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Robust Optimization for Cost Validation in Designing Service Networks

Ashish Chandra
College of Business
Illinois State University
Normal, IL 61761, USA
achand6@ilstu.edu

Abstract

In this work, we examine the cost effectiveness of routing traffic on service networks under random failures. Given a service network, that is subject to random link failures, we analyze the worst-case performance of the network in terms of the total cost incurred in routing the traffic to satisfy all the node pair demand requirements. Given $b \in \mathbb{N}$, we primarily focus on network failure scenarios, where b-simultaneous links are non-functional. It is important to note that computing the worst-case routing cost over a set of link failure scenarios is classified as an NP-Hard problem (Hochba 1997). We propose an approach that leverages recent developments in robust optimization, integer, and linear programming to construct convex relaxation of the original NP-Hard problem. Our approach exploits the intrinsic binary nature of the link functionality (i.e., links are either functional or dead), to construct the convex relaxations, that provide quick and strong upper bounds for the original intractable worst case routing cost problem. To substantiate our findings, we also provide computational results on real life service network topologies.

Keywords
Service networks (SN), Robust optimization, Mixed integer nonlinear optimization, Resilient network design, Service networks under uncertain failures.

1. Introduction
In the era of digital transformation, where the economy hinges ever more on service networks for essential functions, the design and optimization of these networks have become increasingly crucial for meeting the growing demands of the modern society. Service networks, encompassing telecommunications, transportation, supply chains, and more, serve as the backbone of global connectivity and economic activity. Ensuring the reliability of these networks has become paramount (Hong et al. 2018, Almaktoom et al. 2016, Yildiz et al. 2016, Khourshed et al. 2024). Service networks, owing to their constant evolution and global reach, are plagued by frequent failures, see for reference (Ahuja et al. 2018, Potharaju et al. 2013, Govindan et al. 2016, Chandra and Tawarmalani 2022). Thus, the design of such networks is fraught with uncertainties, including fluctuating demand patterns, evolving technology landscapes, and unforeseen disruptions (Yadav et al. 2018, Taha et al. 2015, Shahmoradi-Moghadama et al. 2021). One of the critical challenges in designing a service network is to efficiently route traffic through the network, ensuring full demand satisfaction and keeping in mind various factors such as cost efficiency, congestion, and dynamic demand patterns. Each of these service networks are deigned to perform a critical task, and with network failures becoming a new norm, there is a pressing need to ensure that the service networks perform their assigned tasks in a cost-efficient manner across all the potential failures. Cost validation plays a pivotal role in the design phase of service networks, as it entails assessing the economic feasibility and efficiency of proposed network configurations (Kaur et al. 2017, Bar-Noy et al. 1990, Bottani et al. 2010, Habib et al. 2022). Cost validation in service networks under random failures refers to the process of ensuring that the estimated costs related to service network operations are accurate and reliable, even when the network faces unforeseen disruptions. Effective cost validation helps in mitigating financial risks, optimizing

resource allocation, and enhancing decision-making processes. Moreover, for the service providers that use a service network, it is crucial to maintain a high service level agreement (SLA) amidst the random failures. Due to the competitive environment, service providers wish to provide a high SLA, at a lower cost, hence having the capability to quickly estimate the cost that achieves a high SLA is very critical. For instance, consider a supply chain service provider, having a maximum cost budget of *$C*. Due to a high SLA, the service provider seeks to ensure that all the source-destination demand requirements on the network are fully satisfied amidst random network failures. The question we adress in this paper is, can we come up with a scheme that can quickly give us an upper bound *($U)* on the total cost of routing to ensure full demand satisfaction. This is useful since, if $U \leq C$ then, this guarentees that given the cost budget we can indeed satisfy the required SLA.

Traditional optimization approaches often overlook the inherent uncertainties and variations in network parameters, leading to suboptimal solutions and cost overruns in real-world implementations. The most common methodology that has emerged to address this challenge is via exhaustive enumeration where the worst-case cost performance of the service network is obtained by first enumerating all the possible failure scenarios, and then computing the cost of routing under each of the listed failure scenarios (Matisziw et al. 2009, Albrecht et al. 2015, Ben Hammouda et al. 2020). Validating that the service network can cope with a range of failure scenarios, with an acceptable routing cost is challenging with the enumeration approach, as there are typically exponentially many failure scenarios to list out. For instance, validating a network design with $|E|$ edges across all b-simultaneous link failures, requires us to consider $\binom{|E|}{b}$ failure scenarios. The number of failure scenarios to consider increases exponentially as $|E|$ i.e., the number of links in the network increases. To see this, consider the following service network in Figure 1, with six edges and four nodes (A, B, s, d). There is one source (s) - destination (d) node pair that has a demand requirement to be met. Assuming that the network is subjected to all $b = 1$ simultaneous link failure scenarios, we wish to compute the worst-case traffic routing cost for the network that meets the demand requirement. With the exhaustive enumeration approach, we fist list out all $\binom{6}{1}$ failure scenarios in Figure 2. We note that in Figure 2, there are six graphs each corresponding to one of the six failure scenarios. The red colored link in each of the graphs denote the non-functional link in that failure scenario. Once the enumerated list of all single link failure scenarios is complete, we then compute the cost of routing for each of the six failure scenarios. In the next section, we introduce our approach to solve this problem.

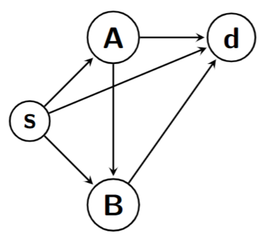

Figure 1. Example of a service network

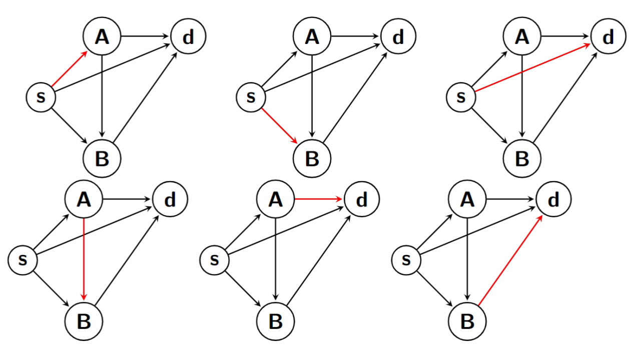

Figure 2. All one link failure scenarios (Red: Failed Link)

2. General Validation framework – Proposed modeling approach

With the advancements in the realm of network optimization, the robust optimization (Yang et al. 2008, Bertsimas 2003, Pishvaee et al. 2011) paradigm has emerged as a powerful tool to address uncertainties and variations inherent in real-world service networks. Robust optimization addresses these challenges by explicitly incorporating uncertainty into the optimization process. Given a set of network failure scenarios, computing the worst-case traffic routing cost to meet the demand requirements is a fundamental task within this domain. Traditional optimization techniques often fall short in handling the inherent uncertainties associated with real-world networks, leading to their incapability in capturing uncertain failures in the service networks. To overcome these limitations, robust optimization has emerged as a promising methodology for addressing uncertainty in traffic routing problems. Robust optimization techniques seek to develop solutions that perform well under a range of potential scenarios. By explicitly accounting for uncertainty and variability in service network parameters such as link capacities, traffic demands, and failure scenarios, robust optimization approaches can yield more reliable and resilient routing strategies (Chatzikontidou et al. 2017, Santoso et al. 2005). The application of robust optimization techniques in the context of cost validation for designing service networks has garnered increasing attention from researchers and practitioners alike. By considering a range of potential scenarios and ensuring that network designs perform well under various conditions, robust optimization methodologies aim to mitigate the risks associated with uncertainty while simultaneously optimizing cost objectives. This approach enables decision-makers to make informed and resilient network design decisions that are robust to uncertain future conditions. Our proposed approach models this worst-case cost analysis of the service network as a robust optimization problem. The general structure of a robust optimization problem is obtained as follows.

$$R^* = \max_{x \in \mathrm{X}} \min_{y \in Y(x)} f(x, y)$$

The above problem is a two-stage optimization problem, where the outer maximization happens over the variables $x \in \mathrm{X}$. Moreover, for any given $x' \in \mathrm{X}$, the inner minimization aims to minimize $f(x', y)$ over the variables $y \in Y(x')$. Typically, as is the case with our problem as well, for a given $x \in \mathrm{X}$, the inner optimization problem is a linear program (LP) in variables y.

3. Methods

Consider a graph, $G(N, E)$ where N and E are respectively the set of nodes and edges in G. Let $d: V \times V \to \Re$ be the traffic between node-pairs and $c: E \to \Re$ be the capacities of the links. The state of a link (i, j) under the failure scenario x is given by $x_{ij} \in \{0,1\}$ where $x_{ij} = 1$ indicates that the link (i, j) has failed and $x_{ij} = 0$ indicates that (i, j) is alive under scenario x. Given a failure scenario x, the network can reroute traffic. The most flexible response is to solve a multicommodity flow problem for the scenario$x$ (Chang, et al. 2019). We leverage this formulation to model the network routing mechanism, which minimizes the total cost of routing on the network. Table 1 and Table 2 respectively provide the list of parameters and variables used in the formulation. In formulation labeled (M), y_{ijt} is the flow destined to node t assigned on link (i, j), and $\delta_{(i=t)}$ is 1 if $i = t$ and 0 otherwise. Constraints (2) and (3) model the capacity and flow balance constraints, respectively. Constraints in (4) ensure that the flow variables are non-negative. The objective function described in (1) minimizes the total cost of routing in satisfying all the node pair demands, where P_{ij} for all links $(i, j) \in E$ is the cost associated with routing a unit traffic flow on link (i, j). For our computational results in Section 4.1, we assume P_{ij} for all $(i, j) \in E$, to be uniformly distributed between 1 and 10. Moreover, as we discussed earlier, given a failure scenario x, (M) is an LP.

Table 1. List of notations

Notation	Meaning of the notation
N	Set of nodes in the network
E	Set of edges in the network
$\boldsymbol{c_{ij}}$	Maximum flow capacity of link $(\boldsymbol{i}, \boldsymbol{j}) \in \boldsymbol{E}$
$\boldsymbol{d_{it}}$	Demand requirement from node $\boldsymbol{i}$ to node $\boldsymbol{t}$
$\boldsymbol{P_{ij}}$	Cost of routing a unit flow on link $(\boldsymbol{i}, \boldsymbol{j}) \in \boldsymbol{E}$

Table 2. List of variables

Variable	Definition of the variable
y_{ijt}	Flow destined to node t routed on link (i, j)
x	Link failure scenario capturing the state of all the links in the network
U	Utilization of the most congested link in the service network
λ, v	Dual variables for the constraints (2) and (3) respectively in formulation (M)

Given a set of failure scenarios X, our objective is to compute the worst-case routing cost among all failure scenarios $x \in$ X. The set X, is referred to as the set of uncertain failures. For our work we will be focusing on the set of all b simultaneous link failure scenarios in the network. This is a commonly used uncertainty set that is used across the supply chain networking and telecommunication community, see (Wang et al. 2010, Chang et al. 2019, Adenso-Díaz et al. 2018, Poudel et al. 2016) for reference.

$$(\mathbf{M}:)\ \min_{y,U} \sum_{t\in N;(i,j)\in E} y_{ijt} P_{ij} \tag{1}$$

$$\sum_{t\in N} y_{ijt} \le U c_{ij}(1 - x_{ij}) \qquad \forall (i,j) \in E \tag{2}$$

$$\sum_{j\in N} y_{ijt} - \sum_{j\in N} y_{jit} = d_{it} - \sum_{j\in N} d_{jt}\delta_{(i=t)} \qquad \forall i,t \in N \times N \tag{3}$$

$$U, y_{ijt} \ge 0 \qquad \forall (i,j) \in E \tag{4}$$

The uncertainty set modeling all the b simultaneous link failure scenarios are defined as follows:

$$\mathbf{X} = \{\, x_{ij} \in \{0,1\}\ \forall (i,j) \in E\colon \textstyle\sum_{(i,j)\in E} x_{ij} = b\} \tag{5}$$

So eventually we are interested to solve the following two stage optimization problem as defined in (6), where the outer maximization capturing the worst-case network performance in terms of the total cost of routing occurs over $x \in$ X. The inner minimization, for a given $x \in$ X, solve the problem defined as in M.

$$\max_{x} \min_{y} \sum_{t\in N;(i,j)\in E} y_{ijt} P_{ij} \ \text{ subject to } (2),(3),(4),(5) \tag{6}$$

We leverage the linear optimization duality techniques to solve the above two stage optimization problem as a single stage optimization problem. For a fixed $x \in$ X, we dualize the inner minimization problem, and due to the zero-duality gap, we can equivalently write the two-stage optimization problem as a single stage problem described as (M1). In the following single stage formulation, λ and v are the dual variables obtained by dualizing the formulation (M) for a given $x \in$ X.

$$(\text{M1}:)\quad \max_{\lambda,v,x} \sum_{\substack{i,t\in N\\ i\neq t}} v_{it} d_{it} - \sum_{t\in N} v_{tt} \sum_{j\in N} d_{jt}$$

$$v_{it} - v_{jt} - \lambda_{ij} \le P_{ij} \qquad \forall t \in N, \forall (i,j) \in E$$

$$\lambda_{ij} \ge 0 \qquad \forall (i,j) \in E$$

$$\sum_{(i,j)\in E} c_{ij}(1 - x_{ij})\lambda_{ij} \le 0$$

$$x \in \text{X}$$

Clearly both the two-stage and the single stage optimization problems are intractable i.e., NP-Hard problems. The former being intractable because the outer minimization occurs over a discrete set **X**, while the latter is intractable due to the nonlinear terms appearing in its constraints and **X** being a discrete set. So, our goal is to construct convex relaxation of M1, which are tractable, and which provide an upper bound for the optimal value of M1. In the subsequent section we discuss more on how we construct the convex relaxation of M1.

3.1 Convex relaxation for the single-stage optimization problem

The optimization problem described in M1, although a single-stage problem, is still an NP-hard problem. It is intractable because of the nonlinear terms appearing in its constraint $\sum_{(i,j)\in E} c_{ij}(1 - x_{ij})\lambda_{ij} \leq 0$, that are obtained as the product of variables x and λ. An optimization problem (R) is a relaxation of a problem (P) if every feasible solution in (P) can be mapped to a feasible solution in (R), and the mapped solution's objective value in (P) is no better than that of its mapping in (R). In this section, we introduce a procedure to construct a relaxation for the problem described in M1. The relaxation we obtain is a linear program, which is quick to solve, however being a relaxation of the original problem, the optimal value obtained provides an upper bound to the optimal objective value of M1.

Next, we describe the reformulation-linearization technique (RLT) (Sherali et al. 2013, 1992), which is a well-known approach to construct relaxations of nonlinear optimization problems. This technique relaxes the nonlinear problem by first taking products of constraints in the original problem and then adding them back in the formulation. This is followed by replacing the nonlinear terms in the formulation by new variables. To see this, consider the following nonlinear optimization problem, we will describe how to construct a relaxation for it using the reformulation-linearization technique.

$$\begin{aligned} (\text{P:})\ \underset{x,y}{\text{maximize}} \quad & x - y + xy \\ & 4 - x \geq 0, x - 1 \geq 0 \\ & 13 - y \geq 0, y - 2 \geq 0 \end{aligned}$$

To construct RLT relaxation of the above problem, we first multiply the constraints for x with the constraints for y i.e., we multiply $4 - x \geq 0$ and $x - 1 \geq 0$ with $13 - y \geq 0$ and $y - 2 \geq 0$ to get $52 - 13x - 4y + xy \geq 0$, $4y - xy - 8 + 2x \geq 0$, $13x - 13 - xy + y \geq 0$, and $xy - y - 2x + 2 \geq 0$. All the constraints obtained post the multiplication step are added in the formulation. This is followed by replacing the product term xy with a new variable z to get the following RLT relaxation.

$$\begin{aligned} (\text{R:})\ \underset{x,y,z}{\text{maximize}} \quad & x - y + z \\ & 4 - x \geq 0, x - 1 \geq 0 \\ & 13 - y \geq 0, y - 2 \geq 0 \\ & 52 - 13x - 4y + z \geq 0 \\ & 4y - z - 8 + 2x \geq 0 \\ & 13x - 13 - z + y \geq 0 \\ & z - y - 2x + 2 \geq 0 \end{aligned}$$

The above relaxation (R) is a linear program, as it no longer has nonlinear terms. Moreover, it is clearly a relaxation for (P) as constraint $z = xy$ needs to be present in (R) to correctly capture the original optimization problem (P).

3.2 Convex relaxation for the single-stage cost validation problem

In this section we leverage the reformulation linearization techniques discussed above to construct a relaxation for M1. We note that M1 has nonlinear terms appearing in the constraint $\sum_{(i,j)\in E} c_{ij}(1 - x_{ij})\lambda_{ij} \leq 0$, involving the product of variables x_{ij} and λ_{ij} for all $(i,j) \in E$. So, to construct the RLT relaxation of M1, we complete the following steps in the listed order:

1. For all $(i,j) \in E$: Relax the binary requirements on x_{ij} to allow $x_{ij} \geq 0$ and $1 - x_{ij} \geq 0$.
2. For all $(i,j) \in E$ and $(k,l) \in E$: Multiply $\lambda_{ij} \geq 0$ with all the constraints involving the variable x i.e., $x_{kl} \geq 0$, $1 - x_{lk} \geq 0$, and $\sum_{(k,l)\in E} x_{kl} - b = 0$.
3. For all $t \in N$, $(i,j) \in E$ and $(k,l) \in E$: Multiply $P_{ij} - v_{it} + v_{jt} + \lambda_{ij} \geq 0$ with all the constraints involving the variable x, i.e., $x_{kl} \geq 0$, $1 - x_{lk} \geq 0$, and $\sum_{(k,l)\in E} x_{kl} - b = 0$.

All the constraints obtained from the above steps are added to the original optimization formulation. This step is followed by relaxing all the nonlinear terms present in the updated formulation as follows:

1. In the newly added constraints, for all $(i, j) \in E$: Replace the product terms $\lambda_{ij}x_{ij}$ with a new variable λ_{ijij}^{x}.
2. In the newly added constraints, for all $i, t \in N$, and $(k, l) \in E$: Replace the product terms $v_{it}x_{kl}$ with a new variable v_{itkl}^{x}.

4. Evaluation

In this section we provide numerical evaluations for the problem of cost validation in designing service networks. We solve this problem using the following approaches already discussed in the paper and compare their optimal cost values and the CPU runtimes.

1. Enumeration approach. (Referred to as approach 1 – A1)
2. Single-stage optimization using M1. (Referred to as approach 2 – A2)
3. RLT relaxation of M1. (Referred to as approach 3 – A3)

We evaluate these approaches using real-life service networks obtained from the Internet Topology Zoo (Knight et al. 2011). We list these networks in Table 3. For the ease of reference, we use the abbreviations stated for the networks while reporting the results. We further used the gravity model (Zhang et al. 2005) to generate the traffic matrices for the service networks. With the numerical results stated in Section 4.1, we observed that the service networks listed in Table 3 get disconnected with two or more link failures, and thus the demand requirements of the network cannot be met if $b \geq 2$, resulting in (M1) being unbounded. We, therefore, modify these service networks to handle higher number of link failures by adding more edges to them. We do this by constructing Erdős-Rényi graphs (Bollobás et al. 1998), using the p-values listed in Table 3.1, the nodes of the corresponding service networks and we use the same traffic matrices. These modified service networks are listed in Table 3.1.

Table 3. Service networks for evaluation

Service Network	# Nodes	# Edges
Sprint (S)	10	34
IBM (I)	17	46
XeeX (X)	22	64
Cwix (C)	21	52

Table 4.1. Service networks for $\boldsymbol{b \geq 2}$ evaluation

Service Network		# Nodes	# Edges
Sprint (S*)	p = 0.90	10	87
IBM (I*)	p = 0.70	17	177
XeeX (X*)	p = 0.40	22	172
Cwix (C*)	p = 0.50	21	195

In Tables 3 and 3.1, the columns labeled "# Nodes" and "# Edges" denote the number of nodes and edges in the service network, respectively. We further note that every undirected edge $(\boldsymbol{i}, \boldsymbol{j})$ in the service network, meant that we had two directed edges $\boldsymbol{i} \rightarrow \boldsymbol{j}$ and $\boldsymbol{j} \rightarrow \boldsymbol{i}$ of the same capacity in the network. From the computational standpoint, all the optimization problems solved to get the results in Section 4.1, were first modeled in Python and then solved using Gurobi 10.0 (Gurobi Optimization 2022). The computations were done on a machine with an Intel Xeon E5-2623 CPU @ 3.00 GHz.

4.1 Numerical results

In Table 4, we report the results of our numerical experiments. Column 1 in Table 4 lists out the service network (N) and the number of simultaneous link failures under consideration (b)**.** For a chosen service network and given the number of non-functional links in it, Column labeled "A1" reports the optimal cost of routing obtained via the enumeration method. This is obtained by first listing out all $\binom{|E|}{b}$ b-simultaneous link failure scenarios, and then computing the routing cost under each listed scenario using the formulation (M) as described in Section 3. The worst-case routing cost among all b failure scenarios is then obtained by taking the maximum cost value among all computed costs. Column labeled "A2" reports the optimal objective value obtained by solving the single stage formulation as described by (M1). Due to the presence of a nonlinear constraint, M1 is still a nonconvex optimization problem, so to solve it using Gurobi optimization solver, we appropriately set the "NonConvex" parameter to two, see for reference (Gurobi Optimization 2022). Column labeled "A3" reports the optimal objective value obtained by solving the RLT relaxation of M1, obtained using the construction as described in Section 3.2. Finally, Columns labeled "T-A1", "T-A2", and "T-A3" report the total CPU run-time required to get the optimal values using the approach A1, A2, and A3 respectively. In Table 4, we also note that the service networks X* and C* cannot fulfill the demand required when the number of link failures are three or more, hence the optimal routing cost is unbounded. We represent this as ** in Columns labeled "A1", "A2", and "A3".

Table 5. Optimal routing cost values via different approaches

N (*b*)	**A1**	***T-A1***	**A2**	***T-A2***	**A3**	**T-A3**
S (1)	47.507	*0.239*	47.507	*0.091*	47.507	0.094
I (1)	87.573	*0.819*	87.573	*0.267*	87.573	0.225
X (1)	108.147	*1.893*	108.147	*0.516*	108.147	0.451
C (1)	91.128	*1.279*	91.128	*0.334*	91.128	0.302

N (*b*)	**A1**	***T-A1***	**A2**	***T-A2***	**A3**	***T-A3***
S* (1)	21.847	*1.211*	21.847	*0.570*	21.847	*0.451*
S* (2)	23.624	*45.941*	23.624	*6.514*	27.851	*5.239*
S* (3)	24.882	*1681.940*	24.882	*112.852*	30.331	*102.314*
I* (1)	26.013	*18.216*	26.013	*4.648*	26.013	*3.652*
I* (2)	32.935	*1530.628*	32.935	*76.891*	35.759	*69.257*
I* (3)	33.945	*64120.274*	33.945	*3156.156*	36.124	*2034.561*
X* (1)	39.849	*10.115*	39.849	*11.239*	39.849	*8.945*
X* (2)	45.311	*921.097*	45.311	*126.616*	47.321	*124.713*
X* (3)	**	-	**	-	**	-
C* (1)	24.659	*264.781*	24.659	*12.011*	24.659	*10.283*
C* (2)	26.391	*3451.328*	26.391	*150.411*	28.978	*130.487*
C* (3)	**	-	**	-	**	-

From Table 4, as expected approaches "A1" and "A2" obtain the same optimal routing cost. This optimal routing cost is the ground truth value. The enumeration approach A1, though requires more CPU run-time than solving the single stage formulation described as in M1. This is also understandable as the list of failure scenarios to be enumerated increases exponentially with increasing size of the service network (more edges in the network). The optimal routing cost values obtained by solving the RLT relaxation of M1, i.e., via approach A3 are exact when the number of link failures is one. However, for higher values of b, this approach provides a valid upper bound on the optimal routing cost. We further observe that the CPU run-times for obtaining the optimal value via approach A3 is smallest of the three approaches. Hence for a general value of b, solving the linear program obtained as the RLT relaxation of M1, provides a quick way to compute a valid upper bound for the optimal routing cost for a service network.

5. Conclusion

In this paper we have addressed the problem of cost validation in designing service networks, where given an uncertainty set, in particular a set of all b-simultaneous link failure scenarios, the goal is to quantify the worst-case routing cost for a routing scheme that ensures all source-destination demand requirements are fulfilled. This problem is a hard problem, and we aim to propose an approach which can quickly provide a valid upper bound on this worst-case routing cost. The approach we propose, uses ideas from mixed integer nonlinear optimization and constructs a convex relaxation of the original problem which can be solved in an efficient manner. Our computation results on real service networks are encouraging. We observe that for single link failure scenarios the proposed approach is exact to the optimal routing cost, however for higher number of link failures, the approach gives useful and quick bounds on the optimal coast. We believe that this approach can help design more reliable and cost-efficient routing schemes for the service networks.

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Biography

Dr. Ashish Chandra is an Assistant Professor of Operations Management in the Department of Management, College of Business, Illinois State University, Normal, USA. He holds a Ph.D. in Quantitative Methods from Purdue University's Krannert School of Management. Before his Ph.D., he earned an MS in Operations Research from the Indian Institute of Technology Mumbai and a BS in Mathematics from UM-DAE Centre for Excellence in Basic Sciences, Mumbai. His research focuses on the convergence of computer science, mathematical optimization, operations research, and applied probability. He specializes in developing optimization techniques for solving NP-Hard stochastic optimization problems, crucial for risk-averse decision-making systems.