Impact of Facility Factors on Robustness of Communication Networks under Natural Disasters

Takeru Inoue, Akira Ito, Kengo Nakamura, and Tatsuya Matsukawa

Abstract

Communication networks are critical social infrastructures, and network failure due to natural disasters can impact severely our daily lives. The research community has extensively studied how to assess the robustness of networks against natural disasters. Although communication networks are protected by facilities such as buildings and underground conduits, conventional studies have not considered networks in robustness assessments. Thus, this study investigated the impact of underground conduits on network robustness during earthquakes. An actual conduit dataset was considered, including tens of thousands of conduits with their attributes (structure, material, length, and age) and damage status from past earthquake inspections. We employed a conduit damage prediction technique, a machine learning method developed in infrastructure engineering, and evaluated the robustness of regional communication networks with and without conduit attributes. The evaluation results revealed that the estimated outage scales could differ by a maximum factor of seven, depending on the conduit attributes. Additionally, a what-if analysis for conduit upgrades was conducted, which involved recognizing conduit attributes. These findings support the significance of facility factors in network assessment during natural disasters, and open up a new interdisciplinary research field between infrastructure engineering and telecommunication networks.

Introduction

Contemporary society strongly depends on telecommunication networks, which are often affected by severe natural disasters such as earthquakes and hurricanes [1]. Thus, network operators should evaluate network robustness during natural disasters and augment them to make them disaster tolerant. The telecommunications network research community has developed several methods for evaluating and augmenting network robustness against natural disasters, including probabilistic models for earthquakes [2], reliability evaluation for compound disasters [3], link augmentation against earthquakes [4], and network planning for earthquakes and hurricanes [5]. These studies focused on the topological aspects of a network and the geographic distribution of hazards. However, telecommunication *facilities* such as buildings and underground conduits (Fig. 1, top), which protect communication media such as transceivers and cables, have been neglected. Communication facilities have unique attributes in terms of structure, materials, and age, and these facility factors could have a significant impact on the network's robustness during disasters; that is, a vulnerable or old facility is likely to fail even if the hazard that strikes it is not strong. To the best of our knowledge, past studies on communication networks have not considered the impact of facility factors on network robustness. Note that the fate sharing among communication cables through the same facility has often been considered, as with the shared risk link group (SRLG), but the facility attributes have not been considered.

The fragility of telecommunication facilities has been studied in infrastructure engineering. Owing to recent advancements in statistical methods, including machine learning, state-of-the-art techniques have successfully identified the fragilities of each facility duet al.ring natural disasters, leveraging large datasets on facilities and disaster hazards. Ito et al. [6] developed a damage prediction method for underground conduits by employing a tree-boosting algorithm with a large training dataset of seismic hazards and conduit attributes. Firdaus et al. [7] examined bridge failures during floods, and Wang et al. [8] investigated the fragility of power towers against typhoon winds. These studies indicate that the fragility of a facility largely depends on its attributes; however, research interests in infrastructure engineering are limited to facilities themselves, and the impact of facility factors on communication networks has not been studied.

Thus, communication networks under a natural disaster have been studied in both the fields of telecommunication network and infrastructure engineering; however, a question remains: *do attributes of individual facilities have significant impacts on the robustness of the whole communication network?* If the answer is yes, we may not have accurately evaluated the robustness, resulting in unexpected network outages owing to the overestimation of robustness or over-augmentation of networks owing to underestimation. This study examines the impact of telecommunications

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ISSN: 0163-6804
Digital Object Identifier: 10.1109/MCOM.001.2300741

facilities on network robustness during natural disasters and provides comprehensive directions for this interdisciplinary research field.

This study assessed the robustness of communication networks using *connectivity-based network reliability* [9], that is, the probability of connecting specified nodes on a network. Network reliability has traditionally been a fundamental metric in network design and forms the basis for other metrics, such as network component criticality [10] and survivability [2].

This study focused on underground conduits against earthquakes as examples of facilities and hazards because damage prediction methods for underground conduits under seismic hazards have matured [6], and communication cables in major networks are usually protected by underground conduits. However, the basic concept of this study can be applied to other facilities and hazards, and we hope that further research will be expanded. Moreover, although the analyses in this study utilized a dataset from Japan, the concept presented is not limited to Japan.

The contributions of this study are summarized as follows:

- A reliability evaluation method was proposed by employing a damage prediction method for underground conduits under seismic hazards.
- A reliability evaluation was conducted using a dataset of actual conduits from NTT, the largest network provider in Japan. This is the first study to evaluate the network reliability using an actual facility dataset.
- The impact of telecommunications facilities on network reliability was demonstrated by considering two recent strong earthquakes in Japan. The results showed that the outage scale (number of disconnected buildings) could shift by a factor of several times without conduit attributes. In addition, a what-if analysis assuming conduit upgrades was conducted, which is impossible without conduit attributes.
- A rich body of interdisciplinary research topics between telecommunication networks and infrastructure engineering was discussed.

Network Reliability Evaluation with Conduit Damages

This section presents a method to evaluate network reliability employing the damage prediction technique for underground conduits against a seismic hazard. The next sub-section overviews the method with a network model including underground conduits. We then elaborate on the conduit damage prediction and describe datasets used in the prediction.

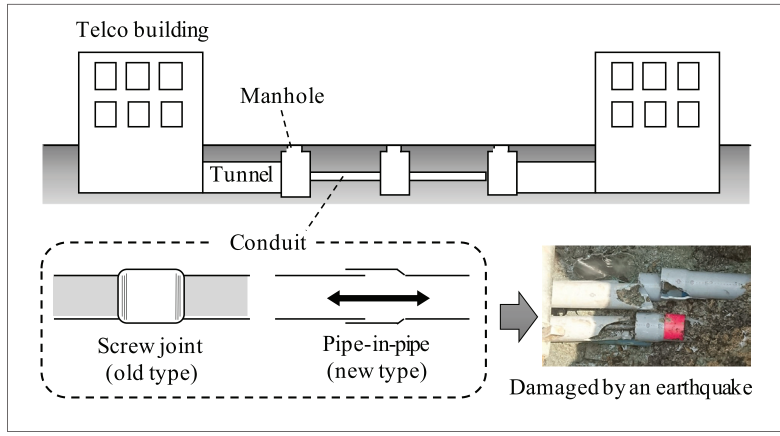

FIGURE 1. Underground telecommunication facilities with conduit structures and damages.

Network Model and Reliability Evaluation Method

This subsection describes the reliability evaluation method for conduit damage prediction, as shown in Fig. 2. First, network and seismic hazards were provided as problem inputs, as shown in the first step in Fig. 2. A network is represented as a graph with telecommunication buildings and manholes as nodes and tunnels and conduits as edges; tunnels are large-scale structures that enable personnel to enter, while conduits are smaller and designed to only accommodate the cables they protect. Communication devices such as transceivers were installed in buildings and connected by communication cables through tunnels and conduits. We neglected the communication "capacity" and focused on the connectivity of networks. A seismic hazard is defined as the ground motion at the location of each conduit, and the details are described below. Note that the red Xs in the first step are marked to illustrate the connectivity later; thus, they are not provided as problem inputs.

Next, a failure model for network components is described. Communication device failures were not considered because telecommunications buildings are very sturdy and contain power generators. Moreover, the failures of the tunnels and manholes were also ignored because they are extremely robust. In this study, only conduit failures were considered; conduits fail stochastically based on the physics of seismic hazards, ground conditions, and conduit attributes. Conduits were divided into sections by manholes installed at approximately 150 m intervals, and conduit failures were examined for each section. A conduit state can be either intact or failed/disconnected, and the buildings cannot communicate through failed conduits; in Fig. 2, the X-marked conduits failed, so building b_2 was disconnected and could

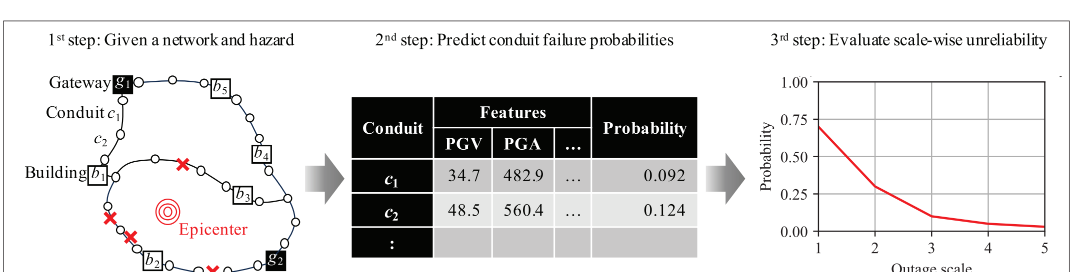

FIGURE 2. Reliability evaluation procedure with the damage prediction technique for underground conduits against a seismic hazard.

	Source	Feature	Mean	Std dev
Numeric features	Seismic	PGV [cm/s]	60.7	30.7
		PGA [cm/s^2]	565.7	203.8
	Ground	Elevation [m]	50.1	95.9
		Angle [degree]	2.42	3.73
	Conduit	Length [m]	137.1	72.7
		Age [year]	34.2	10.1
Categorical features	**Source**	**Feature**	**Categories**	**Ratio of true/mode**
	Ground	Artificial flat terrain	{true, false}	0.078
		Liquefaction	{true, false}	0.115
	Conduit	Type	{SS, SV, SI, PS, PV}	(SS) 0.720

TABLE 1. Features and dataset statistics

not communicate with the other buildings. In the second step in Fig. 2, the failure probability of each conduit was estimated using the prediction technique, assuming independence in conduit failures; details of the prediction technique is discussed below.

Based on the probability of the conduit failure, the reliability of the network was evaluated. In this study, a regional communication network comprising tens of telecommunications buildings in an area of roughly 100 km was considered; a strong earthquake could damage the entire area, but the extent of damage would be quite different within the area. A regional network has gateways through which other buildings can reach external networks, such as the Internet. Gateways are deployed in multiple buildings for redundancy, and other buildings must be connected to at least one gateway. The number of buildings disconnected from any gateway is considered as the *outage scale*; in Fig. 2, only building b_2 is disconnected from the gateways, and the outage scale is one. Communication networks should be designed such that larger outages are less likely to occur; thus, we used a reliability measure called scale-wise unreliability, which reflects outage scales [11]. Scale-wise unreliability plots the probability of disconnecting x or more buildings from any gateway. The third step in Fig. 2 illustrates an example of scale-wise unreliability, which indicates that outages disconnecting two or more buildings occurred with a 30 percent probability. Scale-wise unreliability has been used in the reliability design of communication networks [11], but it has been difficult to apply it to networks under disasters. This is because scale-wise unreliability had to be approximately evaluated by ignoring simultaneous link failures to avoid the high computational burden (#P-complete, a complexity class of a counting problem that is at least as hard as the corresponding NP decision problem), but simultaneous failures could not be ignored during disasters owing to the high failure probability. Recently, Nakamura et al. developed an efficient algorithm that exactly computes the scale-wise unreliability for practical-scale networks [12]; therefore, we employed the algorithm in this study to plot the scale-wise unreliability.

Conduit Damage Prediction and Datasets

This subsection describes the machine learning technique used to predict the probability of conduit failure against seismic hazard [6]. We begin with the features used in the prediction (Table 1):

- The seismic features included peak ground velocity (PGV) and peak ground acceleration (PGA) at the location where the conduit was installed. These two features are representative of seismic indices because other indices such as seismic intensity, spectral intensity, equivalent predominant frequency, and converted displacement are all calculated from the PGV and PGA. The PGV and PGA of earthquakes that occurred and are expected to occur in Japan are available on the J-SHIS website (https://www.j-shis.bosai.go.jp).
- The ground features included the elevation, angle, artificial flat terrain, and liquefaction at the conduit location. Lower elevations are often associated with soft ground such as reclaimed land and alluvial plains. The slope angle is associated with mountainous terrains. Furthermore, artificial flat terrain indicates soft ground, such as an embankment. The occurrence of liquefaction indicates that the location has liquefied in the past. Liquefaction causes the conduits to float and fail. Liquefaction data are available from J-SHIS, whereas other data were obtained from the National Spatial Planning and Regional Policy Bureau in Japan (https://nlftp.mlit.go.jp).
- Conduit features included length, age, and type (structure and material). The length is the traveling distance of the conduit. Age is the number of years elapsed since installation; the older the conduit, the more corroded and brittle it is. Finally, the conduit types are defined by their structures and materials. The NTT has five conduit types: screw-joint steel (SS) pipe, adhesive-splicing vinyl (SV) pipe, screw-joint cast-iron (SI) pipe, push-lock polyethylene steel (PS) pipe, and push-lock vinyl (PV) pipe. They are classified into old and new types based on their joint structure (Fig. 1, lower left); old-type conduits (SS, SV, and SI) are rigidly connected by screw joints or adhesive splices and prone to failure at the joints owing to ground displacement, while new-type conduits (PS and PV) have a pipe-in-pipe structure, which renders them elastic in the axial direction and facilitates displacement absorption. For all types, the conduits were connected by their joints every 5.5 m, and the diameter was approximately 10 cm. Conduit data were retrieved from NTT's facility database.

The sets of seismic, ground, and conduit features are denoted as S, G, and C, respectively. For example, SG refers to seismic and ground features, such as PGV, PGA, elevation, angle, artificial flat terrain, and liquefaction occurrence.

Next, we describe the conduit damage dataset used to build the prediction model (a binary classifier for conduit failure). NTT researchers inspected 32,968 conduits in areas affected by recent strong earthquakes: the 1995 southern Hyogo earthquake (Mw = 7.3), 2004 mid-Niigata earthquake (Mw 6.8), 2007 Niigata Chuetsu-oki earthquake (Mw 6.8), 2011 earthquake off the Pacific coast of

Tohoku (Mw 9.0), and the 2016 Kumamoto earthquake (Mw 7.3). Conduits damaged by bending, breaking, separation, sediment inflow, or flattening were marked as failed conduits (Fig. 1, lower right). The failure rate of the old conduit was 4.5 percent, whereas that of the new conduit was 2.0 percent. Old-type conduits accounted for 89.5 percent of the dataset, with SS pipes, the most frequent type, accounting for 72.0 percent. The inspected conduits were associated with their features, and their statistics are listed in Table 1.

The conduit damage prediction technique [6] builds a binary classifier by employing a tree-boosting algorithm, XGBoost [13], which utilizes an ensemble of decision trees to form a strong predictive model. The hyperparameters of XGBoost, for example, the maximum tree depth and regularization weights, are tuned using a tree-structured Parzen estimator [14]. The entire dataset was divided into training, tuning, and test subsets (6:2:2). The classifier was trained on the training dataset, while the hyperparameters were tuned on the tuning dataset. Then, the prediction performance was measured on the test dataset using a performance indicator called the area under the receiver operating characteristic curve (ROC-AUC). The ROC curve plots the true positive rate against the false positive rate at various thresholds. The AUC quantifies the classifier performance between 0.5 of random prediction and 1.0 of perfect prediction. ROC-AUC is useful for imbalanced class distributions, such as the dataset used in this study, because it is unaffected by the proportion of class distribution. The trained classifier can be used to estimate the probability of belonging to one of the two classes, that is, the failure probability of each conduit.

Our method is not limited to the dataset used in this study; it can be applied to other datasets with the same features.

Impacts of Conduit Attributes on Network Reliability

This section examines impacts of conduit attributes on network reliability. We assumed that the 2016 Kumamoto earthquake and the 2011 earthquake off the Pacific coast of Tohoku would occur again because we had already retrieved the conduit data in the post-earthquake inspections. However, in practice, network operators must perform the same evaluation of *future* seismic hazards. We describe network topologies used in the reliability evaluation below. Then we discuss the impact of conduit attributes on network reliability. Following that, we conduct a what-if analysis of conduit upgrades, which is made possible by the use of conduit data.

Network Topologies Used in Reliability Evaluation

In this study, we performed a network reliability evaluation using real data from telecommunications buildings and conduits. For security reasons, we used *hypothetical* network topologies, that is, we did not disclose how the buildings were linked. In addition, we did not illustrate the geographic conduit routes in the topology maps. The hypothetical topologies were generated as follows: First, for each building pair connected by conduit routes, the shortest route was assumed to connect the buildings because buildings are usually connected along the (almost) shortest route to minimize transmission delay and power. Topologies generated in this manner are likely to have a dense structure; however, regional networks, such as rings, are usually sparse. Thus, we removed longer routes, such that every building had at most five conduit routes. Figure 3 shows the hypothetical network topologies for Kumamoto and Ibaraki (Tohoku) using a map of Japan. The Kumamoto network had 31 buildings, whereas the Ibaraki network had 76. The gray buildings, the farthest node pair, were 60.0 km apart in Kumamoto and 122.4 km in Ibaraki and were designated as gateways. The average travel distances between adjacent buildings were 7.2 km for Kumamoto and 11.0 km for Ibaraki. Certain buildings appeared to have only a single route to a gateway because aerial cables, which are strung above the ground between poles, were omitted in this evaluation.

Network Reliability With And Without Conduit Attributes

The effects of conduit attributes on network reliability were investigated by comparing the results of different feature sets: S, SG, and SGC. As previous studies [2–5] only considered hazard distributions, we used the S feature set (hazard intensities) as the baseline. The seismic hazards were those of two earthquakes (2016 Kumamoto and 2011 Tohoku). The ground and conduit data are described above. The damage prediction models were trained with a dataset excluding the conduits of the target region. The dataset for Kumamoto included 26,109 conduit records, whereas that for Ibaraki had 25,234 records. The prediction performance of the trained model (ROC-AUC) is shown in the left column of Fig. 4. The SGC feature set, including all features, outperformed the other feature sets, with 0.908 for Kumamoto and 0.879 for Ibaraki. Note that we examined feature combinations other than S, SG, and SGC, but none outperformed SGC.

Cumulative distribution functions (CDFs) of the predicted conduit failure probabilities are shown in the center column of Fig. 4. The probability of conduit failure strongly depends on the feature sets. In Kumamoto, the SGC feature set shifted the failure probability to the left, that is, the failure probability decreased; the averages were 0.073, 0.073, and 0.034 for feature sets S, SG, and SGC, respectively. In Ibaraki, the average failure probabilities did not significantly shift: 0.011, 0.012, and 0.009 for S, SG, and SGC, respectively. Interestingly, the most vulnerable conduits with the SGC feature set were not located with the strongest seismic intensity; in Kumamoto, the most vulnerable conduit yielded a PGV and PGA of 52.8 and 565.4, which are less than the averages of 78.5 and 660.9, respectively, in the Kumamoto conduits in our dataset. However, in Ibaraki, the most vulnerable conduit yielded 32.6 and 379.4, which are also less than the averages of 43.5 and 563.1 in the Ibaraki dataset. These vulnerable conduits are old-type SV pipes, indicating that the impact of conduit attributes is not negligible.

For simplicity, we did not distinguish between conduit failure and cable cutting so far. However, even if a conduit fails, the communication cables through the conduit are not always cut. In the following reliability evaluation, a historical

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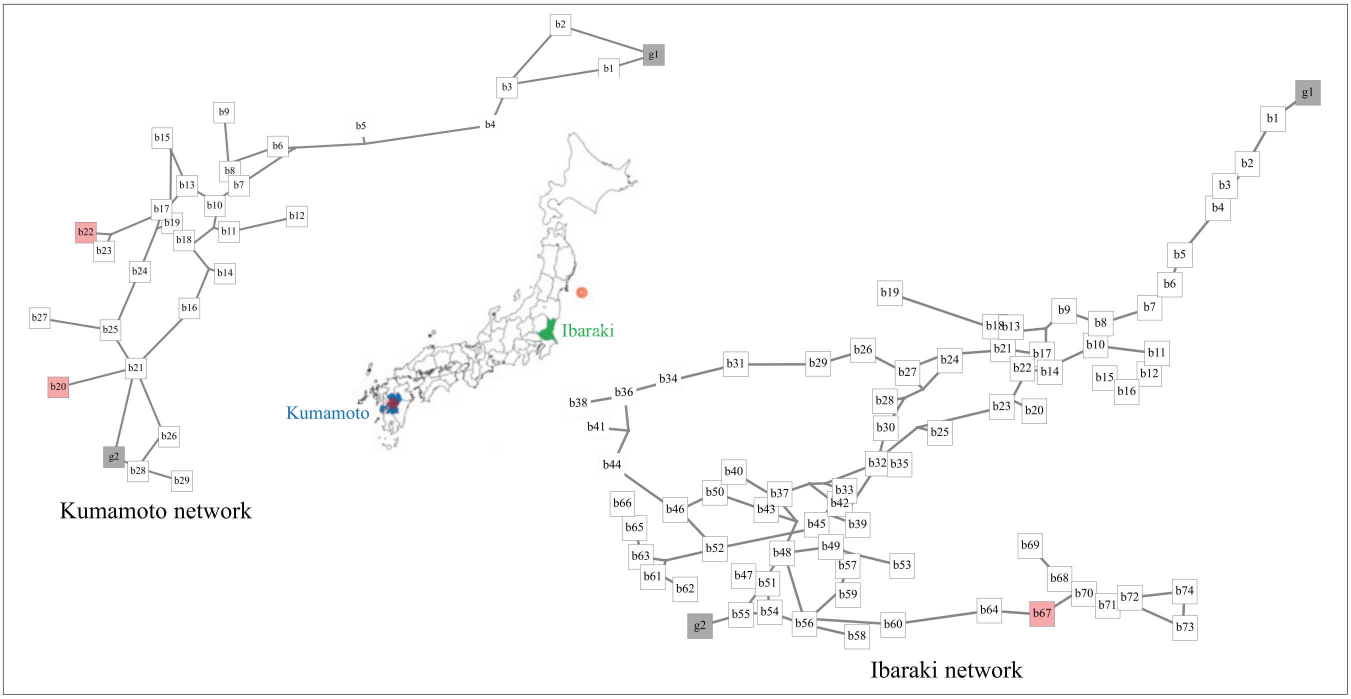

FIGURE 3. Hypothetical regional networks in Kumamoto and Ibaraki. The concentric circles in the Japan map indicate the epicenters.

average of 4 percent was used; the cable was cut with a probability of 4 percent when the conduit failed. Buildings can communicate when all cables between them are intact, even if the conduits fail. Elaboration on a cable-cut model under conduit failure is an important future work and is discussed below

Next, the impact of the conduit attributes on network reliability was examined. The right column of Fig. 4 shows the scale-wise unreliability of the three feature sets. In Kumamoto, the scale-wise unreliability was reduced (improved) according to the decrease in the conduit failure probability, as shown in the center of Fig. 4. Remarkably, the outage scale with a probability of 1 percent was 19 and 22 buildings for the S feature set and SG set, respectively, but only three buildings for the SGC set. We could drastically overestimate the risk ignoring the conduit features. The large gap was obtained because there are 17 buildings overestimating the disconnection probability by a factor of five or more, for example, building b22 had a 14.3 percent disconnection probability with the S feature set and 2.7 percent with the SGC set. Ibaraki did not yield as large a gap as in Kumamoto; however, the risk was underestimated when we ignored the conduit attributes. The outage scale with a probability of 10 percent was eight buildings with the SGC feature set but only two with the S and SG sets, which would be perilous to overlook the risk of isolating eight buildings with a 10 percent probability. A detailed examination revealed that the worst 10 vulnerable buildings underestimated the disconnection probability by a factor of 1.5. For example, building b_{67} had a 10.1 percent disconnection probability with the SGC set, but it had only 4.6 percent with the S set, which resulted in a gap in the 10 building range. Thus, the results show that network reliability strongly depends on the conduit attributes.

What-if Analysis: Conduit Upgrades

A what-if analysis was performed assuming conduit upgrades. As noted previously, old conduits accounted for approximately 90 percent of the dataset, and this ratio was almost the same in Kumamoto (89.8 percent) and Ibaraki (91.3 percent). We replaced all the conduits with new PV pipes, which are less vulnerable owing to their pipe-in-pipe structure. We then evaluated the improvement in scale-wise unreliability. The feature set used was the SGC.

The center column of Fig. 4 shows the conduit failure probabilities for the current-conduit mix (SGC) and upgraded PV pipes. In Kumamoto, the overall failure probabilities were reduced by upgrades. In Ibaraki, the probabilities were reduced for a wide range of x greater than 0.008; however, they were not reduced for very small x values, which could be owing to prediction errors.

The right column of Fig. 4 shows the scale-wise unreliability of the current–conduit mix and the upgraded PV pipes. The scale-wise unreliability was greatly improved by these upgrades. In Kumamoto, it decreased from 36.4 percent to 26.0 percent when the outage scale was one building, and the improvement ratio increased slightly with the outage scale. A closer look revealed that the disconnection probability from gateways was reduced for most buildings; for example, the disconnection probability of building b{20 was largely reduced from 4.5 percent to 1.0 percent because the route to the nearest gateway comprised only old-type pipes.

In Ibaraki, scale-wise unreliability was reduced from 21.0 percent to 14.9 percent when the outage scale was one building, and the improvement ratio increased up to outages with eight buildings. As in Kumamoto, the disconnection probability from gateways was reduced for most buildings, for example, that of building b{67 was largely reduced from 10.1 percent to 3.5 percent

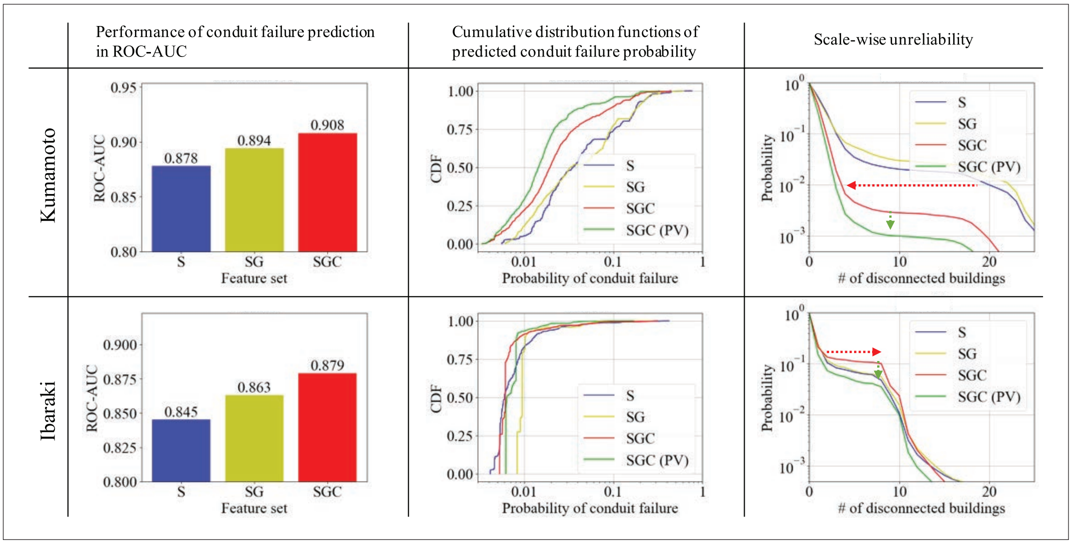

FIGURE 4. Results of reliability evaluation without (S and SG) and with (SGC) conduit attributes. The left column shows that the prediction accuracy is low without conduit attributes. The right column demonstrates that the evaluated network reliability is considerably different with and without conduit attributes, as indicated by the red dotted arrows. PV in the center and right columns assumes that all conduits would be upgraded to PV pipes, a new type, improving network reliability, as indicated by the green dotted arrows.

because the route to the nearest gateway was very long (45.6 km) and mostly comprised old-type conduits (94.8 percent).

Future Research Topics

Facility attributes significantly impact network reliability during natural disasters. Therefore, facility factors should be considered in the evaluation. However, several research topics still need to be addressed to improve the network design against natural disasters.

Gap Between the Conduit and Cable Conditions

Damage prediction techniques for underground facilities were first studied for water and gas ducts in infrastructure engineering. While service would be interrupted if ducts failed to supply water and gas, the service could continue even if conduits failed in telecommunication unless the internal cables were cut. Thus, cable damage prediction is a challenge unique to telecommunications and remains a missing piece. In this study, a uniform probability of 4 percent, the historical average, was applied; however, cable vulnerability should depend on hazards and conduits [15]. Therefore, further research is required. In addition, inspecting the cable conditions is difficult. While conduit conditions can be observed easily, cable conditions must be tested using transmission instruments, such as optical time-domain reflectometers (OTDRs), which increase inspection costs. Moreover, if multiple points on the cable are damaged, it is difficult for an OTDR to identify all the damaged points. Thus, a novel sensing technique that identifies all damaged points is required.

Network Reliability Evaluation for Distance Correlation of Facility Failures

This study assumed independence in conduit failures. However, our conduit inspection dataset revealed a correlation in the straight-line distances separating the conduits. Figure 5 shows the correlation versus conduit distances, that is, for every pair of conduits within x m, we computed

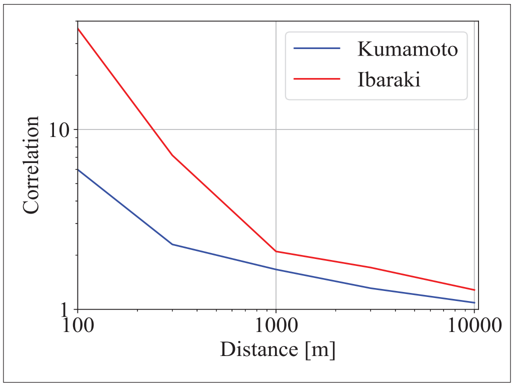

FIGURE 5. Distance correlation of conduit failures for Kumamoto and Ibaraki.

the ratio of *the actual number of simultaneous failures to the expected number of simultaneous failures based on the damage prediction*. The figure shows a positive correlation with proximity, that is, y is greater than 1.0. Note that the hazard data for PGV and PGA were included in our training dataset; therefore, this correlation was not caused by the similarity between PGV and PGA. First, we should study the origin of the correlation, for example, certain seismic features, utilizing the knowledge of earthquake engineering. Subsequently, the research community on communication networks should develop a network reliability evaluation method that addresses the distance correlation between facilities.

Communication Facilities Other Than Underground Conduits

Communication networks comprise various types of facilities. Conduits are not always buried underground but are sometimes installed along bridges to cross a river. Bridge tolerance against floods has been extensively studied in civil engineering [8] and can be applied to the evaluation of network reliability under floods. Communication cables are often relayed aerially in mountainous areas. If damage prediction techniques are developed for aerial cables, most cable route can be covered.

This study makes a practical contribution to the robustness assessment of communication networks. In addition, it contributes academically to the exploration of the interdisciplinary research area between infrastructure engineering and communication networks.

Network Robustness Against Different Types of Natural Disasters

This study focused on earthquakes as natural disasters; however, if the conduit failure prediction model is modified for another disaster, network robustness could be evaluated for the disaster by integrating the modified model into our method.

Network Robustness Against Multiple Natural Disasters Expected in a Region

This study assessed communication networks by assuming a particular earthquake; however, networks must be tolerant of all natural disasters expected in the region. Thus, network robustness must be evaluated by assuming multiple hazards [3].

Optimal Strategy for Upgrading Conduits

The what-if analysis upgraded *all* the conduits in a network; however, in practice, they are partially upgraded under budget constraints. The problem of maximizing network reliability should be studied by selecting the best subset of conduits for upgrading, which could be an NP-hard combinatorial optimization problem.

Network Digital Twins, Including Telecommunication Facilities

Network digital twins have recently attracted attention for optimizing and testing communication networks in real time. Network models with communication facilities allow digital twins to assess external threats such as natural disasters. We must develop a real-time update scheme for facility conditions in a model to track the current network status.

Generality of the Prediction Model

Other network operators could perform a similar analysis with their own datasets. They should be careful to avoid overfitting when training a prediction model with smaller datasets. Theoretically, our trained model is portable to other operators, as long as their test data contain the same standard seismic and ground features and the same conduit types. However, as communication infrastructures often have operator and country-specific aspects, a demonstration is a future challenge.

Benchmark Model of Communication Facilities

A benchmark model representing communication facilities must be developed to facilitate new research on facility-aware communication networks. However, the details of communication facilities are generally undisclosed for security reasons. Nevertheless, we have the following opportunities to develop a benchmark model. Underground conduits are often laid along major roads for maintainability; therefore, the routes are modeled based on roads between telecommunication buildings. Conduit type, length, and age can be determined if a generative model of conduit sequences reflecting neighboring environments is published.

Conclusion

This study makes a practical contribution to the robustness assessment of communication networks. In addition, it contributes academically to the exploration of the interdisciplinary research area between infrastructure engineering and communication networks. Although these research areas have been studied independently, they are both essential components that support telecommunication services. Thus, a collaboration between the two is imperative for disaster resilience, as well as for digital twins in communication networks. This interdisciplinary research field holds great promise for the future. The codes that evaluate the scale-wise unreliability are available at https://github.com/nttcslab/scale-wise-unrel.

References

[1] K. Ramakrishnan *et al*., "Resilient Communication for Dynamic First Responder Teams in Disaster Management," *IEEE Commun. Mag*., vol. 60, no. 9, 2022, pp. 93–99.

[2] A. Agrawal, V. Bhatia, and S. Prakash, "Network and Risk Modeling for Disaster Survivability Analysis of Backbone Optical Communication Networks," *J. Lightwave Technol*., vol. 37, no. 10, 2019, pp. 2352–62.

[3] R. Onaka *et al*., "Exact and Scalable Network Reliability Evaluation for Probabilistic Correlated Failures," *Proc. IEEE GLOBECOM*, 2022, pp. 5547–52.

[4] J. Oostenbrink and F. Kuipers, "Going the Extra Mile With Disaster-Aware Network Augmentation," *Proc. IEEE INFOCOM*, 2021, pp. 1–10.

[5] A. Pašić *et al*., "EFRADIR: An Enhanced Framework for Disaster Resilience," *IEEE Access*, vol. 9, 2021, pp. 13,125–48.

[6] A. Ito *et al*., "Earthquake Damage Prediction of Underground Steel Pipe With Screw Joint Using Machine Learning," *Proc. Lifelines 2022*, pp. 613–20.

[7] P. S. Firdaus et al., "Framework for Probabilistic Connectivity Estimation of Bridge Networks Under Seismic and Flood Hazards," *Proc. Int'l. Conf. Applications of Statistics and Probability in Civil Engineering*, 2023.

[8] T.-Y. Wang and C.-Y. Lin, "Climate Change Impact on Urban Resilience Under Typhoon Disasters Considering Interdependent Infrastructure Systems," *Proc. ICASP*, 2023.

[9] S. K. Chaturvedi, *Network Reliability: Measures and Evaluation*, John Wiley & Sons, 2016.

[10] K. Nakamura *et al*., "A Fast and Exact Evaluation Algorithm for the Expected Number of Connected Nodes: An Enhanced Network Reliability Measure," *Proc. IEEE INFOCOM*, 2023, pp. 1–10.

[11] S. Nojo and H. Watanabe, "Incorporating Reliability Specifications in the Design of Telecommunication Networks," *IEEE Commun. Mag*., vol. 31, no. 6, 1993, pp. 40–43.

[12] K. Nakamura *et al*., "Exact and Efficient Network Reliability Evaluation Per Outage Scale," *Proc. IEEE ICC*, 2023, pp. 4564–70.

[13] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," *Proc. ACM SIGKDD*, 2016, pp. 785–94.

[14] Y. Ozaki *et al*., "Multiobjective Tree-Structured Parzen Estimator for Computationally Expensive Optimization Problems," *Proc. GECCO*, 2020, pp. 533–41.

[15] Y. Yamazaki *et al*., "Development of Earthquake-Resistance Evaluation Technologies for Telecommunication Facilities," *NTT Technical Review*, vol. 8, no. 1, 2010, pp. 1–6.

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