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Research Article

Validating the Accidental Disaster Network Impact Model: A Case Study of the Tohoku 2011 Disaster

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Abstract: Societies have been battling the impact of disasters on their lives from the very beginning of their existence. A disaster is a challenge in more than one aspect, it has a devastating effect on a society and thus forcing change on the way a society lives, this change is the real measure of a disaster's impact regardless of numbers and quantifiers. The impact differs from one society to another, depending on the degree of disaster's preparedness the society possesses. Therefore it is very important to start mitigating disasters before they occur and one important part of this process is insuring a high level of survivability for the infrastructure. This study addresses the effect of accidental disasters on computer networks due to the importance of computer networks for everyday life and even more so during crisis times. The paper uses disaster's information from the Tohoku 2011 disaster and network traffic data from MAWI archive during the time of the disaster to validate the Accidental Disaster Network Impact Model (ADNIM). The model is a tool that estimates the change in network traffic during the event of a topological network failure that is triggered by an accidental disaster. The results from scenarios calculation show that the model is able to calculate scenarios that are closely similar to the real disaster time events.

Keywords: Disaster planning, network failure, network modeling, network planning, network survivability, telecommunication, topological network failure

INTRODUCTION

Disasters are part of life, which can change the way a community lives; it impacts every individual and aspect of living in it. This impact is being changed dramatically with humanity being increasingly technology dependent. The way a community faces a disaster is dependent on its understanding of the disaster, the technology used to face it and the type of effects that the community is trying to overcome. Originally the focus of disaster research was on addressing humanitarian aspects such as search and rescue and evacuation planning (Patterson, 2005; Fillmore *et al*., 2011). By the time IT researchers started performing a role in disaster research, as small as it is (Joshi *et al*., 2007), they followed the main stream of research in humanitarian aspects (Boucher *et al*., 2009). Some focused on disaster management (Shamshiry *et al*., 2011) where a large portion of the researchers studied the use of technology in the monitoring and detection of disasters (Lin *et al*., 2009; Asmara and Aziz, 2011) while other studies focused on providing services during a disaster (Sutjiredjeki *et al*., 2009). Only a few studied disasters' effects before they occur. Some of those studied the role of modeling and simulation to help a community overcome a disaster (Martagan *et al*., 2009), others used modeling and simulation in evaluation and improvement of infrastructure's survivability (Willroth *et al*., 2011). From amongst those a few studied the modeling of disasters' impact on computer networks (Fei and Wenye, 2010) and even smaller group studied the topological impact (Bassiri and Heydari, 2009; Neumayer *et al*., 2009).

In the previous paper (Abbas *et al*., 2012), the Accidental Disaster Network Impact Model (ADNIM) is presented. The model is a tool that studies the impact of accidental disaster on IP computer networks from a topological prospective.

This study aims to validate the model by using data from MAWI LAB's archive (MAWI, 1999) to show the calculations of such scenarios during Japan's 2011 Tohoku disaster.

Throughout the rest of the paper the ADNIM is presented in detail, the model represents the evaluated tool. Then the case study is described, followed by an explanation of the model application, data acquisition and scenario calculations. Later a detailed discussion of the results from the calculations and its comparison with the MAWI data is presented followed by conclusions.

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MODELING NETWORK FAILURE

Network failure is becoming increasingly costly, due to the big part networks play in everyday life and the increasing dependence on technologies, therefore a number researchers have been working on modeling the impact of such failures on a network in terms of survivability, recovery and cost (Guosheng *et al*., 2008; Bassiri and Heydari, 2009). The cause of failure differs from one research to another, but very few chose to address such failure when they are caused by disasters.

Modeling disaster impact: The reason a model is used is to recreate the effects the disaster caused on a network, in order to better understand the effects such events have on infrastructure in general and computer networks in particular and also to show that the model is capable of finding scenarios that are very close to the real scenarios.

The model is designed to simulate the effect of failure or multiple failures on a given network, regardless of the network type. It can be applied to any network-representable system, such as electrical power supply networks, transport networks, etc. More accurate results with less processing can be obtained when more detailed information is provided; unfortunately it is often difficult to acquire such information. The model is also not protocol dependent, meaning that it is possible to change the routing algorithm depending on the network itself. It can also be used to evaluate proposed networks by simulating the effects of different failure scenarios on a network in the design stage and/or upgrading designs.

The model: The model is a graphical one that consists of a number of nodes (N) and links that connect these nodes (L). The relation between each two nodes if they are connected or not is represented by an adjacency matrix (A); the S matrix represents the amount of supply and demand between each two nodes in N, the traffic on each link is represented by (T), (D) represents the distance of each node from the Center node (C), imp-c is the impact center and the distance between them is known as (ImpD) (Abbas *et al*., 2012).

Let:

$N = \{n_1, n_2, n_3, ..., n_m\}$ of nodes,

where,

m = Total number of nodes.

$L = \{l_1, l_2, l_3, ..., l_y\}$ of links,

where,

y = Total number of links

C = A node of N which is the distance reference.

MaxD = The total distance from one end of the net to another

ImpD = The distance between the C node and Imp-center.

$D = \{d_1, d_2, d_3, ..., d_m\}$

where,

d_i = The distance of n_i to C

A = [m x m]

where,

$$\begin{Bmatrix} A_{ij} = 1 \text{ if there is a link } l_{ij} \text{ between } n_i, n_j \\ \text{Else } A_{ij} = 0 \\ S = [m \times m] \end{Bmatrix}$$

where, S_{ij} is the network demand between n_i, n_j.

T = [m x m] where

$$\begin{Bmatrix} \text{if } A_{ij} = 1 \text{ then } T_{ij} = T_{ij} + t \\ \text{Else } T_{ij} = T_{next} + t \end{Bmatrix}$$

where, T_{next} is the next node from N chosen by the routing algorithm and it depends on the network's routing algorithm. In this case it is an IP network and therefore the next node is chosen by the SPF (Shortest Path First) algorithm:

$P = \{p_1, p_2, p_3, \ldots, p_m\}$

where,

p_i = The probability of failure for n_i

ImpP = The Impact probability

$$P_i = \begin{Bmatrix} P_i = 1 \text{ if } |\, ImpD - d_i \,| = MaxD. \\ P_i = 0 \text{ if } d_i = ImpD. \\ \text{Else } P_i = |(d_i - ImpD)/ MaxD\,|. \end{Bmatrix}$$

n_i fail if $p_i < ImpP$ ➔

$A_{ix}= 0$ and $A_{xi}= 0$ ➔

$S_{ix} = 0$ and $S_{xi} = 0$) where x< = m.

CASE STUDY-THE TOHOKU 2011 DISASTER

The disaster in Tohoku 2011, also known as the Sendai 2011 earthquake or the Great East Japan Disaster, is considered one of the major disasters in recorded history. The causalities reached 15,884 deceased and 2,633 missing as in February 2014. The numbers of casualties are much smaller than those in other similar disasters like the 2004 Indian Ocean Earthquake and Tsunami, which killed 230,000 people. Sadly a large number of children were separated from their families because the disaster happened during school time. Although the loss in human lives is beyond cost estimations, this disaster is considered the highest costing natural disaster in history with US$235 billion of economic loss as estimated by the World Bank.

There are a number of reasons that led to choosing the Great East Japan 2011 disaster as a case study for ADNIM. The first reason is the location and geographical nature of Japan that makes it a good candidate for disaster studies in Asia-Pacific region. Along with the fact that Japan possesses one of the most impressive disaster documentation, dating more than a hundred years back, as well as a detailed record of traffic for the WAID Backbone network. The network is in the disaster zone, where part of the network is down and the rest was still functional. This makes a very good basis to apply the model. Another reason is that both the Japanese society and infrastructure is highly prepared for facing disaster due to high frequency of those events there.

One of the most important reasons of choosing Tohoku disaster is the fact that it is one of the largest in the world's history and that it is a good example of the complex disaster where more than one trigger hit the disaster zone and the disaster zone increasing with each trigger that occur. Moreover it is a combination of accidental triggers that include a large variety of both natural and technological triggers.

Disaster triggers: The earthquake started on a Friday at 2:46 p.m. Japan local time. It was centered on the seafloor 72 km east of Tohoku, at a depth of 32 kilometers below the surface. The shaking lasted about 6 min. It is the most powerful recorded earthquake to have hit Japan and the fifth most powerful recorded worldwide. The earthquake was initially believed to be a 7.9 ^{MW} earthquake, then it was quickly increased many times to be decided finally that it was a 9.0 ^{MW} earthquake making it the most powerful to hit the country since 1900. The epicenter was at a relatively shallow depth about 373 km from Tokyo, the nearest city to the earthquake center is Sendai, which is 130 km from the epicenter.

The earthquake triggered a tsunami wave that hit the coast about two hours after the quake. The wave reached as high as 40 m and travels as far as 10 km inland in Sendai, causing more devastation and destruction than the earthquake. That was followed by a meltdown in three nuclear reactors in the Fukushima Daiichi Nuclear Power Plant, which also caused nuclear contamination in food and water and a major electrical power failure when about 4.4 million were left without electricity, as well as thousands of aftershocks that hit Japan.

Although the amount of information and media coverage related to the event of the disaster is quite large, including the information regarding the recovery and rebuilding, very little information and spotlight has been focused on the computer network status through the disaster. This is probably because of the overwhelming nature of the disaster's events or because it is always the case in such events to focus firstly on the human loss, then only economic from a very classical prospective, such as insurance and rebuilding. Networking related information such as loss, role in mitigation and recovery events are generally undermined by the rest of information that is presumed to be more important.

NETWORK INFORMATION-MAWI WORKING GROUP NETWORK

The MAWI (Measurement and Analysis on the WIDE Internet) work group is part of the WIDE project (Esaki *et al*., 2003), the main goal of the group being to monitor live network traffic on the WIDE backbone network Fig. 1 and classify it using AGURI (Aggregation-based Traffic Profiler). The group keeps a daily record of traffic archive (MAWI Data set and Archive) that is available on the group web site. This data is largely used by researchers to evaluate traffic anomaly detectors (Youngjoon *et al*., 2013). The data is also used by researchers in traffic classifiers (Borgnat *et al*., 2009) and security breach detectors (Salem *et al*., 2011). One research team suggests a new data set driven from the original MAWI data set that gives a better insight of the traffic and can provide even more information to researchers and more understanding of the evolving of the Internet. The suggested data set is called MALAWI; the paper also presents an analysis of a month's (3/2011) traffic as a sample of the suggested data set (Araújo and Fukuda, 2011).

Data source-MAWI dataset and archive: The MAWI group has been keeping daily data records of real traffic going through the Japan-US trans-pacific link since 1999 up to date in the MAWI Archive, it records 15 min of traffic every day, from 12:00 to 12:15. The data is taken from a number of sampling points; sample point F is in service up till the day. The data is made available online for researchers to use (MAWI, 2010). The location of the sampling point is not revealed. Apart from the daily recording the working group has run longer traffic traces at different times and from different sampling points to prove the consistency of the data and as part of the "a day in the life of the Internet" project.

The dataset includes protocol headers only; the data payload is removed to insure user privacy, at the same time IP addresses are scrambled for privacy reasons also, so no specific user IP address can be identified from the data. With all the above mentioned the MAWI archive is a very important source of real data for researches, first because it is proven to be consistent, the time period on which the traces have been carried out since 1990-up to date, as well as ease

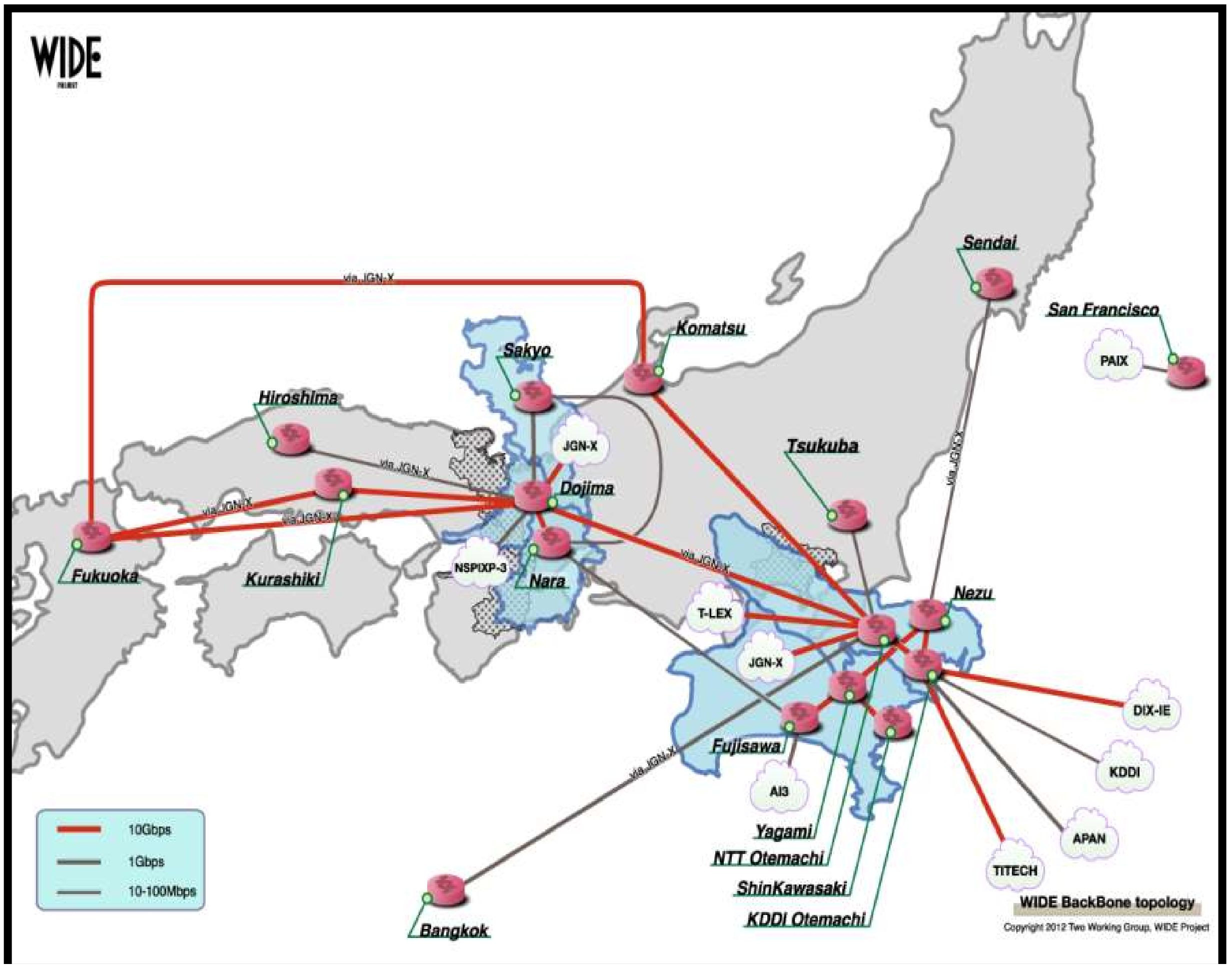

Fig. 1: Wide backbone network (WIDE-Project 2012)

of access since it is available freely on the MAWI website. Needless to say, the data can be used for research purposes only.

Data preparation-disaster data on MAWI: The trigger took place after 2 pm while the MAWI data is recorded every single day from 12:00-12:15 pm, therefore sadly the data regarding the trigger day is not useful in this case. This is because the recording took place before the time of the first event; in this case it is the earthquake. More over there is no data to learn what happened to the network in the first few hours following the trigger; this is also considered as a big loss because if such data existed, it would be very useful to clarify the effect of each single event such as the earthquake, tsunami, power failure, nuclear meltdown on the network.

The data from the MAWI dataset shows that three patterns of data can be observe, first before the disaster takes place, covering the period between 1-11 March 2011, when the average traffic is 303.3664 Mbps. Second is the data for the two weeks after the disaster (Table 1). This data includes the effect of the original trigger along with the tsunami, as well as the

Table 1: MAWI traffic during the disaster

Date	Traffic Mbps
12-Mar	98.63
13-Mar	159.41
14-Mar	118.11
15-Mar	140.48
16-Mar	147.69
17-Mar	139.14
18-Mar	143.2
19-Mar	165.29
20-Mar	150.35
21-Mar	168
22-Mar	129.25
23-Mar	156.64
24-Mar	185.14
25-Mar	151.47
Avg1	146.6286
Avg2	150.3208

reactor failure and power failure; the Tokyo area lost 40% of its usual demand for electricity as shown in the table. An important issue regarding this set is the data from the 12th of March which shows significant difference from the rest of the data for the same period. This is due to the panic and shock of the trigger, therefore the data of this day will not be considered in the calculations. If this day is to be considered the

Table 2: Traffic after scheduled power cut

Date	Traffic Mbps
26-Mar	194.64
27-Mar	206.37
28-Mar	156.91
29-Mar	188.75
30-Mar	199.8
31-Mar	175.45
Avg	186.9867

average will be 146.6286, leading to 51.66617% traffic loss. When ignoring the result from the first day or Panic day the average traffic will be 150.3208 Mbps, meaning that the difference or loss in traffic is 153.0456 Mbps, leading to 50.4491% traffic loss.

The third part as shown in Table 2 covering the data for the period 26-31 of March is after the first major hit is absorbed and measures had been taken to decrease the effect. The damage to the infrastructure is not yet neutralized but some of the effects on daily life are, the scheduled power cuts on the country helped cover most of the shortage in the Tokyo and neutralized the effect on the network demand. The average traffic during this period was 186.9867 Mbps. The loss in traffic was 116.3797 Mbps, resulting in 38.36276% traffic loss. In April the traffic was back to normal or over the normal. The data from the suggested MALAWI data set (Araújo and Fukuda, 2011) concurs with the result from the MAWI dataset.

Scenarios calculation: In order to recreate the circumstances that took place during the disaster for the communication network, several steps of calculations need to be done:

Network map: The MAWI data set represent the traffic on the WIDE network, in order to generate a more manageable map; the map is simplified using the following steps:

- The distance between each two nodes on the map is determined
- All nodes that have a high speed link and are less than 50 km in distance of each other are merged
- The center node (C) according to importance, links and position on the map, is decided
- The distances of external nodes from C are found.

As a result a map is generated as shown in Fig. 2. This new map is used in the model application and scenarios. The A matrix between the nodes is then generated, for each two nodes if there is a link it is given the value of "1", otherwise the value of "0" is assigned to the cell. No value is given to the connection between the node and itself, this is assumed to be internal data and is not included in calculation of traffic. As shown below:

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

The matrix does not include the external nodes named $X_1$and X_2 or their links, first because the nodes would be too far to be in the disaster range and the demand this network satisfies for those nodes do not include the demand between them, because that traffic would not be routed through this network. In order to choose the center node C, the distances between all nodes are calculated using Distance Calculator, an online tool by Daft Logic (Daftlogic, 2008). The results suggest two nodes (N7, N4), after viewing the distance for both nodes from the rest of the network's nodes and because N7 is representing the Tokyo area and it is the link to the external nodes, N7 is chosen to be the C node. Therefore the distance matrix (D) is:

D = {881.9, 559.2, 675.186, 404.29, 309.62, 52.35, 0, 303.75}

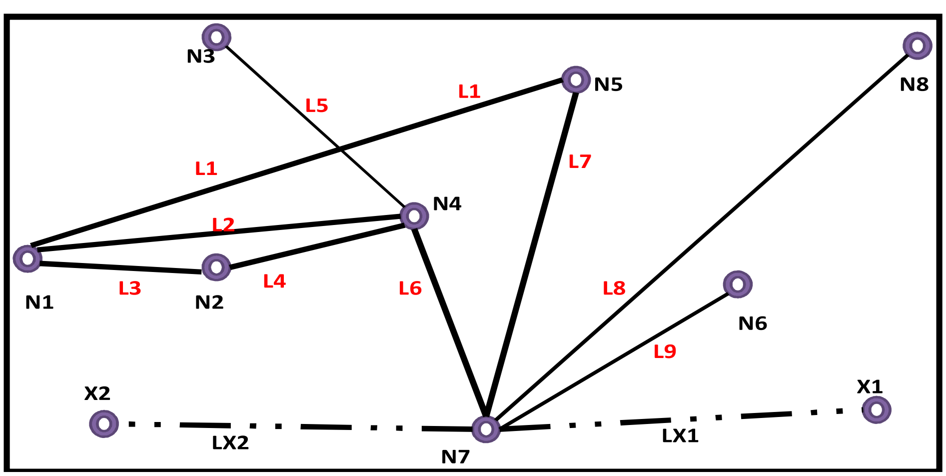

Fig. 2: New network map

Traffic supply/demand and traffic: The nodes in the network demand and supply data to/from each and every other node. The amount of this supply and demand depends on the degree of homogeneity in the network. When the network is homogenous the demand/supply between all the nodes is equal and when the network is less homogenous the difference in the demand between the nodes increases.

It is assumed that for each basic demand between two nodes in the homogenous state of the network there will be "t" traffic generated. If there is a direct link between those nodes then the amount of "t" traffic will be added to the total traffic going through this link. In cases where there is no direct link between the nodes, then the traffic will follow the Shortest Path First Algorithm to choose a path, therefore adding the amount of "t" traffic to each link it passes from the originating node to the destination node. After satisfying all the demand between the nodes and adding the generated traffic to the links it is possible to calculate the amount of traffic generated defined by "t".

Homogenous network supply/demand and traffic: Let S (supply/demand) for each node of N is equal to 1. If the network's demand is homogeneous, then all the nodes will have equal demand among them. Therefore the supply/demand = 1/n-1.

In this case traffic of "t" is generated by one unit of demand between two nodes and is equal to 1/9 of the node demand as shown in Table 3. The cells in column and row N8 represent the supply/demand that is lost when N8 fails. As the node represents Sendai, where the first trigger in this case the earthquake had the biggest impact. On the other hand the cells in column and row N6 represent the lost supply/demand caused by N6 failing because of the second trigger, in this case the Fukushima failure.

Before the disaster and according to the demand, Table 4 shows the links used for the traffic between each two nodes; each time the link appears in the table the amount of "t" traffic is added to the total traffic on that link. The shaded cells represent the links that lost traffic because of the two mentioned triggers. In this way each time a link appears in one of the shaded cells it losses the amount of "t" traffic because of the disaster.

As per the previous assumption that for every unit of demand between each two nodes, there is traffic with the amount of t and the total traffic through the network T is the summation of all t' s; then the amount of traffic is represented in the Traffic1 column in Table 5. This represents the amount of traffic defined by "t" during the normal network functions. After first trigger and after deducting all the traffic shaded, the resulting amount of traffic is represented by the Traffic2 column in the same table; in the same sense the Traffic3 column represents the traffic after deducting the traffic lost in both triggers.

This mean that the total traffic lost is 37t, which is 13.69% of the traffic of the network. If another node falls, like the case of the Fukushima trigger when N6 fell, the traffic will change again. In this case the total traffic lost will be 72t; the lost traffic is 40.223% of the traffic of the network. This is applicable if the network has homogenous demand which is highly improbable; most networks have

Table 3: Homogenous demand /supply before disaster

	N1	N2	N3	N4	N5	N6	N7	N8	X1	X2
N1	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N2	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N3	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N4	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9
N5	1/9	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9
N6	1/9	1/9	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9
N7	1/9	1/9	1/9	1/9	1/9	1/9	/	1/9	1/9	1/9
N8	1/9	1/9	1/9	1/9	1/9	1/9	1/9	/	1/9	1/9
X1	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9	/	/
X2	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9	/	/

Table 4: Links to route traffic between each 2 nodes before disaster

	N1	N2	N3	N4	N5	N6	N7	N8	X1	X2
N1	\	L3	L2,L5	L2	L1	L1,L7,L9	L1,L7	L1,L7,L8	L1,L7,LX1	L1,L7,LX2
N2	L3	\	L4,L5	L4	L3,L1	L4,L6,L9	L4,L6	L4,L6,L8	L4,L6,LX1	L4,L6,LX2
N3	L5,L2	L5,L4	\	L5	L5,L2,L1	L5,L6,L9	L5,L6	L5,L6,L8	L5,L6,LX1	L5,L6,LX2
N4	L2	L4	L5	\	L2,L1	L6,L9	L6	L6,L8	L6,LX1	L6,LX2
N5	L1	L1,L3	L1,L2,L5	L1,L2	\	L7,L9	L7	L7,L8	L7,LX1	L7,LX2
N6	L9,L6,L2	L9,L6,L4	L9,L6,L5	L9,L6	L9,L7	\	L9	L9,L8	L9,LX1	L9,LX2
N7	L6,L2	L6,L4	L6,L5	L6	L7	L9	\	L8	LX1	LX2
N8	L8,L6,L2	L8,L6,L4	L8,L6,L5	L8,L6	L8,L7	L8,L9	L8	\	L8,LX1	L8,LX2
X1	LX1,L6,L2	LX1,L6,L4	LX1,L6,L5	LX1,L6	LX1,L7	LX1,L9	LX1	LX1,L8	\	\
X2	LX2,L6,L2	LX2,L6,L4	LX2,L6,L5	LX2,L6	LX2,L7	LX2,L9	LX2	LX2,L8	\	\

Table 5: Traffic links before and after disaster

Link	Traffic 1	Traffic 2	Traffic 3
L1	13t	12t	11t
L2	15t	14t	13t
L3	4t	4t	4t
L4	14t	12t	10t
L5	18t	16t	14t
L6	34t	27t	20t
L7	15t	12t	9t
L8	18t	0	0
L9	16t	15t	0
LX1	16t	15t	13t
LX2	16t	15t	13t
Total T	179t	142t	107t

levels of demand that change from one node to another and even from time to time because there are so many factors that can have an effect on a network demand.

Inhomogeneous network supply/demand and traffic: In order to find the right scenario that happened during the disaster, it is important to find the right demand distribution. If the network demand is not homogenous, then all possible demand probabilities must be covered; therefore the difference in demand is increased for each node at a time, the change interval chosen is (1-6).

To reach that interval a larger interval (1-9) is first tested, as suggested by Bassiri and Heydari (2009) and the results showed that the resulting demand is a multiple of the previous iterations of lower demand difference. The demand on each node separately is increased from 1 all the way to 6, each time distributing the extra demand from that node on the other nodes in all possible ways. This results in different network situations, in other words resulted in different network's layouts. In the very same layout the demand can be distributed in many ways and all those possibilities need to be addressed, resulting in different scenarios with different traffic and a different amount of lost traffic.

Firstly the network is made less homogenous; this is done by increasing the demand in one of the nodes more than the rest of the nodes by one. Each time the demand is increased by one, the traffic is increased by 9t because originally when the demand was homogenous the total demand is 10. This is because for each node 1/9 generating one t, with a total 9t. If the demand in a certain given node is increased by 1, so the traffic will be doubled. Therefore when the demand is increased by 2 the traffic will increase by 18t. This extra demand/supply need to be divided among the rest of the network. Now the new demand must be distributed in all possible patterns on the network, changing the demand and supply in the entire network not only that given node. Let that node be N7.

Table 6: New demand distribution N7*2

	N1	N2	N3	N4	N5	N6	N7*2	N8	X1	X2
N1	/	1/9	1/9	1/9	1/9	1/9	2/9	1/9	1/9	1/9
N2	1/9	/	1/9	1/9	1/9	1/9	2/9	1/9	1/9	1/9
N3	1/9	1/9	/	1/9	1/9	1/9	2/9	1/9	1/9	1/9
N4	1/9	1/9	1/9	/	1/9	1/9	2/9	1/9	1/9	1/9
N5	1/9	1/9	1/9	1/9	/	1/9	2/9	1/9	1/9	1/9
N6	1/9	1/9	1/9	1/9	1/9	/	2/9	1/9	1/9	1/9
N7*2	2/9	2/9	2/9	2/9	2/9	2/9	/	2/9	2/9	2/9
N8	1/9	1/9	1/9	1/9	1/9	1/9	2/9	/	1/9	1/9
X1	1/9	1/9	1/9	1/9	1/9	1/9	2/9	1/9	/	/
X2	1/9	1/9	1/9	1/9	1/9	1/9	2/9	1/9	/	/

Table 7: Demand distribution in the least homogenous case in the * 2 scenario

	N1	N2	N3	N4	N5	N6	N7*2	N8	X1	X2
N1	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N2	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N3	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9	1/9
N4	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9	1/9
N5	1/9	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9	1/9
N6	1/9	1/9	1/9	1/9	1/9	/	1/9	1/9	1/9	1/9
N7*2	1/9	1/9	1/9	1/9	1/9	1/9	/	1/9	6/9	6/9
N8	1/9	1/9	1/9	1/9	1/9	1/9	1/9	/	1/9	1/9
X1	1/9	1/9	1/9	1/9	1/9	1/9	6/9	1/9	/	/
X2	1/9	1/9	1/9	1/9	1/9	1/9	6/9	1/9	/	/

Table 8: Demand distribution in one of N7* 4 scenarios

	N1	N2	N3	N4	N5	N6		N7	N8	X1
N1	\	L3	L2,L5	L2	L1	L1,L7,L9	*2	L1,L7	L1,L7,L8	L1,L7,LX1
N2	L3	\	L4,L5	L4	L3,L1	L4,L6,L9	*2	L4,L6	L4,L6,L8	L4,L6,LX1
N3	L5,L2	L5,L4	\	L5	L5,L2,L1	L5,L6,L9		L5,L6	L5,L6,L8	L5,L6,LX1
N4	L2	L4	L5	\	L2,L1	L6,L9	*4	L6	L6,L8	L6,LX1
N5	L1	L1,L3	L1,L2,L5	L1,L2	\	L7,L9	*3	L7	L7,L8	L7,LX1
N6	L9,L6,L2	L9,L6,L4	L9,L6,L5	L9,L6	L9,L7	\	*5	L9	L9,L8	L9,LX1
	*2	*2		*4	*3	*5			*5	*7
N7	L6,L2	L6,L4	L6,L5	L6	L7	L9		\	L8	LX1
N8	L8,L6,L2	L8,L6,L4	L8,L6,L5	L8,L6	L8,L7	L8,L9	*5	L8	\	L8,LX1
X1	LX1,L6,L2	LX1,L6,L4	LX1,L6,L5	LX1,L6	LX1,L7	LX1,L9	*7	LX1	LX1,L8	\

Table 9: Traffic for each link before and after each failure in N7*4 scenario

Link	Traffic 1	Traffic 2	Traffic 3
L1	14t	12t	10t
L2	14t	12t	10t
L3	4t	4t	4t
L4	16t	12t	10t
L5	18t	14t	13t
L6	44t	30t	21t
L7	20t	14t	9t
L8	26t	0	0
L9	26t	0	0
LX1	28t	24t	20t
LX2	28t	24t	20t
Total T	238t	146t	117t

Since the demand by the named node is double the other nodes. This could affect the demand through the network in many possibilities; the extra demand could be divided on the other nodes in a homogenous pattern. The extra demand is divided equally among the remaining nodes as shown in Table 6. The cells shaded show the increased demand in N7 and how it was distributed equally among the rest of the nodes.

Then the degree of homogeneity of dividing the extra demand is decreased. Following this process, the distribution is changed in order to cover all possibilities. Table 7 shows the least homogenous distribution of the extra supply pattern the network can have, all possible combinations between those two were covered and afterwards the disaster scenario is applied to each one of those cases and the change in traffic is then calculated as well as the traffic loss.

In each and every case theoretically possible there are different traffic patterns, because although the nodes and the links are the same in every case, the change in network demand thus in network traffic makes each case a standalone network and therefore the effect of the network failure will be different. In the same way the case of demand being 3 times as much as an ordinary node is addressed, just like in the previous case all distributions are generated and the new and lost traffic is estimated.

In the cases where the demand in N7 is 4 times the basic demand in the homogenous scenario, this means the demand is 4*9 = 36 that needs to be divided among the rest of the nodes. Table 8 shows one of those scenarios and Table 9 shows the effect that distribution will have on the traffic on each link. Once more the disaster scenario for each case is calculated. As for the scenario shown in Table 8 the impact of the triggers 1, 2 on the traffic is detailed in the Table 9, where Traffic1 represents the normal traffic, Traffic 2 represents the traffic after N8 and N6 both fail. This means that the total traffic lost because of the two mentioned triggers is 92t. This amount of traffic represents 38.655% of the traffic was lost.

However, even more traffic was lost with 40% of Tokyo's electric power lost consequently resulting in the same amount of loss in the network demand in Tokyo. In other words apart from the loss in demand and therefore traffic caused by N8 and N6 failing N7 also lost 40% of its demand because of losing electric power. Therefore the amount of demand in N7 needs to be deducted by 40%; the remaining demand is 15 units of demand divided among the rest of the nodes. Table 10 shows that case of distribution. As a result even more traffic is lost. The Traffic 3 column in Table 9 details the lost traffic for each link; it also shows that the total amount of traffic lost because of the power outage is 121t, which represents 50.84% of the network traffic.

In the same way the supply/demand, traffic and traffic loss for the case where a node has five times more demand as the rest of the nodes is calculated and all the scenarios related are satisfied. Table 11 shows the distribution of that demand in the network. In this

Table 10: New network after triggers 1, 2 and power outage in N7*4 scenario

	N1	N2	N3	N4	N5		N7	X1	X2
N1	\	L3	L2,L5	L2	L1		L1,L7	L1,L7,LX1	L1,L7,LX2
N2	L3	\	L4,L5	L4	L3,L1		L4,L6	L4,L6,LX1	L4,L6,LX2
N3	L5,L2	L5,L4	\	L5	L5,L2,L1		L5,L6	L5,L6,LX1	L5,L6,LX2
N4	L2	L4	L5	\	L2,L1		L6	L6,LX1	L6,LX2
N5	L1	L1,L3	L1,L2,L5	L1,L2	\		L7	L7,LX1	L7,LX2
								*5	*5
N7	L6,L2	L6,L4	L6,L5	L6	L7		\	LX1	LX2
X1	LX1,L6,L2	LX1,L6,L4	LX1,L6,L5	LX1,L6	LX1,L7	*5	LX1	\	\
X2	LX2,L6,L2	LX2,L6,L4	LX2,L6,L5	LX2,L6	LX2,L7	*5	LX2	\	\

Table 11: Demand distribution N7* 5

	N1	N2	N3	N4	N5	N6		N7	N8	X1	X2
N1	\	L3	L2,L5	L2	L1	L1,L7,L9	*3	L1,L7	L1,L7,L8	L1,L7,LX1	L1,L7,LX2
N2	L3	\	L4,L5	L4	L3,L1	L4,L6,L9	*3	L4,L6	L4,L6,L8	L4,L6,LX1	L4,L6,LX2
N3	L5,L2	L5,L4	\	L5	L5,L2,L1	L5,L6,L9	*1	L5,L6	L5,L6,L8	L5,L6,LX1	L5,L6,LX2
N4	L2	L4	L5	\	L2,L1	L6,L9	*6	L6	L6,L8	L6,LX1	L6,LX2
N5	L1	L1,L3	L1,L2,L5	L1,L2	\	L7,L9	*4	L7	L7,L8	L7,LX1	L7,LX2
N6	L9,L6,L2	L9,L6,L4	L9,L6,L5	L9,L6	L9,L7	\	*6	L9	L9,L8	L9,LX1	L9,LX2
	*3	*3	*1	*6	*4	*6			*6	*8	*8
N7	L6,L2	L6,L4	L6,L5	L6	L7	L9		\	L8	LX1	LX2
N8	L8,L6,L2	L8,L6,L4	L8,L6,L5	L8,L6	L8,L7	L8,L9	*6	L8	\	L8,LX1	L8,LX2
X1	LX1,L6,L2	LX1,L6,L4	LX1,L6,L5	LX1,L6	LX1,L7	LX1,L9	*8	LX1	LX1,L8	\	\
X2	LX2,L6,L2	LX2,L6,L4	LX2,L6,L5	LX2,L6	LX2,L7	LX2,L9	*8	LX2	LX2,L8	\	\

Table 12: Traffic before and after each failure N7*5 scenario

Link	Traffic 1	Traffic 2	Traffic 3
L1	15t	13t	12t
L2	15t	13t	12t
L3	4t	4t	4t
L4	18t	14t	10t
L5	18t	14t	14t
L6	49t	35t	28t
L7	23t	17t	13t
L8	28	0	0
L9	28t	0	0
LX1	30t	26t	26t
LX2	30t	26t	26t
Total T	258t	162t	145t

case the amount of traffic lost when N8 and N6 were lost is 98t, which is equal to 37.20% of the total traffic; this is represented by column Traffic 2 in Table 12. After introducing the power outage impact new demand will emerge that is 40% less than the original before the disaster, that demand is 27 units.

Just as in the previous scenario N8 and N6 are not included in this new network demand distribution because they have already failed by now and are unable to generate demand or provide supply that are no longer part of the functional network. The amount of traffic lost is detailed in Traffic 3 of Table 12, total traffic lost will be 113t, which is equal to 43.79% of the traffic would be lost.

DISCUSSION

When the model is applied to the case study of the Tohoku 2011 disaster, it is clear that there is more than one network in hand for the model to evaluate. First the model needs to evaluate different demand patterns in the network by initially evaluating a homogenous network first, in order to find the basic traffic on each link in the network as a result for the demand and supply between the nodes. Having achieved that, the amount of demand needs to be changed for each node separately and for each the amount of demand is increased in all possible combination of sub-change of the extra distribution is changed again therefore resulting in a new network each time. Although the nodes and links are still the same, the demand is not and therefore the traffic is not. So in each case, the way the network reacts to change represented by failure or disaster is different. It is important to clarify that if the actual demand patterns or the usual everyday traffic between the nodes are provided, then calculations can be much simpler and much more accurate.

The other reason for dealing with a number of networks is the disaster/failure itself. Once part of the network has failed the network changes by losing some of the components, such as nodes, links, demand and traffic. This loss can be a temporary short-term effect, or a long-term effect. Short-term effect like the power outage in the Tohoku disaster case and long-term is similar to the Fukushima effect.

It is important to mention that such failures both short-term and long-term do not necessarily mean that damage has occurred in nodes, links or that network components are damaged in the failure zone; they could be still functional but have failed for other reason such as evacuation or power outage.

Nevertheless a new network will emerge with different components and different traffic, as was clear in Table 9 to 11 that show the impact of power failure on Tokyo and it is the most basic goal of this model to be able to find how an accidental failure can affect the network.

Another important thing to notice is that the model can reach scenarios that are very close to the actual events that have taken place during the disaster; this is clear when comparing the results in the scenario from Table 7 and 8 with the actual results driven from the MAWI Dataset (Table 1). Those results show that the total traffic lost because of the nodes' failure is 92t; this is equal to 38.6% of the network traffic. This result represents the time when the power shortages were neutralized by scheduled cuts around Japan.

The percentage of lost traffic for this period 26-31 March is 38.36%. In reaching this result the impact of the power cut was introduced, by decreasing the traffic in node N7 by 40% to simulate the effect of the loss caused by power outage and the results showed that the lost traffic after calculating the traffic lost because of the power outage 121t, is equal to 50.84% of the network traffic. This also applies to the actual data that represented the second period this time during the period 12-25 March with the full impact of the disaster in effect, the percentage for the same period of time from the data set is as previously mentioned at 50.45%.

CONCLUSION

The case study describes in this study shows that the model was able to simulate a scenario that actually has taken place in a real life disaster. The traffic analysis by Araújo and Fukuda (2011) also concurs with these results.

It is reasonable to believe that, if there was more information about the network in term of traffic and demand, the results would have been reached with more accuracy and with less number of scenarios calculated. In the same way more information about the disaster, such as more details on each trigger point and its effect on the network, would have positively affected both calculation time and result, in this way more could have been learnt from this disaster.

The case study also shows that disaster that escalates rapidly will result in familiar disaster triggers, which produces after effect impact of an unfamiliar disaster triggers, like technological disaster such as power outage and network failure. From the case study the ability of the model to address such complex disasters with multiple triggers is highlighted through the models ability to calculate the impact of the electric failure on the computer network. This is achieved by the models ability to address partial node failure.

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