The Effect of Coping Capacity Depletion on Critical Infrastructure Resilience

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ABSTRACT

Coping capacities (CCs) are often implemented at Critical Infrastructure (CI) facilities to ensure a continuous supply of vital services and products for a population during lifeline disruptions. Through various restrictions, these redundant backups are frequently limited and, hence, only allow a supply continuity for a short duration. The capacity depletes with the duration of the disruptions. In this paper, we discuss how this decrease is evaluated in disaster management. To get an enhanced insight, we introduce to a representative decision problem and used a demonstrative example of a power outage to discuss how decision maker consider the effect of CC depletion and how analytical approaches could address this issue. For doing so an expert survey and an analytical approach were implemented and applied. The comparison and the discussion of the results motivate further research directions on this topic.

Keywords

Coping Capacity Consumption, Expert Estimations, Multi-Attributive Value Theory, Critical Infrastructure Resilience, Power Outages.

INTRODUCTION

In adverse conditions of service disruptions or system failures, the implementation of coping capacities (CCs) allow operators from Critical Infrastructures (CIs) to maintain a timely limited supply of vital services and products. This makes CCs to one of the most important parameters for CI resilience for which various definitions can be found in the literature. Regularly, resilience in the CI protection context is understood as an ability to maintain a function under adverse conditions. This includes all interactions which enable CI operators to anticipate, absorb, adapt to, or rapidly recover from a potentially disruptive event (OECD, 2014). In this paper, we define CCs as a key enabler for CI resilience which reduces the magnitude of the disruptive event and delays the point in time at which these events have the potential to lead to supply shortages. Therefore, we concentrate on backups and substitutions which are implemented as redundancies and ensure limited business continuity during disruptions.

Power outages are impressive examples for such disruptions. Current severe power outages such as experienced in February 2014 in Slovenia have shown how important CCs like emergency power units are to ensure business continuity of e.g. hospitals, nursing cares or pharmacies. However, the power units have only limited fuel tank volumes and the individual CI resilience decreases with shrinking fuel reserves. For decision makers from the local level of disaster management it is important to know this critical point in time at which all capacity is depleted. At this tipping point, CI operators are no longer able to avoid adverse effects on its functionality. In the context of a blackout, this is the case when a refueling of the tanks is requested because all fuel capacity of a CI is consumed.

Such tipping points are potential indicators for serious escalations in which a disrupted supply in one domain can propagate as domino and cascading effects in the whole CI-system due to the high interdependency of CIs (Rinaldi, Peerenboom, and Kelly, 2001). Furthermore, a drastic slump in supply can lead to severe situations in which the provision with vital services and products is no longer secured. Both aspects are of high importance and make CI resilience and the consumption of CCs strongly relevant topics in disaster management planning.

CI models can assist decision making in disaster management. Although some of such models consider aspects of CCs (for a more detailed comparative study see Ouyang, 2014). However, the results do not allow an estimation of CI resilience which takes into account the depletion of CCs. The reason can be found in the observation level which is often strategic and only enables a generic or abstract analysis. Additionally, some models use metrics which only implicitly address resilience aspects (Giannopoulos, Filippini, and Schimmer, 2012) and do not display time effects caused by the consumption of CCs. At this point the question arises as how CI resilience, which may change over time due to the depletion of CC, is considered regarding its influence on the level of risk. In addition, beside the consideration of CC depletion also other parameters like the number of affected CIs is important. A crucial question is how decision maker deal with these considerations and how analytical approaches could address this issue.

To take first steps for shedding more light on this issue, we briefly present a comparative analysis of the results from an expert survey and an analytical approach which both addresses the same problem of estimating CI resilience. Both methods focused on the question of how the depletion of resources (decreasing CC) on the one hand and the increased risk for a CI to suffer under the adverse effects of a supply disruption at the other hand could be estimated. For this purpose, we introduce to a decision problem which considers different durations of a power outage as a demonstrative example. The example consists of different number of affected CIs which have different degrees of preparation. This simplified setting allows us to discuss the results of an expert survey and an analytical approach which, finally, enhance the understanding of evaluating CI resilience taking into account CC depletion.

The paper is structured as follows. In the first section we introduce to a representative decision problem in which estimating CI resilience is important. According to this problem, we introduce to the design of a demonstrative example which will be used for the expert survey and an analytical approach. For this purpose, the method of the analytical approach is described in section two and the expert survey in section three. We compared the results and summarized first cautious conclusions in section four. In the third section, we discuss and critically remark our findings, and outline future research directions.

A REPRESENTATIVE DECISION PROBLEM CONCERNING CC DEPLETION

A power outage can be caused by destruction (e.g. by storm) or imbalances in the grid system (e.g. resulting in load reduction procedure) (Münzberg, Müller, Möhrle, Comes, and Schultmann, 2013). Sometimes and depending on the initial causes, the electricity in parts of the electricity grid in a given district can be maintained by special circuits or by the implementation of mobile emergency power systems during a power outage. These parts are often geographically defined by the voltage transformation substation structure according to the grid topology. The CIs which are situated in maintained grid areas are still supplied with electricity. All other CIs are depending on their CCs.

To ensure an appropriated and continued provision of vital services and products, disaster management authorities have to rank the parts of the grid regarding their priority for supply. The grid areas should be prioritized using a scale between 0 which induced low effects on the provision of vital services or products and 100 which induced potentially severe effects and a high need for a maintained supply. Hence, the higher the priority, the more important is a grid area for the overall supply of the population from the point of view of the authorities.

This estimation includes the number of CIs located in a grid area and their individual resilience. Both aspects make the decision challenging because the CIs are distributed irregularly in a district and each CI has a different degree of preparation. The prioritization provides a ranking of the grid areas that could be used to assist the management in situations in which response resources are limited or the availability of electricity is restricted.

DESIGN OF THE DEMONSTRATIVE EXAMPLE

The demonstrative example comprises a district which is supplied by a grid with five voltage transformation substations. Each substation supplies a grid area with electricity in which various CIs are situated. Each grid area can be individually circuit or supplied by mobile power units in case of emergency.

We distributed nine CIs of the same type and size in the five grid areas. For a better understanding we assume that each CI supplies a vital service or product for 100 citizens. In three areas we located one CI, in two areas we located three CIs. The information about the implemented CC at each CI is given (see Figure 1). CCs are displayed by the durations in which a continuous service is ensured during a power outage due to the use of emergency power units and the depletion of their fuel tanks. The estimation should be made for three queries which each address different durations of a power outage (for 30, 60, and 90 minutes). For all queries we assume a constant consumption of CC.

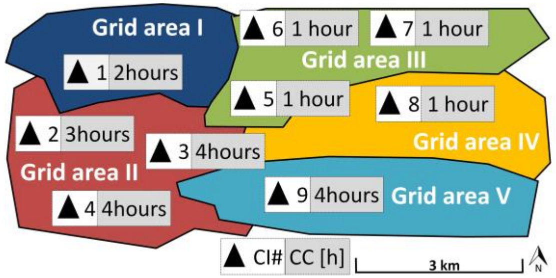

Figure 1. A fictitious district consisting of five grid areas. There are nine CIs distributed in the district (see chronological numbering). Each triangle represents one CI from the same size and type. The information about the individual CC is given in the grey boxes

AN ANALYTICAL APPROACH

We use an analytical approach to assess the risk of grid areas and to compare the results of the expert estimation. The analytical approach is based on a weighted sum referring to the Multi-attribute Value Theory (for more information see Belton and Stewart, 2002). In a second step we derive the priority values for each grid area based on this resulting risk calculation.

For the purpose of the analytical approach, we understand risk as an inherent character of a grid area to suffer from the adverse effects of a power outage. It is determined by the number of affected CIs which are located in a grid area and their CCs. Due to the example considers CIs from the same type and size, all CIs have the same relevance in providing a vital service or product. This simplification allows using a weighting factor that takes this aspect into account. With g determining the number of all CIs with the same size and same type in the district, the proportion between a CI i (with i $\in \{1, \ldots, g\}$) that is located in a grid area p and the overall supply is assumed by the weighting factor $w_{i,p} = \frac{1}{g}$.

The affected CI consumes its CC during a blackout. The more the fill level in the fuel tank sinks, the higher increases the level of the risk. Hence, we assume that the risk value depends on the percentage of the CC of a CI that has been consumed. This dependence is described by a consumption function $C_{i,p}(t)$ for a CI i that is situated in a grid area p and for a point in time during a power outage t. In practices, there is only limited information available to public to derive a consumption function based on the physical depletion which also depends from daytime specific demands. In addition, the isolated perspective on the physical depletion would not include that with sinking level of the fuel tanks less time is available to organize and prepare further coping measures like refueling. Hence, we assume that the graph of $C_{i,p}(t)$ is not linear and can be presented by various functions which selection need to be considered carefully. For a simplified setting, we exclude daytime-depending consumptions and use an exponential function which describes the risk increasing between the beginning of a power outage ($C_{i,p}(t) = 0$) and the point in time at which the coping capacity of a CI is fully consumed ($C_{i,p}(t) = 100$). During this duration, $C_{i,p}(t)$ increases exponential from 0 to 100.

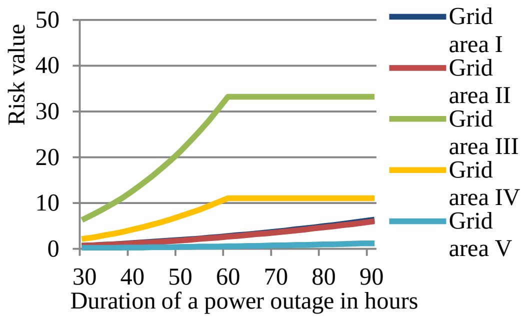

Figure 2. Results of the analytical approach displaying risk profiles for each grid area

The risk of a grid area $R^p(t)$ is determined by a weighted sum of the consumption function and the weighting factor of all CIs that are situated in the grid area: $R^p(t) = \sum C_{i,p}(t)\, w_{i,p}$. This allows a time-depending illustration of the increasing vulnerability of grid area during a power outage displayed in Figure 2.

We assume that the priority of the grid areas can directly be derived from the calculated risk values at the considered points in time of 30, 60, and 90 Minutes. Therefore, we used a linear normalization. The results are shown in Figure 3.

EXPERT ESTIMATION

In 2014, we invited experts from disaster management and health authorities in Germany to a workshop on disaster planning for power outages. Due to the federal character of the German disaster management system, we addressed the invitation to representatives on the administrative level of districts and cities which are operationally in charge to prepare for and cope with the effects of power outages. All experts are responsible for drawing disaster management plans. During the workshop we collected 22 expert estimations.

The experts were provided with all information about the CI locations and their CCs. All important assumptions were provided to the experts: a) the daytime-depending consumptions of CC is excluded, b) with sinking level of fuel in the tanks, the risk increases, c) the CIs are from same type and size, and, hence, d) they have the same influence in providing vital services and products.

The experts were asked to prioritize the areas individually for the considered blackout durations of 30, 60, and 90 minutes. The experts documented their priority estimations by a direct ranking method (similar to direct weighting, see Pöyhönen and Hämäliänen, 2001). The experts assigned a priority value for each area using a scale between zero (lowest ranking, rather unimportant) and one hundred (highest ranking, very important). In each query, the assignments of the experts were normalized to receive a priority value for each grid area.

COMPARISON OF BOTH PRIORITIZATION RESULTS

In Figure 3, the results of the expert estimation and of the analytical approach are shown as diagrams in which each line represents the priority value of a grid area for the considered time points. Both approaches came to the same priority order of the grid areas. However, there are some differences of the results with regard to the values and the deviations between the priority values of the areas.

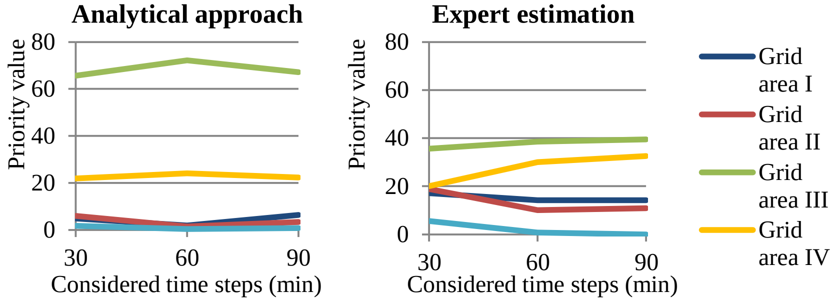

Figure 3. The diagrams show the priority value for each grid area and for the considered time steps

These differences allow only first cautious conclusions. Compared to the result of the analytical approach, it seems that the experts overestimate slightly the priority of the grid areas one and two. One receives the impression that compared to the results of the analytical approach, the expert underestimate the number of affected CIs in a grid area and overestimates the role of CCs consumption. This first impression is induced by the priority estimations of the grid areas three and four in the second and third queries (60 and 90 Minutes). The CIs located in both grid areas have the same amount of CC. The only difference is the number of CIs which are situated in the grid areas (three in grid area three and one in grid area four). In a logical interpretation, the grid area with the higher number of CIs would have a higher priority (here grid area three). There is no comprehensible reason why this is not clearly recognisable in the results of the expert estimation. To interpret this phenomenon in a prudent way, it could be imaginable that even this simplified setting is too complex and put expert estimation to its limits.

With regard to the analytical approach, the number of CIs in a grid area is considered by weighting factor. Hereby, the results show a higher deviation.

DISCUSSION AND FURTHER RESEARCH DIRECTIONS

Although the results of both approaches show some apparent deviations, the priority order is the same. This fact could indicate comparability but provides no clear evidence for verification. We showed that the CC depletion is an important effect that is taken into account by experts of the field and can also be displayed as a discrete and logical course of risk over time by an analytical approach.

The analytical approach proposed is also helpful in assessing potential impacts and tipping points. In our upcoming research, we will include the consideration of different CI sizes, types and their daytime specific demands to use more realistic settings. In doing so, we aim at assisting the creation of a common understanding about the courses of power outages among all involved actors in a district.

There are some aspects that need to be critically remarked. Due to the concentration on the initial impacts, the interdependencies between the CIs are excluded. However, interdependencies become interesting during long-term disruptions in which CC are no longer allowing a continuous business. Furthermore, day-time changing demands of supply are aspects that need to be critically remarked. Referring to a blackout for instance, the electricity demand changes between day and night times. Hence, the speed of CC depletion could differ. This could also be of great interest in estimating CI resilience.

For the analytical approach we used an exponential consumption function to take into account the increasing risk the more of the CC is depleted. Also other functions could be considered and it would be from interest which kind of function would be representing an expert estimation. For this purpose, further surveys could enhance the understanding of trade-offs between the number of affected CIs in a grid area and their CC consumption. We also assume that the type of a CI has a relevant influence on the prioritization. The change of prioritization depending on the CI type could also be an interesting research direction in the future.

ACKNOWLEDGMENTS

We are thankful for the support by the Helmholtz Association and the Center for Disaster Management and Risk Reduction Technology (CEDIM).

REFERENCES

1. Belton, V. and Stewart, T.J. (2002) Multiple Criteria Decision Analysis: An Integrated Approach. Kluwer Academic Publishers: Dordrecht.
2. Giannopoulos, G., Filippini, R., and Schimmer, M. (2012) Risk assessment methodologies for Critical Infrastructure Protection. Part I: A state of the art, EUR 25286 EN – 2012.
3. Münzberg, T., Müller, T., Möhrle, S., Comes, T., and Schultmann, F. (2013) An Integrated Multi-Criteria Approach on Vulnerability Analysis in the Context of Load Reduction, proceedings of the 10th ISCRAM 2013, Baden-Baden, Germany.
4. OECD (2014), Boosting Resilience through Innovative Risk Governance, OECD Publishing. http://dx.doi.org/10.1787/9789264209114-en.
5. Ouyang, M. (2014) Review on modeling and simulation of interdependent critical infrastructure systems, Reliability Engineering & System Safety, Volume 121, 2014, Pages 43–60.
6. Pöyhönen, M., and Hämäliänen, R.P. (2001) On the convergence of multiattribute weighting methods, EJOR, 129, 569-585.
7. Rinalidi, S.M., Peerenboom, J.P., and Kelly, T. (2001) Identifying, understanding and analyzing critical infrastructure interdependencies, IEEE Control System Magazine, 2001, pp. 11–25.