $(\vec{\rho}^0, \vec{\mu}^0)$ is the starting solution;

step i: (iteration i) $(\vec{\rho}^i, \vec{\mu}^i)$ is the current solution;

i_1: compute the following:

$$L(\vec{\rho}^i, \vec{\mu}^i) = \sum_{k=1}^{M} (c_k^* \gamma_k)^{\alpha_1} + (c_k^* p_k \Gamma_k)^{\alpha_2}$$

$$+ \sum_{k=1}^{M} \rho_k^i \Big(\sum_{k=1}^{M} c_k^* p_k - f_k \Big) + \sum_{k=1}^{M} \mu_k^i \Big(\sum_{k=1}^{M} c_k^* - C \Big)$$

i_2: compute the following:

$$g^i = \sum_{i=1}^{M} c_i p_i - f_i \text{ and } g_2^i = \sum_{i=1}^{M} c_i - C$$

two subgradient vector of L at $(\vec{\rho}^i, \vec{\mu}^i)$.

i_3: update: $\vec{\eta}^{i+1} = \{\vec{\eta}^i + \Xi_i (g / \|\vec{g}^i\|\}$;

i_4: increment: $i \leftarrow i+1$

i_5: if the stopping criterion is satisfied, then go to end step, else go to step i;

end step: stop.

In the above algorithm, Ξ_i is the step size and many different possible strategies for the choice of the step size Ξ_i have been proposed thus far, and we refer to References [13] and [15] for more details. We have considered a simple and efficient way of choosing Ξ_i as:

$$\Xi_i = \Xi_0 (\psi)^i \text{ where } 0 < \psi < 1.$$

Extensive computational experience [14] shows that a value of ψ between 0.05 to 0.005 is well suited for most applications. Actually the best sustainable rate of convergence depends on the condition Lagrangean L.

An interesting feature of the method is that when the condition for convergence is fulfilled, i.e. when $\vec{\rho}^i \rightarrow \vec{\rho}^* \ (i \rightarrow \alpha)$, an upper

(Total capacity C=96000 bps, No of links M=18, No of nodes=12)

capacity	reliability
c[01]=6001.49	p[01]=0.60
c[02]=4974.17	p[02]=0.47
c[03]=5764.42	p[03]=0.57
c[04]=5448.32	p[04]=0.53
c[05]=5764.42	p[05]=0.57
c[06]=4420.99	p[06]=0.40
c[07]=4737.09	p[07]=0.44
c[08]=7028.82	p[08]=0.73
c[09]=8530.29	p[09]=0.92
c[10]=4025.87	p[10]=0.35
c[11]=4974.17	p[11]=0.47
c[12]=3788.79	p[12]=0.32
c[13]=3630.74	p[13]=0.30
c[14]=5369.29	p[14]=0.52
c[15]=6554.67	p[15]=0.67
c[16]=8530.29	p[16]=0.92
c[17]=4737.09	p[17]=0.44
c[18]=2208.29	p[18]=0.12
Total effective capacity $\overline{C}$ = 55,656 bps	

Tab. 1. Results obtained for the network of Figure 1

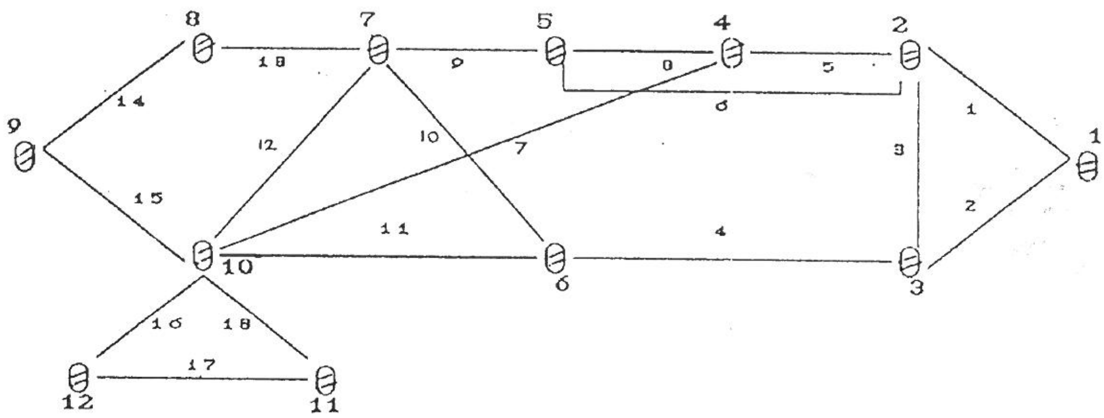

Fig. 1. A test network of 12 nodes and 18 links

bound on the distance between $\vec{\rho}^i$ and $\vec{\rho}^*$ is given by

$$\sum_{j=i}^{\alpha} \Xi_j = \Xi_0 \sum_{j=i}^{\alpha} (\psi)^j = \Xi_0 \frac{(\psi)^j}{1-\psi}.$$

The subgradient optimization procedure thus provides, in a finite number of iterations, an approximate solution $\vec{\overline{\rho}}$ of dual problem so that:

$$L(\vec{\overline{\rho}}) \leq L(\vec{\rho}^*) \leq L(\vec{\overline{\rho}})) + \tau,$$

where τ is a small positive deviation. Obviously, τ can be made as small as desired by allowing an increased number of iterations.

5. Computational Results

The model and the algorithm presented in this paper are currently implemented on a HP 9000 system. The software allows for an easy and flexible definition of the topology to be used and of the model parameters. After each iteration of the outer loop which contains an inner loop for a given number of subgradient iterations, control is returned to the user so that the user can stop the procedure if the solution is found to be satisfactory. Also at the beginning of each iteration of the outer loop, the user has the flexibility to change the values of some model parameters which control the procedure. The comprehensive output corresponding to the best feasible solution generated so far is written to the output file at the end of each iteration.

Extensive numerical experiments have been performed with the algorithm presented in this paper. Some of the results are presented here while a more detailed presentation can be found in Ref [14]. The experiments are conducted with two main purposes in mind: first, to test the performance of the algorithm and second, the impact of the various parameters on the solution generated, and thus to get a feeling for the appropriateness of the model to be used as a flexible design tool. A simple network with four nodes was first tested and the corresponding results are found quite satisfactory. Then we tried the algorithm with bigger networks [14] and were successful in obtaining either optimal or near optimal solutions quickly in 90% of the cases. One of these results obtained from a non-trivial 12 node topology (Figure 1) has been given in Table 1.

Since no previous work (excepting our earlier works [11,12]) has taken into consideration both the link reliability parameter and the grade of service constraint together, it would not be justified to compare our results with those obtained by other reserchers. This is why we have compared this solution with our previous work based on a single variable cost function [12]. For the 12-node network shown in Figure 1, we applied both the algorithms to obtain the link capacities, keeping the link reliability values unchanged for the sake of comparison. All other input parameters, such as α (=2), C (=96 Kbps), γ, g, f, and Γ, are also taken to be identical for both the cases. The comparative values of the capacities are shown in Table 2, and the corresponding graphs of link capacity versus link reliability are drawn in Figure 2.

(Total capacity $C = 96000$ bps, No of links $M = 18$, No of nodes = 12)

capacity values for two variable algorithm	reliability values for both algorithms	capacity values for one variable algorithm
c[01]=6001.49	p[01]=0.60	c[01]=5550.52
c[02]=4974.17	p[02]=0.47	c[02]=4790.47
c[03]=5764.42	p[03]=0.57	c[03]=5375.12
c[04]=5448.32	p[04]=0.53	c[04]=5141.26
c[05]=5764.42	p[05]=0.57	c[05]=5375.12
c[06]=4420.99	p[06]=0.40	c[06]=4381.21
c[07]=4737.09	p[07]=0.44	c[07]=4615.07
c[08]=7028.82	p[08]=0.73	c[08]=6310.57
c[09]=8530.29	p[09]=0.92	c[09]=7421.41
c[10]=4025.87	p[10]=0.35	c[10]=3908.88
c[11]=4974.17	p[11]=0.47	c[11]=4790.47
c[12]=3788.79	p[12]=0.32	c[12]=3613.49
c[13]=3630.74	p[13]=0.30	c[13]=3507.56
c[14]=5369.29	p[14]=0.52	c[14]=5082.80
c[15]=6554.67	p[15]=0.67	c[15]=5959.78
c[16]=8530.29	p[16]=0.92	c[16]=7421.41
c[17]=4737.09	p[17]=0.44	c[17]=4615.07
c[18]=2208.29	p[18]=0.12	c[18]=2144.18
Total = 95589.21 bps		Total = 90004.39 bps1
Cost = 5.614e + 08 units		Cost = 4.88 e + 08 units
Total effective capacity $\overline{C} = 55.656$ bps		Total effective capacity $\overline{C} = 42.280$ bps

Tab. 2. Comparative results obtained for the network of Figure 1

From Figure 2, it is clear that the solution quality has improved from the single variable case to the two variable case as the capacity values have increased for the same reliabilty values. The net increase in the effective capacity is 13,368 bits per second (from 42,288 bps to 55,656 bps) as noted in Table 2. This justifies our claim that the incorporation of link reliability into the cost function enhances the chance of obtaining a tighter lower bound [5,6]. Thus the two variable problem is more realistic than the corresponding one variable problem. However, this gain in solution quality is achieved at the expense of more computational cost involved. Although the rate of convergence of the algorithm is not affected by the added complexity in the cost function for the two variable case, the minimum cost increases from 4.88e+08 units (for one variable case) to $5.614e + 08$ units (for two variable case) as shown in Table 2. This is due to the fact that the cost function in the two variable case consists of two partial costs corresponding to two variables. But we must remember that, considering such a complex cost, function produces a better quality solution which is more accurate and better suited to practical situations.

The results of Table 2, when scrutinized carefully, indicate that the capacity increases linearly with the link reliability i.e., a less failure prone link should have more capacity. This relationship was noticed for our previous algorithm [12] too. A real life situation also demands so i.e., (C /p) should be constant. This result has been vindicated by nontrivial design examples, too [14]. A plot of C_i versus p_i in Figure 3 (in increasing order of p_i) for the design problem, whose network is given in Figure 1, clearly shows that this linear relationship holds true for both the *single variable* and the *two variable* formulations of the problem.

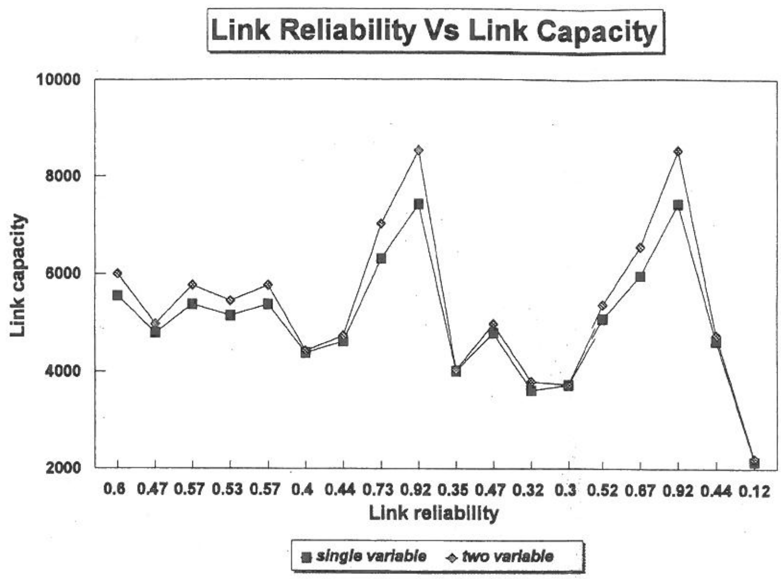

Fig. 2. A comparative result of link capacity against link reliability for one and two variable of formulations

6. Conclusion

In this paper, a design technique for computer communication networks with non zero link failure probabilities is considered. The design problem under reliability constraints has been formulated mathematically as a two variable non-linear optimization problem, which can be solved by Lagrangean based subgradient optimization technique.

The unreliable links model the failure of not only the links themselves, but also the network components which may directly or indirectly lead to a fall in effective network capacity. Unreliable links cause packets to be received in error or late or not at all, due to unacceptable delay, congestion, buffer overflow, high call-blocking probabilities and so on. Thus, in addition to the link capacities, the effect of link performance degradation should be taken into account in a network design.

The main value of this approach is that the model, as well as the optimization proce-

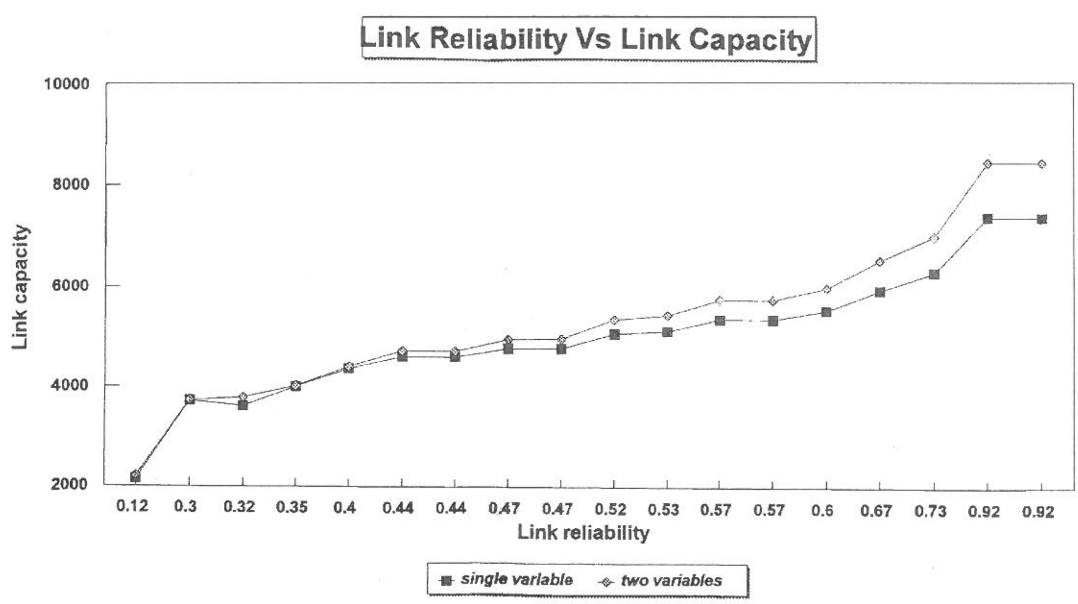

Fig. 3. Relationship between link capacity and link reliability for one and two variable of formulations

dure, deal simultaneously with both aspects of the problem, thus driving the solution closer to the optimum. As a possible extension of this work, the model introduced here can be further refined so that the sets of candidate capacities associated with each link will no longer be a part of the input set and will, instead, be dynamically generated within the model.

From the computational experience with the present procedure, it can be concluded that the procedure is both efficient and effective in identifying robust solutions that are satisfactorily close to the lower bound. The present model can be generalized to deal with hierarchical networks characterised by different clusters and levels [7]. The work is currently in progress in modelling and developing the solution technique for this hierarchical case. Another possible direction of future work could be to adapt our model to the existing works on network dimensioning [17] and cost allocation in capacitated networks [16].

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