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# Behaviour Analysis of Interdependent Critical Infrastructure Components upon Failure

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## 1 ABSTRACT

Urban life increasingly depends on intact critical infrastructures (CIs). For this reason, protecting critical infrastructure systems from natural disasters and man-made hazards has become an important topic in urban development research in recent years as a prerequisite for building and optimizing smart cities. To increase efficiency, the connections between CIs have been strengthened increasingly, resulting in highly interdependent large-scale infrastructure systems that are vulnerable to cascading failures. Hence, studying the cascading and feedback effects caused by the failure of a CI component in a given system can help strengthen this system. Understanding the response of the system in the event of a disaster can lead to better disaster management and better planning of critical infrastructures in the future. The population heavily depends on water, electricity, and the transportation network. These three components also depend on each other to function individually. This complex nature of interdependencies must be studied in order to understand the effects induced in one system due to the failure of another.

The three systems (water, transport, and electricity) and their interdependencies can be modeled using graph theory. Water, transport, and electricity networks can be further broken down into smaller components. For example, the water network comprises water treatment plants, water storage tanks, pumping stations, sewage treatment, etc. interdependency factors into the model when, for instance, a pumping station depends on electricity. Graph theory can be used to depict the pairwise relationship between the individual components. Each node in the graph represents a critical infrastructure and the edges between these critical infrastructures represent their dependency. The modeled graph is a multigraph (inter-network dependency) and multidirectional (mutual dependence of two or more components). The idea behind building this model is to simulate the response of the interdependent systems upon failure. Building a simulation tool with an underlying interdependency graph model can not only help in understanding the failure response, but can also help in building a robust system for preserving the infrastructures. The data obtained from the simulation results will contribute to a better emergency response in the event of a disaster.

The failure response of a system depends largely on the failed component. Hence, three cases are considered to simulate and identify the state of the system upon failure of a component: The failed component can be a node with maximum outward dependencies, a node with maximum inward dependencies, or a random failure of a component. If a component has the maximum number of outward edges, the simulation tool will help visualize the cascading effects, whereas a system with the maximum number of incoming edges will contribute to the understanding of the feedback response as the outward nodes are not affected immediately. Another goal of CI failure analysis is to develop an algorithm for the partial restoration of specific critical services when a CI is not working at full capacity. The selection of critical infrastructure components for restoration is based on the number of people being affected.

## 2 INTRODUCTION

Maintaining essential public services such as access to mobility, electricity, and water is directly connected to the intact function of the necessary CIs. CIs are technologically complex systems with numerous intersectoral interdependencies. Damaging events within an infrastructure system or sector can lead to failures cascading onto connected systems and sectors. This causes hard-to-predict damage propagation which endangers the population's security of supply. We have therefore developed a framework of systemic and intersectoral dependencies between linked infrastructures for the sectors water, transport, and power supply. This framework combines input-output modeling with graph theory techniques to simulate cascading failures, to support policy makers and infrastructure operators, and to make large-scale systems more resilient towards natural, technological, and man-made disasters.

Our framework is a prototype that can be expanded by additional CI sectors. The definition of critical infrastructure sectors is slightly different for different countries, but most lists of critical systems include telecommunications, electric power systems, natural gas and oil, banking and finance, transportation, water


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supply systems, government services, and emergency services [OUANG 2014]. In an ideal model, all sectors should be depicted, but due to the high connectivity of each sector, the complexity of the model rises fast with every added infrastructure component, which is why the presented framework is limited to three sectors.

So far, several techniques for modeling and simulating interdependent CI networks exist that EUSGELD ET AL. grouped into eight categories [EUSGELD ET AL. 2008]: agent-based modeling, system dynamics, hybrid system modeling, critical path method, high-level architecture and petri nets. OUANG proposed a different subdivision in a more recent publication and divides existing modeling and simulation techniques into empirical approaches, agent-based approaches, economic-theory-based approaches, network-based approaches, and other approaches [OUANG 2014].

The model approaches differ both in their requirements regarding the accuracy of the data and in the scale at which the networks and cascading failures are depicted. We decided on a network-based approach since acquiring usable data to validate the model posed a significant problem during the development of the model, as is described in more detail below. The model approach was therefore chosen for its great intrinsic validity, as is common for graph models depicting networks. The network topologies which constitute the basis are known in detail and can be reconstructed without access to confidential data. Graph-based models furthermore come with the advantage that they can simply depict complex systems at a large scale through a multigraph. The largely hierarchical structure of infrastructure systems which produce their output centrally and then supply their product to local consumers via a wide distribution network can be depicted accurately through directed acyclic graphs which are connected at intersectorally dependent nodes. In addition, a software-based simulation of the "system of systems" of critical infrastructure sectors can be realized as a multigraph at much lower memory capacity and computing time than with more data-intensive solutions such as agent-based models. Models explained in the following sections were researched, simulated and analyzed in cooperation with Siemens AG. We thank them for the resourceful support they offered in taking this work forward."

## 3 GRAPH-BASED MODELING OF CASCADING FAILURES

According to a widespread definition by RINALDI, CIs are highly connected in multiple ways that can be classified as physical, cyber, geographic, and logical interdependencies [RINALDI 2001]. Physical interdependencies describe the dependency of one infrastructure on the material outputs of other infrastructures. Cyber-interdependencies occur whenever one infrastructure depends on information from another infrastructure. Interdependencies on information technology exist in all computer-aided infrastructures. Geographic interdependencies are created by the physical proximity of several infrastructures to one another, for example two transport infrastructures overlapping, such as a railway bridge and a road. Damage to the railway bridge may lead to road closure, which would cancel the redundancy of the two physically close systems even though they do not depend on one another physically or in terms of information technology. Logical interdependencies describe interdependencies of mechanisms other than physical, cyber, or geographic, such as dependencies caused by political or financial circumstances.

ZIMMERMANN proposes a different approach and groups interdependencies into the categories functional and spatial. Functional interdependencies occur where the operation of one infrastructure is necessary for the operation of the dependent infrastructure, while spatial interdependencies refer to the proximity between infrastructures [ZIMMERMANN 2001]. We refer to this definition as we see physical, cyber-, and logical interdependencies as three different types of functional interdependencies that can be modeled the same way, while geographical and spatial interdependencies are synonymous and appear fundamentally different in our framework.

Analyzing the fragility of interdependent networks is extremely relevant when it comes to planning resilient infrastructures. One fundamental characteristic of interdependent networks is cross-system damage propagation. Concerning this issue, BULDYREV ET AL. studied abstract systems. The main result of their research was the analytical proof that broad-scale degree distributions that confer resilience in individual networks increase the vulnerability of interdependent networks to random failures [BULDYREV ET AL. 2010].

The issue of fragile infrastructure systems was already covered in 2003 in FIKSEL's study. The author focuses on planning inherent resilience in the system design, which is achieved through diversity, efficiency, adaptivity and cohesion [FIKSEL 2003].

In 2006, HOLMGREN suggested using graph theory to model large infrastructure networks. However, he limited the application of graph theory to modeling power supply, the structure of which is strictly hierarchical [HOLMGREN 2006]. The researchers SVENDSEN and WOLTHUSEN modeled an interdependent system using graph-theoretical methods in 2007. Their approach is suitable for assessing the stability of a municipal supply system quantitatively. By removing edges from a multigraph, system failures at all supply levels can be simulated, allowing users to estimate the damages caused by component failures. Since then, graph-theoretical models have continuously been adapted and developed further. In 2015, CHOPRA AND KHANNA published a model to predict disruptions in CI for the economy of the USA [CHOPRA AND KHANNA 2015]. GIORGIO AND LIBERATI developed a bayesian network-based approach as a continuation of the basic graph-theoretical model [GIORGIO AND LIBERATI 2011, GIORGIO AND LIBERATI 2012].

Interdependency graph models depict infrastructure components as directed multigraphs which can be expanded by additional functions to define the relation between the components [SVENDSEN AND WOLTHUSEN 2007]. Each of the components is represented as a node and produces one output each, for which it requires the input of another component. If a component is unable to create the required input itself, it depends on the higher-ranking, input-providing component. This dependency is depicted as an edge. If the input-giving component fails, this causes a failure or impediment of all successive dependent components, which is modeled by removing the edge that failed initially and all successive dependent edges.

Depending on the damage event, a single edge can be removed (e.g. because of an isolated terrorist attack), or a geographic area can be defined in which all output fails (e.g. due to floods or fires). One way to stop the cascading failures are buffers, i.e. local utilities such as standby generators, or local utilities working independently, e.g. water treatment plans generating energy from sewage. In addition, damage propagation during a component failure can be prevented. In order to do so, redundant connections to other components can be set up, as is the case with the n-1 rule in power transmission.

Inputs and outputs can be services as well as physical products. Each output constitutes the input for at least one other component of the system and must be assigned as the input of a geographic location accordingly. When a component is supplied with all its required inputs, it operates normally. If one of the supplying components fails, which can be modelled by removing an edge, the component now enters an irregular mode of operation, which includes both limited operation and failure. Outputs are provided for geographically defined supply areas. The number of people that live or work in each supply area and are affected by a cascading failure determines the criticality of the system.

A general weakness of our model, as well as of all existing infrastructure-interdependency-modeling approaches, is that validation is difficult, which is the result of a lack of data available. Three types of data are required in order to develop and validate a framework for the depiction of cross-sector infrastructure interdependencies and the resulting damage propagation in the event of a failure:

- Geo-referenced data to depict the position of all infrastructure components to be covered
- Data about the capacities each infrastructure has, including existing buffers and redundancies that exist in the system
- Data recorded during disasters depicting the actual spread of damages

Geo-referenced data and infrastructure capacity data for the depiction of local technical infrastructure systems is recorded by operators and municipalities, but is highly confidential. Non-confidential geo data such as the position of buildings is available from the municipalities, but often at high costs. The third data type required for infrastructure system modeling, data on the effects of real disasters, is difficult to generate since electronic systems recording such data may be affected by the failure themselves, scientific data collection is a low priority in the event of disasters, and conducting experiments on urban infrastructure systems essential to supply is impossible [SIMPSON ET AL. 2010].

## 4 TOPOLOGY OF THE ELECTRIC POWERSUPPLY NETWORK

To explain our framework in detail, we have chosen an exemplary part of the electricity supply network topology that is linked with parts of the transport sector and industrial facilities, as shown in Figure 1. The model has been kept abstract in order to illustrate the dependencies and lay a framework for further analysis.

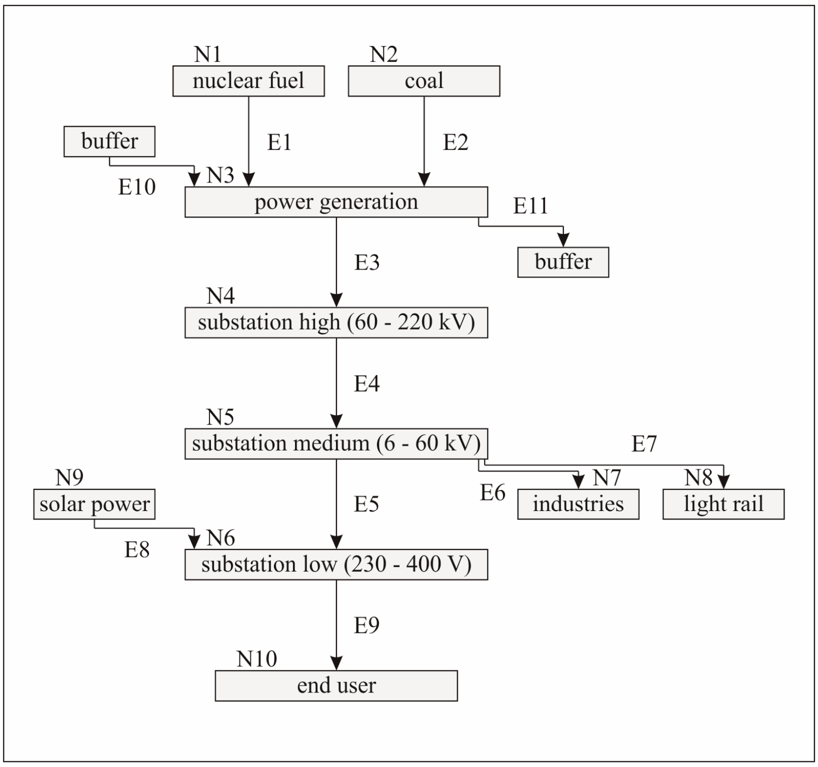


Figure 1: Illustration of electric power supply network using graph model (Source: Author's own)

Complex models can be built further  for a comprehensive analysis. As the model is hiearchical, nuclear fuel and coal sit on top of the graph model because of their major contribution to the electric power generation in Germany [GRAUS AND WORRELL 2009]. Electricity generated from coal or nuclear fuel, is sent to the substations for stepping down the voltage for various purposes.

Although the fuels consumed for power generation is not limited only to nuclear and coal, to keep the model simple and understandable we have neglected the remaining fuel sources. Buffers in the graph model increase the resilience of the system in times of emergency. The edge connecting the buffer unit and power generation unit is bidirectional. The bi-directional nature of the buffer is owed to the fact that the buffer is utilized for power generation during emergencies and subsequently restored back when the power generation unit is working to its full capacity. The high-voltage lines are stepped down at subsequent substations for power distribution. For example, substations which handle high voltage (60 kV to 220 kV) distribute power to large-scale industries and to medium voltage substations. Medium-voltage substations handle voltage between 6 kV to 60 kV. They distribute electricity to medium-scale industries, light rail transit systems and to regional low-voltage substations. Low-voltage substations (230 V to 400 V) are partly also fed by solar power generation units. Solar power is fed to the low-voltage substations which consequently feed the end users. End users comprise public facilities, commercial enterprises, private households, etc. This completes the description of our abstract model representing electrical power supply network. However, it is important to note that the network described above is only a small part of the complete multi-graph model. The complete multi-graph model describing the network topologies of electricity, transport and water networks is a lot more complex. For the graph model described we developed three algorithms to simulate cascading failures that will be discussed in the following sub sections.

### 4.1 Discrete simulation of disruptions

For a complex infrastructure system with several interdependencies, initially it is important to understand the ramifications. Every interdependent system has few nodes which are majorly responsible for the smooth functioning of the system. SHUAI ET AL. and HAVLIN AND KENETT suggested methods for analysis of complex interdependent systems from a network analysis perspective [SHUAI ET AL. 2015, HAVLIN AND KENETT 2015]. While SHUAI ET AL. suggested generalized model for understaning the cascading effects with changing network topology, degree of nodes and number of nodes, Havlin and Kenett 2015 focused on the application of the model suggested by Shuai et al. in economic sector. The insight gained from these methods is to identify the size of largest functioning interdependent cluster with changing influential parameters (network topology, degree of nodes, and number of nodes) upon failure of a fraction of nodes in the model. Cluster is defined as the formation of independent interdependent system upon fragmentation of network due to failure. The information obtained from the analysis can be used to model the system based on network theory, such that even upon disruption, large part of the network is still functional. But our approach is not based on redesigning the existing network topology but making it robust by identifying the nodes which carry maximum significance for the uninterrupted running of the major part of our model. This in turn can be used to minimize the number of people affected due to cascading failure. As a simple example, failure or disruption of a power generation unit would affect all the dependent nodes lying in the same sector as well as the transport sector which would not be the case upon failure of a low-voltage substation. Hence, to discern and distinguish between the nodes of our complex interdependent model we work with a discrete status model. In the discrete model every node has discrete state of operation, either “Running” or “Failed”. In the graph model every node has an attribute describing its running status and name. Initially the running statuses of all the nodes are marked as “Running”.

The graph model can be read by the program using GraphML file format. The GraphML parser reads the edges, nodes, and their attributes, which can be used for further computation and analysis. The direction of an edge is always from head node to tail node as the former is higher in the hierarchical model than the later. The program starts by looping over the edges of the graph model. Attributes of the current edge, its head node and tail node are stored. If the status attribute of the head node is equal to “Failed” then the attribute of the tail node is changed to “Failed”. The program comes to an end with the last edge of the graph model. As explained, the rationale behind this approach is to find the critical nodes in the system. Failure criteria such as failure of random node, failure of node with maximum-minimum outgoing edges, or failure of maximum-minimum incoming edges can be selected for the failure of the head node. Vulnerability of an infrastructure component can be determined and studied in multiple ways, as has been suggested in several papers [EINARSSON AND RAUSAND 1998, GEORGE AND DOUGLAS 2005]. EINARSSON AND RAUSAND defined vulnerability of the industrial system as the ability to endure threats and survive accidental events that originate from within and outside the system boundaries. GEORGE AND DOUGLAS proposed a methodology for ranking the infrastructure components based on performance index, which is the sum of the weights of individual performance measures (PM) multiplied by the disutilities of each component for that particular PM. Methodology proposed by EINARSSON AND RAUSAND is theoretical and can be applied only to industrial systems, whereas GEORGE AND DOUGLAS’s approach is based on weight and disutility of performance measures through deliberation in workshops. The approach we chose for the graph model analysis is closer to what has been described by JÖNSSON, JOHANSSON AND JOHANSSON [JÖNSSON, JOHANSSON AND JOHANSSON 2008]. JÖNSSON, JOHANSSON AND JOHANSSON defined criticality or vulnerability of an infrastructure as the magnitude to which the complete interdependent model will be affected upon failure. They focussed more on the affect of failure sets rather than individual component failures. We divide the total number of nodes ($NF_i$) affected by the failure of a node ($C_i$) by the total number of nodes in the system ($N$), which indicates the criticality of the failed node. Here, $i$ denotes the infrastructure node of interest spanning from $1$ to $N$.

$$C_i = \frac{NF_i}{N}$$

The range of $C_i$ is between $1/N$ and 1.0 as $NF_i$ cannot be greater than $N$. An analysis can be performed for the whole model by iteratively choosing one node after the other. If the criticality of a selected node is ($1/N$), that shows that no other node is dependent on the selected node. A criticality of 1.0 would mean that all the other nodes in the system are dependent on the selected node. Table 1 shows the criticality of the nodes in our graph model (Figure 1). As the graph model is hierarchical, it can be observed that criticality of node reduces as we move down the graph. Node set {N7, N8, N10} has no dependent nodes and hence their criticalities are 0.1. This means no further failures in the system takes place due to the failure of these nodes. Although


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this model is a good starting point for analyzing the graph model, the major drawback is equal weights for all the edges. This disadvantage is covered in the continuum model for the simulation of disruptions.

| Failed node number | Criticality of node ($C_i$) |
|---|---|
| N1 | 0.8 |
| N2 | 0.8 |
| N3 | 0.7 |
| N4 | 0.6 |
| N5 | 0.5 |
| N6 | 0.2 |
| N7 | 0.1 |
| N8 | 0.1 |
| N9 | 0.3 |
| N10 | 0.1 |

Table 1: Criticality of failed nodes (Source: Author's own)

## 4.2 Continuum model for the simulation of disruptions

The discrete model discussed above describes the dependency of one infrastructure component on others with unweighted edges and a discrete state of operation. But in reality the complete interdependent system works dynamically on the basis of many factors as described by BROWN [BROWN 2007]. MIN ET AL. described a system dynamic methodology for identifying and quantifying risky nodes and edges and, evaluating the effects of system redundancies, the impact of buffers, and the positive/negative impact created due to interdependencies [MIN ET AL. 2007]. In general an infrastructure node comprises many independent components which are clubbed into one. Power generation node contains power generated from different fuels. The nodes can either be split into many individual components or additional edges can be added describing the input feed type. If a city generates 10% of the total electricity using renewable resources and rest using coal or gas, this means that the edge between power generation and the end user will not have the weight same as the edge between solar power and low-voltage substation. In this approach we work with unit less working status. The working status ($WS_i$) of a node is always between 0.0 and 1.0. If a node's working status ($WS_i$) is equal to 1.0 that means all the nodes are functioning to full capacity. Here, *i* denotes the infrastructure node of interest spanning from *1* to total number of nodes in the model (*N*).

| Edge number | Weight of Edge ($W_j$) |
|---|---|
| E1 | 0.5 |
| E2 | 0.5 |
| E3 | 1.0 |
| E4 | 1.0 |
| E5 | 0.9 |
| E6 | 1.0 |
| E7 | 1.0 |
| E8 | 0.1 |
| E9 | 1.0 |

Table 2: Weights of edges (Source: Author's own)

To ensure that the maximum $WS_i$ at which a node can work is 1.0, sum of weights of all the incident edges on a node must be equal to 1.0. This means that edge E8 would have a weight of 0.1 and edge E5 would have a weight of 0.9, under the assumption that 10% of electricity is generated from solar power and 90% from coal, gas etc.The criticality approach chosen for the continuum model is slightly different from the discrete model. In this approach, the failure of a node is described by the weight of the edge. **Fehler! Verweisquelle konnte nicht gefunden werden.** Table 2 describes the weights of all the edges when the system is working at full capacity. The working status of a node is calculated by multiplying the weight of the edge with the working status of its head node. If a node has failed completely, we mark the working status of the node as 0.0 and iterate over all the remaining nodes to calculate the working status of every other node based on the formula:

$$WS_i = \sum_{j=1}^{M} W_j * WS_k$$

Here, $j$ is the index of the edge connecting the $i^{th}$ node to the $k^{th}$ node where the $i^{th}$ node is dependent on the $k^{th}$ node and $M$ is the total number of edges incident on the $i^{th}$ node. After the calculation of the working status of all the nodes upon failure of a node, the criticality of a node is calculated on the basis of the following formula:

$$C_i = 1.0 - \frac{\sum_{j=1}^{N} WS_j}{N}$$

A failure analysis for every node is performed and the criticality of every node is noted in Table 3. An adjacency matrix with working status can be constructed as described by CHOPRA AND KHANNA [CHOPRA AND KHANNA 2015]. Such an approach is used mainly in supply-demand models for identifying final demand due to a disruption. The criticality of nodes calculated using the continuum model is a better approximation than the discrete model due to its ability to analyse partial failure along with complete failure. It is possible that a fraction of infrastructure has failed unlike the test case we chose. In such a scenario the weights of the edges will help in identifying the current state of operation of dependent nodes.

| Failed node number | Criticality of node ($C_i$) |
|---|---|
| N1 | 0.44 |
| N2 | 0.44 |
| N3 | 0.68 |
| N4 | 0.58 |
| N5 | 0.48 |
| N6 | 0.2 |
| N7 | 0.1 |
| N8 | 0.1 |
| N9 | 0.12 |
| N10 | 0.1 |

Table 3: Criticality of failed nodes (Source: Author's own)

Table 3 shows that N4 (power generation) is the most critical node in our model. This establishes the rationale behind adding buffers to N4. The present continuum model establishes a good strategy for analysing the functional dependency.

### 4.3 Spatial dependency coupled with functional dependency

The models discussed above describe the functional dependence of one infrastructure on the other. In this model we satisfy spatial dependence on the basis of proximity between infrastructures. Different methods for risk assessment of georeferenced data have been proposed by SUMATHIPALA AND WIJESEKERA, STEPNOWSKI AND KULAWIAK, KULAWIAK AND LUBNIEWSKI [SUMATHIPALA AND WIJESEKERA 2008, STEPNOWSKI AND KULAWIAK 2010, KULAWIAK AND LUBNIEWSKI 2014, RIEGEL ET AL. 2015]. Based on the criticality or vulnerability of an infrastructure, a distance based function can be defined to assess the spatial impact. Such an analysis has already been suggested by STEPNOWSKI AND KULAWIAK. The model they proposed can be used for understanding independent infrastructure components upon attack but not for interdependent infrastructures. We have chosen a different approach for identifying cascading effects as STEPNOWSKI AND KULAWIAK do not take functional dependency into account. The functional dependence describes the relationships between infrastructures. Spatial data can be visualized using geo referenced data pointing to the infrastructures on the real map. The graph model is a layer describing the functional dependence which is supplied to the georeferenced layer in order to satisfy spatial dependence. Spatial dependence gives an in detail understanding of one to many relationships. This kind of relationship is important because in principle a high-voltage substation node can have many high-voltage substation infrastructures on the georeferenced map which are dependent on a single power generation infrastructure. Actually we move on from a macro model to a micro model using the relationships.

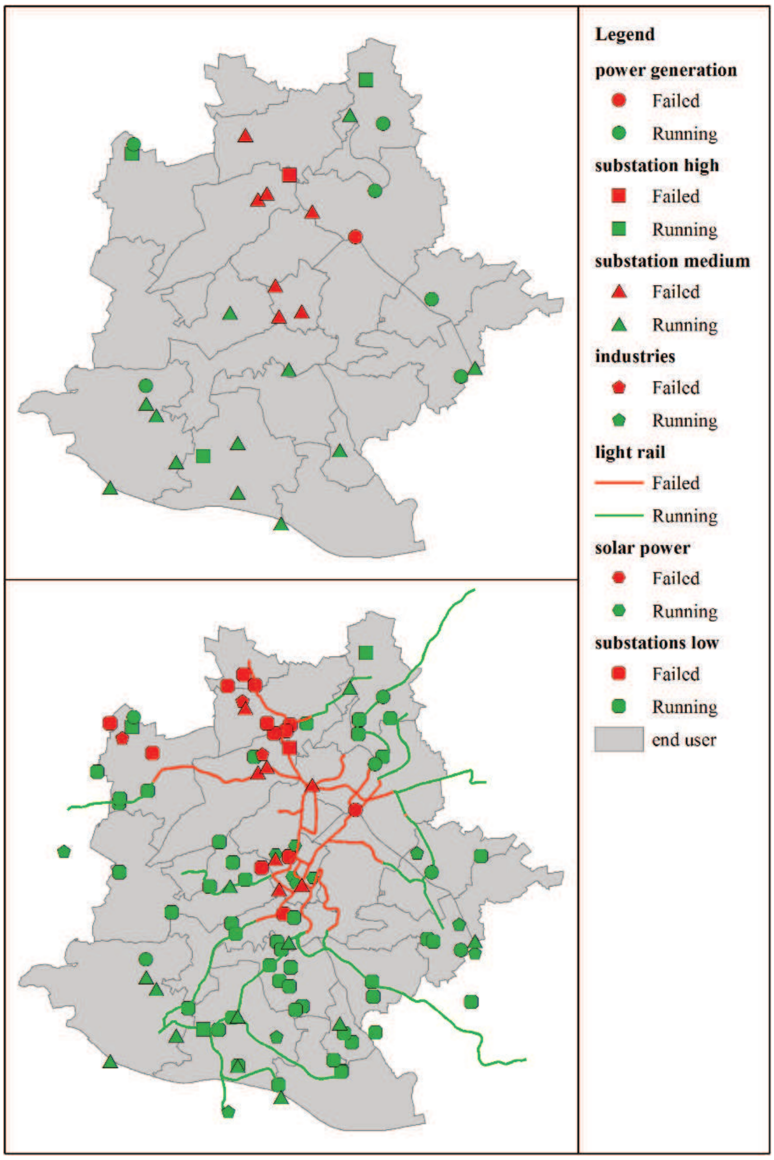


Figure 2: Visualization of cascading failure due to failure of a power generation component (Source: Author's own)

For the macro model and functional dependence model, we work with the graph model. In the case of functional dependence model coupled with the spatial dependence model, we work with shapefiles along with the graph model. Shapefiles contain the georeferenced data for every infrastructure with spatial coordinates. We are dealing with a relatively simple interdependent system. Hence, dependence between the components of an infrastructure and another can be obtained through survey. Moving on to a complex model would require us to establish a framework for the tail node component to identify its head node. A distance based approach can be used to identify the head infrastructure for each dependent infrastructure. This one-to-many relationship is achieved by finding out the nearest head node for every tail node.

A shapefile is used for storing the geographic coordinates, shapes, and attributes of geographic features. Shapes represent the physical form of the geographic infrastructure component for visualization. A simple example is representation of light rail using lines, municipalities using polygons and industries using points. The end goal is to identify the number of people affected by the cascading failures induced upon failure of a particular infrastructure. The number of people affected is directly proportional to the criticality of failed infrastructure. Figure 2 shows the cascading effects induced in the interdependent model due to functional and spatial dependency. When running the model, the disruption starts with the failure of a component in the power generation unit. All the high-voltage substation components dependent on the failed power generation infrastructure fail. This leads to the selective failure of medium-voltage substations, industries, light rail and low-voltage substation on the basis of spatial proximity. Figure 2 (top) shows the georeferenced infrastructures up until medium-voltage substations and Figure 2 (bottom) shows all the georeferenced infrastructures in our model. In order to satisfy functional dependency, we have worked with the discrete model as we want to establish a simple framework which can be later extended to the continuum model.

## 5 CONCLUSION

Understanding and analysing interdependent critical infrastructures has become an area of interest for minimizing the number of people affected by infrastructure failures. The methods proposed facilitate the identification of vulnerable interdependent technical infrastructures. A discrete simulation model was explained initially to underline the importance of edge weights in the interdependent graph model. The discrete model is not a precise method for analysis of critical nodes due to the assumptions that edges do not carry any weight and state of operation is discrete. This led to development of continuum model where we analyse the system to a greater detail by understanding the constituents of infrastructures and their supply of resources to the dependent nodes. The continuum model ensures that the weights of the edges are accounted for the calculation of working status. The working status in turn would help us in calculating criticality of the nodes. Criticality of the nodes was considered for ranking the critical infrastructure components. The identified critical infrastructure was connected to a buffer to increase the resilience of system upon failure. Discrete and continuum models explain the dynamics of cascading failure based on the functional dependency. Continuum model can be extended from single infrastructure failure to multi infrastructure failure based on spatial proximity. This would help us in gaining insight not only from a functional failure perspective but also on an attack based failure perspective.

To quantify the number of people affected by an infrastructure failure, spatial dependence model was introduced. RIEGEL ET AL. proposed an approach to determine the number of people affected due to an infrastructure failure based on spatial proximity but the coupled model proposed by us defines a relationship between the functional dependency model and spatial dependency model using the real geographical co-ordinates of the infrastructures. This coupling enables us to identify the cascading effects on infrastructures at a micro level, pointing to their real geographical coordinates. Functional dependence model and spatial dependence model is one way coupled. Changes made to functional dependence model would reflect in the micro level but the vice versa is not true. Need for a two way coupled model does not arise as functional model does not depend on the micro level model for its operation. Micro level model can be used to identify and strengthen weak links at micro level. Analysing and strengthening weak links at macro level would add unoptimized redundancy to the system. The models proposed can be used for strategic analysis and urban planning so that the number of people affected by such failures is kept at minimum. In the future work, we will investigate the conceptual Bayesian network, which will help in the bottom up analysis of the hierarchical model. Another scope for future work would be, to establish a framework in order to identify shortest path between two critical infrastructures in multi graph model based on DIJKSTRA's algorithm [DIJKSTRA 1959]. The information gained from this framework can be used in restoration of critical infrastructures falling in the shortest path first upon disruption.

## 6 REFERENCES

BROWN T.: Multiple modeling approaches and insights for critical infrastructure protection. In: NATO SECURITY THROUGH SCIENCE SERIES D-INFORMATION AND COMMUNICATION SECURITY, Vol. 13, pp. 23-35. 2007.

BULDYREV S.V., Parshani R., Paul, G., Stanley H.E., Havlin S.: Catastrophic cascade of failures in interdependent networks. In: Nature, Vol. 464, 15 April 2010, pp.1025-1028. 2010.

CHOPRA S., Khanna Vikas: Interconnectedness and interdependencies of critical infrastructures in the US economy: Implications for resilience. In: Physica A 436 (2015), pp. 865-877. 2015.

DIJKSTRA E.W.: A note on two problems in connexion with graphs. In: Numerische mathematik, Vol. 1, Issue 1, pp. 269-271. 1959.

EINARSSON S., Rausand M.: An Approach to Vulnerability Analysis of Complex Industrial Systems. In: Risk Analysis, Vol. 18, Issue 5, pp. 535-546. 1998.

EUSGELD I., Henzi D., Kroger W.: Comparative evaluation of modeling and simulation techniques for interdependent critical infrastructures. In:ETH Zurich scientific report, pp. 1-50. 2008.

FIKSEL J.: Designing resilient, sustainable systems. In: Environ. Sci. Technol. 37, pp. 5330-5339. 2003.
GEORGE E.A., Douglas M.L.: A Screening Methodology for the Identification and Ranking of Infrastructure Vulnerabilities Due to Terrorism. In: Risk Analysis, Vol. 25, Issue 2, pp. 361-376. 2005.
GIORGIO A.D., Liberati F.: Bayesian network-based approach to the critical Infrastructure interdependencies analysis. In: IEEESystem Journal 2012 6(3), pp. 510-519. 2012.
GIORGIO A.D., Liberati F.: Interdependency modeling and analysis of critical infrastructures based on dynamic Bayesian networks. In: Proceedings of the 19th Mediterranean conference on control and automation. Aquis Corfu Holiday Palace, Corfu, Greece, June 20-23, 2011.
GRAUS W., Worrell E.: Trend in efficiency and capacity of fossil power generation in the EU. In: Energy Policy, Vol. 37, Issue 6, pp. 2147-2160. 2009.
HAVLIN S., Kenett Dror Y.: Cascading Failures in Interdependent Economic Networks. In: Proceedings of the International Conference on Scial Modeling and Simulation, plus Econophysics Colloqium, pp. 87-97. 2015.
HOLMGREN A.: Using graph models to analyze the vulnerability of electric power networks. In: Risk analysis 2006, 26(4), pp. 955-969. 2006.
JÖNSSON H., Johansson J., Johansson H.: Identifying critical components in technical infrastructure networks. In: Journal of Risk and Reliability, Vol. 222, Issue 2, pp. 235-243. 2008.
KULAWIAK M., Lubniewski Z.: SafeCity — A GIS-based tool profiled for supporting decision making in urban development and infrastructure protection. In: Technological Forecasting and Social Change, Vol. 89, pp. 174-187. 2014.
MIN H.S., Beyeler W., Brown T., Son Y.J., Jones A.T.: Toward modeling and simulation of critical national infrastructure interdependencies. In: IIE Transactions, Vol. 39, Issue 1, pp. 57-71. 2007.
OUANG M.: Review on modeling and simulation of interdependent critical infrastructure systems. In: Reliability Engineering and System Safety 121, pp. 43-60. 2014.
RIEGEL C., Tietz H.P., Vallée D.: Die Berücksichtigung des Schutzes kritischer Infrastrukturen in der Raumplanung: zum Stellenwert des KRITIS-Grundsatzes im Raumordnungsgesetz. No. RWTH-2015-03094. 2015.
RINALDI S.M.: Identifying, understanding and analyzing critical infrastructure interdependencies. In: IEEE Control System Magazine, pp. 11-25. 2001.
SHUAI S., Xuqing H., Eugene S., Shlomo H.: Percolation of localized attack on complex networks. In: New Journal of Physics, Vol. 17, Issue 2, pp. 023049. 2015.
SIMPSON D. M., Lasley C. B., Rockway T. D.Weigel T.A.: Understanding critical infrastructure failure: examine the experience of Biloxi and Gulfport, Mississippi after Huricane Katrina. In: International Journal of Critical Infrastructures 6, Issue 3, pp. 246-276. 2010.
STEPNOWSKI A., Kulawiak M.: Algorithms for spatial analysis and interpolation of discrete sets of Critical Infrastructure hazard data. In: Zeszyty Naukowe Wydziału ETI Politechniki Gdańskiej. Technologie Informacyjne, Vol. 18,pp. 287-292. 2010.
SUMATHIPALA W.G., Wijesekera N.T.S.: Using GIS for Assessment of Terrorist Attack Risk Along a Major Road and to Propose Security Options. In: ENGINEER, Vol. 41, Issue. 05,pp. 87-94. 2008.
SVENDSEN N.K., Wolthusen S.: Multigraph Dependency Models for Heterogeneous Critical Infrastructures. In: Proceedings of the First Annual IFIP TC 11.10 International Conference on Critical Infrastructure Protection (Hanover, NH, USA, Mar. 2007). Springer-Verlag, pp. 337-350. 2010.
ZIMMERMAN R.: Social implications of infrastructure network interactions. In: Journal of Urban Technology, Issue 8, pp. 97-119. 2001.