An Optimization Approach for Multi-Domain Disaster Recovery

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Abstract: This paper develops a novel optimization scheme for multi-domain optical network protection under multiple probabilistic failures arising from large-scale disasters. The model is solved using an approximation approach and the results compared with some advanced heuristics.

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I. Introduction

Multi-domain backbone networks provide vital high-bandwidth connectivity for many new services running across wide geographic domains, e.g., such as on-line storage, content distribution, cloud, etc. As these services become more common, operators are being asked to provide a very high level of continuity, even under challenging disaster conditions. In particular, these occurrences can yield multiple spatially/temporally-correlated failures and include natural disasters, cascading power outages, and malicious \textit{weapons of mass destruction} (WMD) attacks.

Now various pre-provisioned protection schemes have been developed for multi-domain recovery, mostly based upon heuristic designs [1]. For example, hierarchical routing is commonly used to build abstract multi-domain views and compute skeleton primary/backup paths [2],[3]. Simpler decentralized strategies have also been proposed to achieve per-domain protection [4]. However these schemes only address isolated single (node, link) failures and are problematic for large disaster-type scenarios with multiple network node/link failures. Indeed, disaster recovery under such conditions is very challenging and is compounded by limited resource visibility between domains (due to privacy and scalability concerns). To address these concerns, [5] presents a novel “risk-aware” scheme that tries to lower joint path-pair failure probabilities for pre-defined probabilistic shared risk link group (p-SRLG) [6] regions. However, although this solution incorporates \textit{traffic engineering} (TE) efficiency concerns, it is still sub-optimal. Hence there is a strong need to develop more formal optimization models to bounds multi-failure performance.

In light of the above, this paper presents a novel integer non-linear programming (INLP) model for multi-domain disaster recovery. The solution extends upon the single-failure multi-domain protection optimization scheme in [7] by adding extensive new provisions for multi-failure p-SRLG regions. The overall optimization pursues several objectives—including throughput maximization, resource minimization, and risk avoidance—and the primary/backup routes are optimized at both the intra- and inter-domain levels, i.e., two-stage approach. This paper is organized as follows. Section II presents the hierarchical multi-objective optimization model along with a linear approximation. Section III then presents some performance evaluation results, as well as comparisons with the advanced heuristic scheme in [5]. Note that this work can also be generalized for “non-optical” bandwidth provisioning networks as well as emerging \textit{elastic optical networks} (EON).

II. Optimization Model

A new integer non-linear programming (INLP) optimization is presented for multi-domain lightpath protection under multiple probabilistic failures. The framework assumes a-priori demands and pre-specified failure risk regions. The solution also models realistic hierarchical routing setups, where domain state is compressed to provide global abstract topologies. Namely, full-mesh abstraction [1],[5] is used to reduce a domain to a mesh of links between its border nodes. All domains are transparent (all-optical) but have full wavelength conversion at the border nodes. This is a valid representation as most carriers use bit-level service level agreement (SLA) monitoring at boundary points. Overall, the optimization uses a two-stage approach, i.e., first computing skeleton primary/backup lightpath pairs over the global “abstract” topology and then resolving them over the individual domains, Fig. 1. This hierarchical approach mimics inter-domain heuristic schemes and provides a good reference. Although it is difficult to guarantee failure recovery for all multi-failure conditions, risk mitigation is still critical. Hence the solution tries to minimize joint path-pair failures while trying to control resource usages. Consider the requisite notation first.

A backbone network is defined with $D$ domains, with the $i$-th domain represented by sub-graph, $G_i(V_i,L_i)$. Namely, here $V_i = \{v_{i1}, v_{i2}, \ldots\}$ is the set of nodes and $L_i = \{e_{ij}^i\}$ is the set of intra-domain links, $e_{ij}^i$ interconnecting nodes $v_{ij}$ and $v_{ij}$. Inter-domain links between the border nodes are also defined in the set $\{e_{ij}^{i}m\}$, where $1 \leq i,j \leq D$, and $i \neq j$. Using this, a global \textit{abstract} topology is defined by the graph $G(U,E)$. Namely, $U = \{v_j\}$ is the set of border nodes in all domains and $E = \{e_{ij}^{i}m\}$ is the set of global links, i.e., both physical inter-domain links ($e_{ij}^{i}m$ between domains $i$ and $j$) and \textit{abstract} intra-domain links ($e_{ij}^i$ in domain $i$). Without loss of generality, intra- and inter-domain link sizes are also set to $C_1$ and $C_2$ wavelength channels, respectively. Meanwhile, the p-SRLG model from [6] is used to specify a pre-defined set of mutually-exclusive stressor events, $R$, where each event $r \in R$ has an occurrence probability $P_r$, and $\Sigma_r P_r = 1$. Probabilistic failure regions are also defined for each stressor to model its impact regime, i.e., via non-zero conditional failure probabilities for each link $e_{ij}^i$ within the geographic region of
event \( r \), i.e., \( p_r^{f,skm} \). As per [6], it is assumed that all link failures within a region (for stressor \( r \)) are independent. Finally, all user requests are denoted by the set \( N = \{ (s, d, r) \} \), where the \( n \)-th request has source node \( s_n \), destination node \( d_n \), and requested capacity \( r_n \) wavelengths. Some other variables are also defined here. Namely, \( f_n \) denotes the number of wavelengths allocated to the \( n \)-th request, \( x_n^{skm} \) denotes the number of wavelengths routed over link \( k_{km} \) for the primary path for request \( n \), and \( y_n^{skm} \) denotes the number of wavelengths routed over link \( k_{km} \) for the backup path for request \( n \). Assuming single-wavelength requests, i.e., \( r_n = 1 \), all \( x_n^{skm} \) and \( y_n^{skm} \) become binary variables. Finally, the vectors \( x = \{ x_n^{skm} \} \) and \( y = \{ y_n^{skm} \} \) are used to denote the primary and backup path routes for a request.

Now the conditional failure probability of a primary path \( x \) given stressor \( r \), \( F(r, x) \), is computed as a product of link failure probabilities, Eq. 1a (and similarly \( F(r, y) \) for the backup path \( y \), Eq. 1b). Since routes \( x \) and \( y \) are link-disjoint, their conditional path-pair failure probability is also given by the product term in Eq. 2. Leveraging the above, the first optimization stage computes skeleton primary/backup path-pairs over \( H(U,E) \) using the multi-objective function in Eq. 3. Namely, this function comprises of three weighted components to maximize throughput \( (F_1) \), minimize resource usage \( (F_2) \), and minimize joint failure probability/risk \( (F_3) \), i.e., \( \omega_1, \omega_2, \) and \( \omega_3 \) are arbitrary weighting factors. Furthermore, additional equations are also introduced to bound the solution, i.e., Eqs. 4 and 5 for flow continuity, Eq. 6 for link-disjointness, Eq. 7 for link capacity bounds, and Eqs. 8-10 for binary conditions.

\[
F^c(x, y) = \prod_{e \in E} (1 - p_{e, p, y}) \quad F(x, y) = \prod_{e \in E} (1 - p_{e, x, y})
\]

(1a,b)

\[
F(x, y) = (1 - p_{x, y})
\]

(2)

\[
F = \sum_{(j,m) \in R} \sum_{(j,m) \in E} x_{km}^{ij} - \sum_{(j,m) \in E} \sum_{(j,m) \in E} y_{km}^{ij} = \begin{cases} f_n; & \text{if } v_n = s_n \\ -f_n; & \text{if } v_n = d_n : n \in N \\ 0; & \text{otherwise} \end{cases}
\]

(3)

\[
\sum_{(j,m) \in R} \sum_{(j,m) \in E} x_{km}^{ij} + \sum_{(j,m) \in E} y_{km}^{ij} \leq f_n : n \in N, e_{km}^{ij} \in E
\]

(4)

\[
\sum_{(j,m) \in R} \sum_{(j,m) \in E} x_{km}^{ij} + \sum_{(j,m) \in E} y_{km}^{ij} \leq C_2 : n \in N, e_{km}^{ij} \in E
\]

(5)

\[
x_{km}^{ij} \in \{0,1\} : n \in N, e_{km}^{ij} \in E
\]

(6)

\[
y_{km}^{ij} \in \{0,1\} : n \in N, e_{km}^{ij} \in E
\]

(7)

\[
f_n \in \{0,1\} : n \in N, e_{km}^{ij} \in E
\]

(8)

\[
f_n \in \{0,1\} : n \in N, e_{km}^{ij} \in E
\]

(9)

\[
f_n \in \{0,1\} : n \in N, e_{km}^{ij} \in E
\]

(10)

Figure 1: Two-stage optimization approach

Skeleton paths generated in the first optimization stage specify all traversed domains. These results drive the second optimization stage to expand the local intra-domain sub-path routes, i.e., “all-optical” segments. The same multi-objective function in Eq. 3 is re-used here at the local domain, i.e., by defining optimizations for \( G(V,L') \). After local sub-path optimization is complete, most-used (MU) wavelength selection is used to select wavelength channel colors, i.e., as it known to give lower blocking [7]. Finally, combining intra-domain segments (with the same request index) with their respective inter-domain links in \( H(U,E) \) gives the completed end-to-end lightpaths pairs.

However, most INLP problems pose high computational complexity and are difficult to solve for generalized network scenarios. Hence a reduced integer linear programming (ILP) approximation is also developed here. Namely, the joint (conditional) failure probability expression in Eq. 2 is expanded and all its higher-order product terms (with three or more probabilities) are removed, i.e., assuming low conditional failure probabilities, \( p_r^{f,skm} \). This results in a modified/simplified expression for the (aggregate) joint risk function, \( F_3 \), as follows:

\[
\text{Min } F = w_1 \sum_{n \in N} (1 - f_n) + w_2 \sum_{n \in N} \sum_{e_{km}^{ij} \in E} (x_{km}^{ij} + y_{km}^{ij}) + \sum_{n \in N} \sum_{r \in R} \sum_{e_{km}^{ij} \in E} \sum_{e_{km}^{ij} \in E} \pi_{e_{km}^{ij}, e_{km}^{ij}, e_{km}^{ij}} x_{km}^{ij} y_{km}^{ij}
\]

where \( x_{km}^{ij} \) is a new binary variable introduced to replace the product of two binary variables \( x_{km}^{ij} y_{km}^{ij} \). Overall, the above ILP formulation is much more scalable and also more amenable to existing LP solver packages.

III. Performance Evaluation

The optimization solution is analyzed using a 6-domain network with 25 inter-domain links and 4 equiprobable p-SRLG failure regions, Fig. 3. Inter-domain links have double the wavelength counts of intra-domain links \((C_1 = 8/C_2 = 16, C_1 = 16/C_2 = 32 \text{ channels})\), and the ILP approximation is solved using a combination of the PuLP
modeler and the GPLK solver. The respective objective function weights in Eq. 3 are also set to \( \omega_1=6, \omega_2=0.0001, \) and \( \omega_3=1, \) i.e., to emphasize throughput maximization. Furthermore, all tests are done for mid-range link failure probability values, i.e., \( p'_{ijkl}=0.5. \) Performance is also compared to the heuristic multi-failure recovery scheme in [6], which jointly computes link-disjoint path-pairs to lower failure probability and TE cost. These tests are done using OPNET Modeler® simulation, and requests are processed in random sequential order (infinite holding times).

The number of successful setups is first plotted in Fig. 4 for differing random batch sizes. At lower loads, both the heuristic and optimization schemes give very competitive results, as resource contention is low. However, for medium-high load regimes, the optimization scheme does significantly better, yielding almost 50% more setups. The number of non-failed demands (i.e., unaffected primary and/or backup routes) is also plotted in Fig. 5. Again, the ILP solution gives much better survivability, especially under more challenging heavy load conditions, e.g., almost 35% less failures for increase link sizes. Finally, the average primary/backup hop counts are also shown in Fig. 6 and indicate slightly higher values with the optimization strategy, i.e., 10-25% (note that similar findings are also observed for single-failure protection optimization [7]). In addition, the ILP results also show a slight decline in resource usage at higher loads. Note that the above tests are also re-run for lower/higher link failure probabilities, i.e., \( p'_{ijkl}=0.2 \) and 0.8, and findings re-confirm optimization gains in term of lower blocking and non-failed requests.

This paper presents a novel optimization scheme to protect multi-domain lightpath connections under probabilistic multi-failure conditions. This necessitates a non-linear formulation, which is then solved using a linear approximation approach to provide notably-improved bounds on blocking and failure recovery rates.

References


