Super Cat characterization through deconstruction of stochastic event cascades

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ABSTRACT :

Losses generated by major catastrophes are generally estimated from a characterization of the damages caused by the (primary) event (an earthquake) without fully modeling the following secondary events (FFEQ, landslide, liquefaction, etc.), and some subjective amount of losses, with large uncertainty, is added to account for the un-modeled part. We have developed a method that models our sphere of living, working, and sustenance as a complex system. Some usually well-characterized elements (ie. Bridges, hospitals, interstate highways, emergency organization) constitute the well-defined network of nodes and links. The myriad of other small components, which have a small relative effect on the whole, but jointly can have a large importance, are modeled statistically. This method specifically accounts for the situations where more and more small secondary cascading events occur. Of great interest are the cases when the cascade of events causes a gradual degradation of the entire socio-economic matrix of a region, leading to a situation akin to a phase change in the behavior of the system. Such conditions generally lead to extreme losses, and are often referred to as Super-Cat. The progression of events in the hurricane Katrina of 2003 is one example of such a condition, in which the entire infrastructure and administrative matrix collapsed. Our method uses a deconstruction of historical catastrophic events, and we formulate a model of stochastic occurrence of cascades. We use the concept of disruption to quantify the effect of un-modeled events on the final losses.

KEYWORDS:

Catastrophic losses, complex systems, events cascades, Super Cat events, un-modeled losses, insurance.

1. INTRODUCTION

We define a Super Catastrophe, or Super Cat, as a major catastrophic event whose outcome is far beyond what previous analysis would have predicted, resulting in substantial un-modeled losses. The 2005 hurricane Katrina is a good example of a Super Cat event. It is the result of a confluence of conditions, including the occurrence of an extreme event, and an extreme concentration of exposure. The 1906 Great San Francisco Earthquake is another example of a Super Cat. Deconstructing these events and trying to understand their phenomenology gives insights to identify the important characteristics that are missing in our current modeling. Some of the major elements are:

- Containment failure, that add to the existing damages
- Evacuation, that leads to further deterioration and delays, and
- Macro economic impact with inflation and delays.

Current methods of estimation of the “un-modeled” losses generally consider mean-value effects in spite of the fact that Super Cats appear to be the results of extreme conditions. The series of events that follow an earthquake, a hurricane, or any other severe primary event, create disruption. This causes damages to the infrastructure that provide life sustenance and functional support to businesses. When the infrastructure is damaged and loses part, or all of its functionality, it creates a type of disruption that can cause evacuations; days lost, and consequently generates business interruption (BI) losses that can become a substantial part of the losses. These losses are often called un-modeled losses because they are currently not specifically modeled. Current methods of loss estimation acknowledge their existence and use a mean-values amplification factor of the losses for an entire region. This factor is regional and it does not have enough granularities to identify sub-regions of enhanced losses, to identify the parts of the infrastructure that are the dominant contributors, or to identify the specific perils that caused the losses. It was calibrated on a small sample of amplification data available for known Super Cat events, such as the 2005 hurricane Katrina.

The method presented in this paper is an improvement on the current method as it leverages more information, including qualitative information about the phenomenology of a Super Cat. First, it systematically identifies all the possible "things –that-can-go-wrong" following a major event and, second, it models their impact on the infrastructure and last, it quantifies the resulting disruption, and BI losses. It allows the determination of geographic locations where losses can be extreme, and it identifies the causative peril. For example, an earthquake can trigger the weakening of a dam, causing inundation, and evacuation.

The greatest practical impact on losses is from the disruption that leads to interruption of activities, or Business Interruptions (BI). Another important thing we learn from studying these extreme events is that it is practically impossible to predict the final state of the system conditional on knowing all the details of the primary event. For example, to confidently predict the final state of the city of New Orleans, after a repeat of hurricane Katrina, one would need to know exactly, without uncertainty, at which point and under which loading each of the levees would fail. This is clearly impossible in the present state of knowledge, and the best we can achieve is to have a probabilistic description of their behavior. This un-determinacy of the outcome is the result of the stochastic nature of a wide range of interdependent events that can occur in cascade, as illustrated in Figure 1. This type of behavior is best modeled probabilistically.

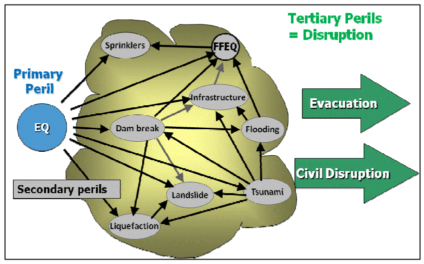

Figure 1. Conceptual representation of secondary events occurring in cascade

In the following sections, we describe a framework to model the entire range of possible outcomes one could expect from a specific primary event, emphasizing the possibility of extremes, and their probability distribution. We also give preliminary results of loss calculations for the Hayward-Oakland corridor, to demonstrate that the observed outcome is only one random sample among many, some more and some less likely.

3. FRAMEWORK FOR MODELING DISRUPTION

3.1 Modeling disruption

We assume that all the elements that provide the support for life sustenance and business activities are part of a network of interdependent sub-networks that we model by a collection of nodes and links. The nodes provide the functions and commodities needed, and the links are for their distribution to the entire area of interest.

Disruption occurs when the functionality of a node is lost, entirely or partially, or when a link is severed. Our disruption model is based on estimating the amount of functionality that is lost, through the loss of links, or loss of nodes, when elements of the infrastructure are damaged.

For completeness, we distinguish three levels of systems, which call for different types of models:

- Macro, or Global level
- Meso, or standard level
- Micro, or diffuse, or distribution level

3.2 Macro level

Figure 2, shows an example of a macro network which identifies the greatest global perils and their correlation. It is the result of work by a group of world leading risk experts (World Economic Forum, 2007) who were asked to identify what they considered were the most important risk in today's (2007) economy.

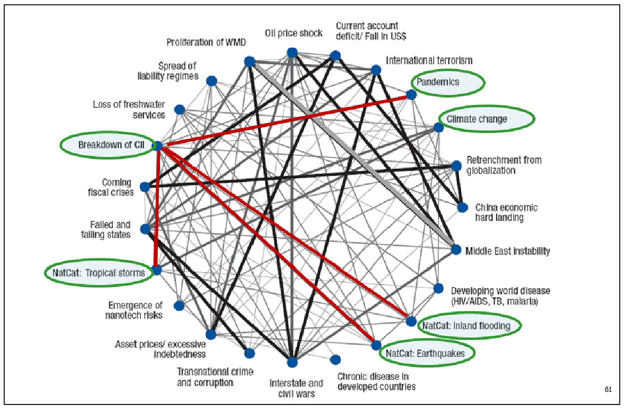

Figure 2: Network representation of Global Risks: Interdependencies between perils could lead to a global cascade of events(World Economic Forum, 2007)

Modeling these perils, many socio-economic and political in nature requires a specific approach with a behavioral content, such as game theory. At this point, we have not considered this type of perils.

3.3 Meso level

The standard practice in modeling large interdependent systems is to characterize their sub-elements independently and to build up models of behavior based on the knowledge of behavior of each element separately. This method, called the reductionistic approach (Kaplan, 1981) because it reduces the entire system to a collection of independent elements, was very successful for fully engineered large systems, such as nuclear power plants, and space systems, where the assumption can be made that the behavior of the whole is the sum of the behavior of all its components. Although the specific behavioral properties of each components of this type of system are usually known with some uncertainty, their topology is determined, and for this reason we call them deterministic, by contrast with stochastic networks, which we consider in the next section.

As a simplification, we model the major network layers of the infrastructure whose topology and engineering characteristics are well defined and available (or obtainable), with a reductionistic approach. This applies to the major parts of the infrastructure, including the following components:

- Electric power production and transmission lines
- Water storage, major pipelines, aqueducts and canals
- Waste water
- Interstate roads, major other roads, with their major interchanges, bridges and tunnels
- Transportation
- Ports, airports
- Critical government services
- Emergency services, hospitals and health care

For each layer we determine the remaining functionality after the cascade of events, starting with the primary event. We quantify the resulting disruption by the number of days necessary to restore the services and we calculate an index of disruption which we later aggregate across all layers, for each location.

3.4 Micro level

At the local level, distribution networks exhibit complex systems behavior. They can be very intricate, and their detail topology is not very well known. They can also be very large, and considering them as deterministic systems for analysis would be difficult, and probably impossible with present tools. These systems are characterized by scoring parameters expressing average values, such as areal densities, average lengths, and number of persons, businesses served, and the like. Another characteristic of these micro systems is that they usually have not been engineered as a whole but progressively in the wake of a region growth, in a quazi organic fashion.

Complex systems have specific characteristics that make them different from other systems. They are systems that develop organically, where the addition of a component is dictated by optimal energy considerations. Typical examples of complex systems are the organization and growth of cells in biology, the behavior of large crowds or the make-up of interdependent global economies. Out of a collection of individual components in a complex system, can emerge a new behavior that may not be observed in any of the individuals. Such systems can completely collapse, because they have a few nodes that are connected to many other nodes. It makes those few nodes critical to the reliability of the system. For example, a region that depends entirely on one sea-port for all its cargo transactions would see its local economy drastically damaged, as actually happened in the case of the 1995 Kobe earthquake, (Kobe City Office, 2008). Suspension of operations at the Port, which used to handle approximately 30% of Japan's container cargo, greatly affected not only the daily lives of Kobe citizens, but also nationwide distribution and economic systems. The port activities completely stopped for two months, and complete restoration took more than two years. In the mean time, the port had lost a competitive hedge over the port of Osaka. A similar situation exists in several US ports, including in the ports of Los Angeles, Oakland and Seattle which are cities within a high earthquake risk area.

Albert-Laszlo and Albert, (1999) have shown that such systems can be modeled as networks, see Figure 3(c), where the probability distribution of the number of links for each node follows a law of the type shown in Figure 3 (d). In Figure 3(b) and 3(d), k on the horizontal axis, represents the number of links to a node, and the vertical axis represents its probability of occurrence in the network. Because the mathematical derivation of a mean value of the number of links does not converge for this type of function, such a system is called scale-free. This is in contrast with a system where there exists a mean value such as the one shown in Figure 3(a), where the distribution, Figure 3(d), of the number of nodes is Exponential.

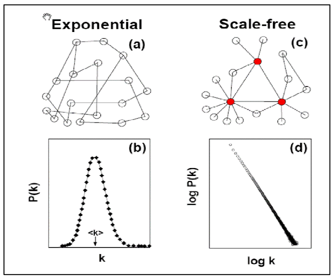

Figure 3: Example of networks. Scale-free networks have few nodes that are connected to many links, making them particularly susceptible to "weak-link" effects. (Taken from Jeong et. al, 2000)

To calculate disruption, we consider regions of uniform scoring properties. The total budget change of functionality in one such region is determined by the change in functionality of the networks at the meso level, and using the mathematical properties of scale-free networks, we derive the net change in number of nodes in the region from the probability distribution on the number of links (Eqn. 3.1), and the net change in nodes for the region:

$$P\left(N \mid L = l\right) \propto l^{-\gamma} \qquad (3.1)$$

Where: N is the number of node which has *l* links
P is the probability distribution of the number of links per node, and
γ is a parameter that is specific to the way the network organically developed.

Typically, the value of γ is between 2 and 3, although it can sometimes be between 1 and 2 (see Albert and Barabasi, 2002. The variation in the number of connections remaining, for a given change in the total number of nodes in the region, is derived as the relative change in the parameter C in Eqn.3.2.

$$\frac{d\bar{C}}{C} \propto \frac{(1-\gamma)}{(2-\gamma)}\frac{dl}{l} \propto \frac{1}{(2-\gamma)}\frac{dN}{N} \qquad (3.2)$$

This is the percentage change in the number of connections, and it is equal to the disruption index in the region, which we aggregate with the disruption due to the physical damages immediately after the primary event.

4. CALCULATION OF LOSSES DUE TO DISRUPTION

4.1 Days lost

The first impact of damages to the infrastructure manifests itself by outages and loss of services, which translate into losses from BI. For engineered structures, approaches similar in HAZUS (HAZUS, 2007) are used to determine the restoration functions. The final restoration time is determined for each location using simple rules of precedence. Then, BI losses are calculated by applying the rates of losses per day for each contractual condition.

4.2 Evacuation

In addition to the disruption created by outages and loss of services, it may happen that the general disruption in an area is beyond an acceptable level to stay in or conduct business. Evacuation can then be called for by the authorities, usually based on measurements or predictions of physical parameters, e.g. inundation depth, wind speed, fire intensity and progress. Most cities have evacuation plans based on such criteria. However, some areas may have no damages, but essential services may be curtailed and the level of disruption for these areas

Table 1. **Disruption Intensity Scale**. This table gives the percentage of population evacuated for a given level of disruption, or equivalently, the probability of all the population of an area to be evacuated, for a given level of disruption.

INTENSITY (Index of Disruption)	Description of conditions in the affected area	Evacuation parameters	Percent of population evacuated in affected area
	All utility systems severely damaged, most completely destroyed.	Complete and generalized over a large area,	
1	Infrastructure severely damaged. Restoration times in months	possibly the entire urban area.forced evacuation.	100.0%
	All people's life is endangered	No shelters, or not enough of them	
	Many casualtie, in the thousands or millions. Social networks fully broken	All People displaced to remote locations, out of State	
	Extends to entire urban area.Restoration times in years to decades	Every body complies or is forcefully removed	
0.8	Utilities severely damaged, completely destroyed in some places	Evacuation over large sections of the metro area	95.0%
	Infrastructure barely usable.	Sheltering not adequate, many people not taken care of	
	Many casualties, in the thousands. People flee the area	Many people move to other cities	
	Restoration time from 10 to years	Recalcitrants are removed by force	
0.6	All utility systems are affected, most are severely damaged,	Called forced evacuation for at least a large section of the city.	70.9%
	but not destroyed. Many places with collapsed infrastructure	People can find shelter in other parts but not sufficient	
	Casualties in the hundreds, possibly thousands, many people displaced	Some people start moving to other cities	
	Restoration time from 5 to 180 days, even years for some systems	Very few people disregard call	
0.4	Most utility systems are affected, some in a major way but not all	Calls for localized forced evacuation	39.3%
	Some localized areas with collapsed infrastructure	Displaced people can find shelter in other parts	
	Many people can be displaced, but casualties are not many	of the city but are at full capacity	
	Restoration times from 3 to several months	Some people decide to disregard the calls	
0.2	Onset of dysfunction. Local blobs	Calls for localized, mostly voluntary, evacuations	11.8%
	Some major utilities severely damaged in localized areas	Shelters sufficiently available in the area	
	Few casualties, few people displaced		
	Restoration times from 1 to 90 days	High rate of disregard for the call	
0.15	Minor utility dysfunctions, sporadic over the area	Some people decide to leave on their own	6.9%
	Only few utility networks affected,	They usually find shelter close by in other parts of	
	No caualties	city	
	Restoration times in hours to few days		
0	No major systems dysfunction	No evacuation needed	0.0%

is such that evacuation must be called for. For a lack of available standard in this matter, we propose a representation of the evacuation criteria, given in Table 1. Table 1 is our first attempt at defining a Scale of Disruption Intensity, based on study of past events. For use in the calculations, we fitted a function that gives the average number of days lost at a location, for a given amount of disruption expressed in percentage of total lost functionality

5. APPLICATION TO THE HAYWARD-OAKLAND CORRIDOR

Although our analysis is not complete yet, we have applied a simplified version of the method described herein, but preserving the basic concept of using cascade of secondary events, and damage to the infrastructure. The results shown in Figure 4 are preliminary and should not be used. It shows the importance of representing rare, but extreme events in a more realistic fashion than in the current methods. The overall uncertainty tends to increase, and a there is a wider range of possible losses, including more extreme events.

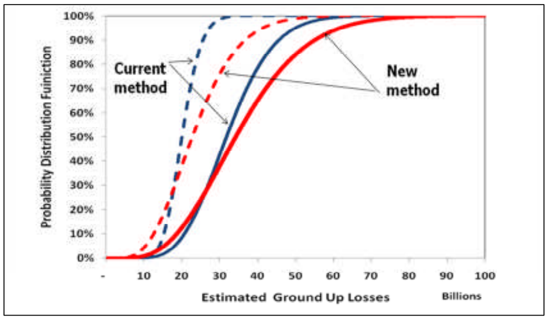

Figure 4: Preliminary results showing the conceptual difference in estimated losses with the proposed method of accounting for "un-modeled" outcomes.

6. CONCLUSION

We developed a new method for accounting more realistically for secondary effects of major damaging events, The method is based on considering a range of cascade of secondary events, and their impact on the infrastructure which in turn generates disruption at the local level, and generates losses due to loss of service and days of work lost.

The method treats layers of network functionality in a generic fashion and allows to consider special cases, such as pipeline networks, including distribution pipelines that are connected to distinct networks, such as onshore distribution and offshore collection. Because the method considers the effects locally, it also allows us to construct a specific model of portfolio dependence on remote facilities to tackle the problem of contingent BI. This capability, however will necessitate the collection of new types of data that most exposure data bases do not have at this time.

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