Disaster-Resilient Network Upgrade

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***Abstract*—The manifold impacts of the current pandemic have highlighted the importance of reliable communication networks and services. As more and more people and services rely on this critical infrastructure, single link failure resilience is not sufficient anymore; networks must be disaster resilient. In this paper, we analyze the effects of disasters from a connectivity perspective and focus on reducing the likelihood of network disconnection in the event of a disaster through targeted link upgrades.**

In particular, we formalize the generalized Minimum Cost Disaster Resilient Network Upgrade Problem (DNP) (based on the previously published eFRADIR framework). We prove that this problem is NP-hard and as hard to approximate as the Knapsack Problem (KP). We present several methods for solving the DNP, in particular an ILP and two heuristics. We evaluate their performance on real networks and earthquake data and show that the upgrade cost of our disconnection probability based heuristic is only 3.5% higher than the optimum, while its resource consumption is negligible compared to the ILP.

I. Introduction

The diverse impacts of the current - still raging - pandemic have stressed the importance of reliable communication networks and services. In addition, the proliferation of mission-critical services such as telesurgery, the stock market, AR/VR, and the spread of concepts such as tactile internet and the Internet of Everything (IoE) further underscore the need for survivable networks. An important part of network management is ensuring the required level of service availability of network services. For optical backbone networks, this is usually explicitly specified in a contract between the communication service provider (CSP) and the customer, called a service-level agreement (SLA). Violation of the agreed service availability can result in a financial penalty for the CSP. Therefore, CSPs must accurately estimate the availability of their services and, if necessary, reserve protection resources, implement recovery schemes, and upgrade infrastructure to meet availability requirements.

Despite the increased requirements, today's communication networks are still designed only to protect against single link or link-pair failures and are not prepared for disaster scenarios [1]. The problem of correlated failures of network elements has become a concern in recent decades due to the increased use of virtual environments whose physical structure is usually hidden from the user. Nonetheless, the network elements remained the same and consists of optical cross-connects and fibers that are susceptible to physical failures. Some of these failures are isolated, but in many cases, multiple nodes and links in a geographic area fail simultaneously, e.g., due to a natural disaster such as an earthquake, hurricane, or tsunami. Such geographically correlated failure events are also referred to as regional failures and are attracting increasing attention due to their significant impact.

It has been shown in [2] that most networks are easily disconnected by disasters. Survivable routing algorithms can ensure uninterrupted communication even in case of regional failures, but only if the network remains connected upon a failure. Therefore, we analyze the effects of disasters in a connectivity point of view and focus on decreasing the disconnection probability of the network in case of a disaster through targeted link upgrades.

In particular, in Section III we generalize our earlier work (presented in [3]) and formalize the Minimum Cost Disaster Resilient Network Upgrade Problem (DNP), which supports any type of disaster, intensity functions, link tolerance models, and upgrade cost functions. In Section IV we prove that this problem is NP-hard and as hard to approximate as the Knapsack Problem (KP), and we present several methods for solving the DNP. Finally, in Section V we evaluate our methods using data from real disasters, in particular earthquakes.

II. Related Work

Disaster resilience of communication networks is a widely researched topic [4]–[6]. Numerous works investigate the impact of natural disasters on terrestrial [7]–[10] and on underwater links [11], [12]. In general, the following methods can be considered to improve the resilience of links against disasters: more robust outside cabinets, longer power backup supplies, underground cabling instead of above ground, or the use of strong shielding to protect cables [13]. Although network failure modeling does not directly contribute to disaster resilience, it is a vital aspect because it is essential to properly model the environment and the network, and therefore it is a well-studied topic [7], [9], [14], [15].

To cope with multiple link failures, the concept of Shared Risk Link Groups (SRLGs) was introduced. An SRLG consists of a set of links that are assumed to have a high probability of failing simultaneously. Regional failures, by definition, correspond to a joint failure of nodes/links located in the affected geographic area [7], [14], [15], forming different sets of SRLGs. Most of these failure modeling approaches attempt to find the right trade-off between the accuracy and the state space explosion (i.e., the number of SRLGs).

In addition to the improved topology, the end-user's perceived disaster preparedness can also be improved by thorough connection design i.e., proper routing [16]–[18]. In particular, General Dedicated Protection (GDP [17], [18]) is a family of survivable routing algorithms which is able to ensure the

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TABLE I
NOTATIONS USED IN THIS PAPER.

Notation	Description
$\mathcal{G}(\mathcal{V}, \mathcal{E})$	Input graph, its node set and link set, respectively
$\mathbf{t}$	The tolerance of the network
$t(e)$	Tolerance of link e
$c_e(t)$	Upgrade cost function of link e
M	Set of minimum cuts
S	Set of links in a minimum cut
D	Set of disasters
p_d	Probability of disaster $d \in D$
$I_d(e)$	The intensity of disaster d at link e
$D^*(\mathbf{t})$	Set of disconnecting disasters at network tolerance $\mathbf{t}$
$P_D(\mathbf{t})$	Probability that the network with tolerance $\mathbf{t}$ will fall apart because of the next disaster
T_D	Disconnection probability threshold

protection of the services even in case of regional failures and elaborate SRLG lists, as long as the network remains connected upon a failure.

In [2], the FRAmework for DIsaster Resilience (FRADIR) was introduced, the first framework to jointly leverage failure modeling, network planning, and survivable routing together to provide disaster resilience. It was shown that it is not sufficient to plan the network only for the steady state, since the network is very frequently disconnected by disasters. The framework was refined in several steps, but always using a specific family of survivable routing algorithms (GDP [17], [18]), which ensures instantaneous recovery from any protectable failure pattern. In [19] independent random failures and regional failures were jointly considered (Euclidean distance based probabilistic regional failure model [20] was applied) to properly model the impact of disasters. Based on the SRLG list, a link upgrade strategy was proposed to reduce the probability that the regional failures in the list will disconnect the network. Although FRADIR/FRADIR-II demonstrated the benefits of jointly considering many protection mechanisms against disasters, there was still room for further improvements. Most issues were addressed by eFRADIR introduced in [3]. It improved the FRADIR-II framework in several aspects (e.g., network upgrade and routing costs or algorithm runtime) to obtain more accurate disaster models and algorithms that help meet the requirements of mission-critical communication services. It utilized a novel earthquake model built on historical seismic data for more realistic failure scenarios.

III. Problem Formulation

In this section, we generalize the problem introduced in [3], i.e., we formalize the so-called Minimum Cost Disaster Resilient Network Upgrade Problem (DNP). In particular, we first introduce the network and disaster model, and then present the Disaster Resilient Network Upgrade Problem.

A. The network model

The network is represented by a connected graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of undirected links. Each link $e \in \mathcal{E}$ has a tolerance value $t(e)$ and a non-negative tolerance-upgrade cost function $c_e(t)$. The tolerance of the network is denoted as $\mathbf{t}$ where the tolerance of link e can be accessed as $t(e)$. The initial tolerance of the network is $\mathbf{t_0}$ with $t_0(e)$ initial link tolerances. The tolerance of the link shows the volume of the link's protection against a certain disaster-type (like earthquake), greater tolerance means better protection i.e., lower probability of failure.

To increase the tolerance of e from $t_0(e)$ to t, $c_e(t)$ upgrade cost must be paid. The assignment of new tolerance values ($t_{max}(e) \geq t(e) \geq t_0(e)$) to the links is called a network upgrade and its result is a new network tolerance $\mathbf{t}$. Therefore, the cost of the network upgrade resulting in $\mathbf{t}$ is

$$C(\mathbf{t}) = \sum_{e \in E} c_e(t(e)). \tag{1}$$

B. The disaster model

The disasters are represented with a disaster list D which consists disasters of the same type (e.g., earthquakes). Each disaster d has a probability $0 \leq p_d \leq 1$ which is the probability that it will be the next disaster. The sum of the probabilities of all disasters is equal to 1. The strength/intensity of the disasters at the links is determined by the intensity function I. The intensity of disaster d at link e is $I_d(e)$, which usually depends on the distance between the epicenter of the disaster and the link. If $t(e) < I_d(e)$ then e fails if d occurs; otherwise it remains functional.

To address the challenge of network disconnections, we need to analyze the network from the point of view of connectivity. In graph theory, a cut-set is a set of edges whose removal from the graph would disconnect it. A cut-set is minimum if the size or weight of the cut-set is not larger than the size of any other cut-set. Since each cut-set is a superset of at least one minimum cut-set, it is sufficient to examine the effects of disasters on the minimum cut-sets. The set of the minimum cut-sets is denoted as M and a minimum cut-set is denoted as S.

We say that a disaster disconnects the network if its occurrence would cause the failure of each link of at least one minimum cut-set. By this definition, the set of disconnecting disasters (D^*) is a subset of D and can be defined as follows:

$$D^* = \{d \in D \,|\, \exists S \in M, \, \forall e \in S, \, I_d(e) > t(e)\}. \tag{2}$$

The sum of the probabilities of the disconnecting disasters is the disconnection probability of the network: $P_D = \sum_{d \in D^*} p_d$. In other words, it is the probability that the next disaster will disconnect the network. It is trivial that D^* and P_D depend on the tolerance of the network. Therefore, for a given network tolerance $\mathbf{t}$, the set of disconnecting disasters and the disconnection probability are denoted as $D^*(\mathbf{t})$ and $P_D(\mathbf{t})$.

C. Disaster Resilient Network Upgrade

The disconnection probability can be reduced by increasing the tolerance of the links which may remove some disasters from the set of disconnecting disasters. To remove disaster

d from D^*, the tolerance of the links must be increased in such a way that there is not a minimum cut-set where d causes the failure of each link. To meet the SLA requirements and manage the disconnection probability of the network we introduce the disconnection probability threshold (T_D). Our goal is to find a network tolerance $\mathbf{t}$ for which $P_D(\mathbf{t}) \leq T_D$. Since increasing the tolerance of the network is expensive, the cost-effectiveness of the network upgrade is a top priority. Therefore, we define the main problem investigated in this paper as follows.

Problem 1. ***Minimum Cost Disaster Resilient Network Upgrade Problem (DNP):*** *Given $\mathcal{G}(\mathcal{V}, \mathcal{E})$, set D, intensity function I and disconnection probability threshold T_D. Find a network tolerance $\mathbf{t}$ where $P_D(\mathbf{t}) \leq T_D$ and $C(\mathbf{t})$ is minimal.*

IV. Minimum Cost Disaster Resilient Network Upgrade Problem

In this section, we prove that the Minimum Cost Disaster Resilient Network Upgrade Problem (DNP) is NP-hard and as hard to approximate as the 0-1 Knapsack Problem (KP). We then present the generalization of our network upgrade methods from [3] to solve the DNP. In Section IV-A we present the generalized Integer Linear Program (ILP), and in Section IV-B we present the two heuristic methods.

Theorem 1. *DNP is NP-hard and at least as hard to approximate as KP.*

Proof: In a nutshell, we prove the theorem by converting an arbitrary instance of 0-1 knapsack problem (KP) into an equivalent instance of DNP in polynomial-time whose optimal solution appoints the optimal solution of the KP. Thus, any approximation factor for our problem would imply a same factor for KP as well.

Given an arbitrary instance of KP which consists a set of n items where the i-th item has weight $w_i \leq W$ and value $v_i > 0$, we want to select a subset of items with total weight bounded by W while maximizing the total value. Let $x_i \in \{0, 1\}$ indicate the selection of the i-th variable where $x_i = 1$ means that the i-th item is selected, otherwise not. Then the problem can be expressed in the following form.

$$\underset{x}{\text{maximize}} \sum_{i=1}^{n} v_i x_i, \quad \text{subject to } \sum_{i=1}^{n} w_i x_i \leq W. \tag{3}$$

In the corresponding instance of DNP the network is a tree with $n+1$ nodes and n links: $\mathcal{E} = \{e_1, e_2, \ldots, e_n\}$. The initial tolerance of the links is zero: $t_0(e) = 0 \ \forall e \in \mathcal{E}$; and the tolerance values are restricted to be either 0 or 1: $t(e) \in \{0, 1\} \ \forall e \in \mathcal{E}$. The upgrade cost of e_i equals to the value of the i-th item: $c_{e_i}(t) = v_i t \quad i = 1, \ldots, n$.

The disaster list contains n disasters: $D = \{d_1, d_2, \ldots, d_n\}$. The intensity function ensures that each disaster affects only the corresponding link and enables that if a link is upgraded ($t(e) = 1$) then it cannot fail:

$$I_{d_i}(e_j) = \begin{cases} 0.5 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{4}$$

The probability of the i-th disaster is the normalized weight of the i-th item in KP:

$$p_{d_i} = \frac{w_i}{\sum_i w_i} \quad i = 1, \ldots, n. \tag{5}$$

Since the network is a tree, therefore the failure of any link disconnects it, meaning that each link is a minimum cut-set:

$$M = \{S_1, S_2, \ldots, S_n\}, \text{ where } S_i = \{e_i\},\ i = 1, \ldots, n.$$

In this translated problem, D^* will contain every disaster where the tolerance of the corresponding link is 0, i.e., the link is not upgraded. Initially no link is upgraded, therefore, $P_D(\mathbf{t_0}) = 1$. For a given $\mathbf{t}$ the disconnection probability:

$$P_D(\mathbf{t}) = \sum_{d_i \in D^*(\mathbf{t})} p_{d_i} = \frac{\sum_{d_i \in D^*(\mathbf{t})} w_i}{\sum_i w_i}. \tag{6}$$

In other words, the disconnection probability is the total normalized weight of the items corresponding to the not upgraded links. Accordingly, we define the disconnection probability threshold:

$$T_D = \frac{W}{\sum_i w_i} \tag{7}$$

These definitions already outline our reasoning. Let us make two trivial observations that help us prove the theorem:

Lemma 1. *In the constructed DNP instance, minimizing the total upgrade cost of the upgraded links is the same as maximizing the total upgrade cost of the not upgraded links.*

Proof. It is clear, that the links can be partitioned into two subsets based on the network tolerance $\mathbf{t}$: upgraded and not upgraded links. If the total upgrade cost of the links is $V = \sum_i v_i$ and $C(\mathbf{t})$ is the total upgrade cost of the upgraded links, then necessarily the total upgrade cost of the not upgraded links is $V - C(\mathbf{t})$ proving our proposition. □

Lemma 2. *If the total weight of some items of KP is less than W, then in the corresponding DNP, the total probability of the disasters corresponding to these items is less than T_D, and vice versa.*

Proof. Assume that set A contains the indexes of the selected items, then $\sum_{i \in A} w_i \leq W$. Dividing this inequality by $\sum_i w_i$ gives us the corresponding inequality in the DNP:

$$\frac{\sum_{i \in A} w_i}{\sum_i w_i} = \sum_{i \in A} p_{d_i} \leq \frac{W}{\sum_i w_i} = T_D \tag{8}$$

The same logic can be applied the other way around. □

In order to conclude our proof, we have to demonstrate that in the optimal solution of the above DNP instance the upgraded links correspond to the items not included in the optimal solution for the KP instance. Therefore, the not upgraded links determine the items in the optimal solution for the KP instance.

(DNP $\Rightarrow$ KP) Assume that $\mathbf{t}$ is an optimal solution to DNP. In this case, one can see that the i-th item is included in the knapsack if the i-th link was not upgraded in DNP:

$$x_i = 1 - t(e_i), \ \ i = 1, \ldots, n \tag{9}$$

Since $\mathbf{t}$ is a solution, the total probability of the disconnecting disasters is bounded by T_D, thus according to Lemma 2, the total weight of the items in the knapsack is bounded by W. Additionally, since $\mathbf{t}$ is optimal, the total upgrade cost of the upgraded links is minimal. According to Lemma 1, that also means that the total upgrade cost of the not upgraded links is maximized. Hence the the total upgrade cost of the not upgraded links equals the total value of the items in the knapsack, that is maximal too. We showed that the constructed solution of KP satisfies the weight constraint and the total value of the selected items is maximal, therefore it is an optimal solution.

(KP $\Rightarrow$ DNP) Assume that $\mathbf{x}$ is an optimal solution for KP. In this case, if the i-th item is included in the knapsack then the i-th link is not upgraded in DNP:

$$t(e_i) = 1 - x_i, \ \ i = 1, \ldots, n \tag{10}$$

The argument is the same as in the other case. Since the total weight of the items in the knapsack is bounded by W, therefore $P_D(\mathbf{t}) \leq T_D$. Additionally, $\mathbf{x}$ is optimal meaning that the total upgrade cost of the not upgraded links is maximized, consequently the total upgrade cost of the upgraded links is minimal. ■

A. Integer Linear Program for Network Upgrade

To ensure the connectivity of the network with a certain probability level for the minimal total tolerance upgrade cost, an ILP was implemented. The ILP has four types of variables:

1) $x(e, d)$ is a binary variable, which indicates if link e fails in the case of disaster d;
2) $y(S, d)$ is a binary variable, which indicates if link group S fails ($x(e, d) = 1$, $\forall e \in S$) in the case of disaster d;
3) $z(d)$ is a binary variable, which indicates if disaster d disconnects the network;
4) $t(e)$ is an integer variable, it is the tolerance of link e. $t_{max}(e) \geq t(e) \geq t_0(e) \ \ \forall e \in \mathcal{E}$

The ILP is formalized as follows:

$$\min \sum_{e \in \mathcal{E}} c_e(t(e)) \tag{11}$$

subject to the following constraints.

1) Link Failure Constraints: Eq. (12) ensures that if the intensity of disaster d at link e is higher than the tolerance of the link ($t(e)$) then the link fails:

$$x(e, d) \geq 1 - \frac{t(e)}{I_d(e)} \quad \forall e \in \mathcal{E}, d \in D, \tag{12}$$

while Eq. (13) says that if the intensity of a disaster at link e is less than or equal to the tolerance of the link ($t(e)$) then the link remains functional:

$$x(e, d) \leq \frac{I_d(e)}{t(e)} \quad \forall e \in \mathcal{E}, d \in D. \tag{13}$$

2) Min-cut Failure Constraints: Eq. (14) grants that link group S fails if every link in S fails:

$$y(S, d) \geq \sum_{e \in S} x(e, d) - |S| + 1 \quad \forall S \in M, d \in D, \tag{14}$$

while Eq. (14) says that if any link in S remains functional, S does not fail:

$$y(S, d) \leq x(e, d) \quad \forall e \in \mathcal{E}, \forall S \in M, d \in D. \tag{15}$$

3) Network Disconnection Constraints: Eq. (16) ensures that if a disaster does not hit any minimal cut, the network remains connected:

$$z(d) \leq \sum_{\substack{S \in M \\ d \in D}} y(S, d), \tag{16}$$

while Eq. (17) assures that if a disaster hits any minimal cut, then it disconnects the network:

$$z(d) \geq y(S, d) \quad \forall S \in M, d \in D. \tag{17}$$

4) Disconnection Probability Constraint: Eq. (18) enforces the disconnection probability to be lower than or equal to the disconnection probability threshold:

$$\sum_{d \in D} p_d \cdot z(d) \leq T_D. \tag{18}$$

B. Heuristics for network upgrade

Since the size of the network, the number of min-cuts and the length of the disaster list heavily affect the number of variables and constraints in the ILP, we devised heuristic algorithms for finding feasible network upgrades in a suboptimal way. Both algorithms were introduced in [3] where they were applied in an earthquake specific scenario. To solve the DNP, we made some modifications to the algorithms, however, the logic remained the same therefore, we only give a short summary regarding their operation.

1) Baseline Heuristic (BH): This method is our simplest solution, which serves as a baseline and demonstrates that a more complex method is necessary to approach the optimal solution. The algorithm repeats three phases until $P_D(\mathbf{t}) > T_D$:

1) Calculate $P_D(\mathbf{t})$ and return the solution if $P_D(\mathbf{t}) \leq T_D$.
2) Rank the links according to their occurrence count in the min-cuts.
3) Increase the tolerance of the link with the highest occurrence count by 1. In case of tie, choose the one with the lowest upgrade cost.

2) Disconnection Probability Aware Heuristic (DPH): This method is also an iterative approach, but the selection is based on the cost-effectiveness of the links' tolerance upgrades which are calculated from the probability decrease of P_D that the link's upgrade would entail and the tolerance upgrade cost of the link together. Similarly to BH, the algorithm repeats 3 phases:

1) Calculate $P_D(\mathbf{t})$ and return the solution if $P_D(\mathbf{t}) \leq T_D$.
2) Rank the links according to their cost-effectiveness.

TABLE II
MAIN PARAMETERS OF THE DNP FOR THE INVESTIGATED NETWORKS.

Network	$\|\mathcal{V}\|$	$\|\mathcal{E}\|$	$\|M\|$	$\|D^*(\mathbf{t_0})\|$	$P_D(\mathbf{t_0})$
Italy [21]	25	35	26	4890	0.0245
Janos-US [22]	26	42	28	6344	0.0070
COST 266 [22]	37	57	59	24711	0.0022
Germany [22]	50	88	46	5325	0.0184

3) Increase the tolerance of the most cost-effective link by 1. In case of tie, choose the one with the lowest upgrade cost.

V. EXPERIMENTAL RESULTS

In this section, we present our results using data from real disasters, particularly earthquakes. First, we describe the simulation settings and the methods we use to generate the inputs required for our problem. Then, we compare the upgrade methods based on the tolerance upgrade cost. Finally, we analyze the runtime and scalability of the upgrade methods.

A. Simulation settings

Table II provides information concerning the main parameters affecting the size of the problem in case of the used network topologies. The Italy network is obtained from [21] while the Janos-US, COST 266, and Germany network topologies are taken from [22]. Similarly to [3], the tolerance values must be integers, and the initial and maximal tolerance values of all links are 6 and 9, respectively. The upgrade cost function of each link depends on the volume of the tolerance upgrade and the length of the link: $c_e(t) = l(e)(t(e) - t_0(e))$, where $l(e)$ is the length of link e in kilometers.

In this work, we evaluate the model of [21] on the most recent published earthquakes catalogs ([23], [24]) that cover long periods of time. Additionally, we use the intensity prediction equations and the SRLG enumeration method of [25]. We conduct our simulations on a virtual machine with 8 cores (Intel® Xeon® E5-2630 v3 @ 2.4GHz) and 32GB of RAM running Ubuntu 18.04.1 LTS. The simulation environment and the algorithms are implemented in Python 3.8.2. The ILP instances are created with the Gurobi Python Interface and solved with the Gurobi solver (version 9.5) [26].

B. Upgrade Cost Analysis

In this section, the performance of the disaster-resilient upgrade methods is analyzed for the networks. The cost-efficiency of the three network upgrade methods (two heuristic methods and the ILP) were compared through several T_D values from the [0.0005, 0.01] range. Each method started from the same initial state and it had to provide an upgraded network with $P_D \leq T_D$. Fig. 1 shows the tolerance upgrade costs of the upgrade methods as a function of T_D for the Italy network. The same trends are observable for every other network for which the data is accessible on GitHub[1].

[1]https://github.com/mogyi006/DNP_Results

As expected, the DPH and the optimal ILP solution outperform the BH by a large margin in every scenario in terms of the cost efficiency of the tolerance upgrade. On average, the solution of BH is 50% more expensive than the optimal. The gap is much smaller between the DPH and the ILP and in many cases the heuristic is able to find the optimal solution even at low T_D values. Concerning the cost efficiency of the tolerance upgrade, DPH provides results within 3.5% of the optimal one (i.e., returned by the ILP), on average.

C. Runtime and scalability analysis of the proposed methods

In this subsection, we analyze the runtime and scalability of the upgrade methods. The computation times of the methods for the Germany network are shown in Fig. 2. We can see that the runtimes of the heuristic algorithms are negligible compared to the ILP, which are over 10 hours in some cases. As expected, the BH has the lowest runtime, always less than 5 seconds. The DPH takes more time, but even at the lower T_D values, it provides solutions in less than a minute. Note that the resource consumption of the ILP does not scale well with the size of the problem, as it increases rapidly as the size of the network and the disaster list increases. Therefore, we recommend the DPH upgrade method for larger networks.

Fig. 3 shows the runtimes of DPH for 10 T_D values in each network's case. The first T_D value is close to $P_D(\mathbf{t_0})$ (e.g., for Italy: $P_D(\mathbf{t_0}) = 0.0245$ and $T_{D1} = 0.02$) and the last T_D value is one tenth of the first one. It is clear that many factors affect the runtime of the upgrade method: the network characteristics, the disaster list, the number of minimal cuts and disconnecting earthquakes. The runtime of DPH is in close connection with the node and edge count of the networks. The Italy and Janos-US networks have similar size which is reflected in the DPH's runtime (always less than a minute) while in case of the two times bigger Germany network it is always more than 80 seconds. The runtimes of the COST 266 network are higher than the runtimes of Italy and Janos-US networks and slightly lower than the runtime of the Germany network. To summarize, the DPH method provides close to optimal results and scales much better than the ILP.

VI. CONCLUSION

In this paper, we investigated the network planning aspects of disaster resilience. We formalized the generalized Minimum Cost Disaster Resilient Network Upgrade Problem (DNP), which aims to reduce the probability of network disconnection through targeted link upgrades, and proved that this problem is NP-hard. We presented an ILP and two heuristics to solve it, and evaluated their performance on real networks and earthquake data. The simulations proved that the upgrade cost of DPH is only 3.5% higher than the optimum. Note that ILP is not suitable for large networks and disaster lists due to its runtime and resource consumption, so in these cases it is recommended to use the DPH.

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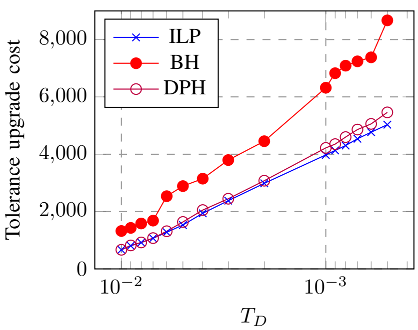

Fig. 1. Comparison of the tolerance upgrade cost referring to different methods for several probability thresholds (T_D), for the Italy network.

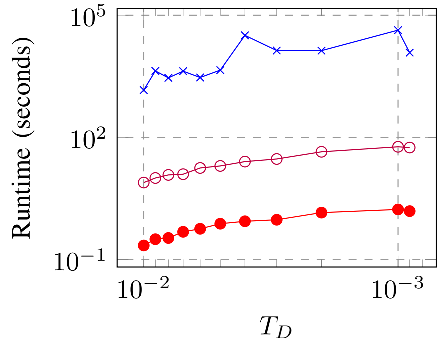

Fig. 2. Comparison of the computation time values of the three tolerance upgrade methods for different probability thresholds (T_D) for the Germany network.

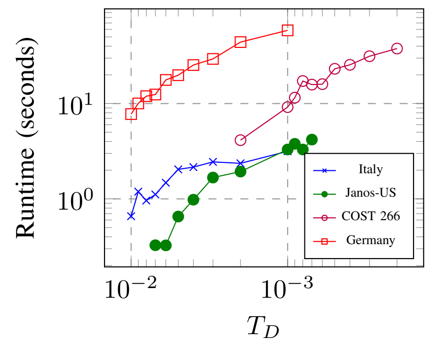

Fig. 3. Comparison of the computation time values of the DPH upgrade method for different networks and probability thresholds (T_D). For each network the upgrade is computed for 10 T_D values.

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