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Modeling Impact Of Power Outages On Interdependent Critical Infrastructure

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Abstract

This paper presents a network modeling approach which covers a diverse set of different critical infrastructures and their mutual interdependencies. It aims at the understanding and quantification of the effects of severe disasters, e.g., large-scale, long-lasting power outages, in order to quantify the resilience of both the full grid as well as individual infrastructures. To this end, damage cascades based on various interdependencies are simulated, i.e., the temporal evolution of the system breakdown is evaluated. As an application, data from OpenStreetMap is used to construct an exemplary grid for the medium-sized city of Freiburg, Germany for which the effects of a severe power outage are simulated.

Keywords: critical infrastructures, resilience quantification, graph-based modeling, interdependencies, power outage

1. Introduction

The functioning of modern societies depends on an elaborate net of many critical infrastructures (CIs). To name just a few, hospitals treat injuries, grocery stores provide the possibility to buy food and other necessary items, the water grid gives access to fresh water and fuel stations enable private transportation. This relevance demands a comprehensive understanding of the resilience of CIs, in order to identify and quantify risks, which might lead to severe disturbances of their operation. Applying the concept of resilience to CIs became a highly active field of research in recent years. Systematic resilience management processes were developed (Häring et al., 2017) which aim at a holistic understanding of the vulnerabilities of the system under consideration. The application of such a process can be found, e.g., for the gas (Ganter et al., 2024) and telecommunication grid (Häring et al., 2021) or renewable energy industries (Köpke et al., 2023). Key Performance Indicators (KPIs) are typically used to quantify the system performance before, during and after different types of disturbance harming the system operation. Concepts like ‘resilience sectors’, where KPIs are mapped to the technical, organizational, social and economic domain (Bruneau et al., 2003), or ‘resilience phases’, which cover the temporal aspect of resilience (Thoma et al., 2016), can be used to check if a set of selected KPIs is truly encompassing or if some aspect is underrepresented.

Considering CIs, it needs to be noted that most of them depend on each other in different ways. Most notably, there is a heavy dependence on the proper operation of the power grid, which represents one of the most critical technical facilities of modern societies. Due to the rise of electric mobility and electric heating, it can be expected that the importance of the power grid will only increase in the future. In consequence, it is necessary to get an understanding of the effects of a failure of the power supply on the diverse, interconnected networks of CIs. But real-world data of power outages and other disturbances of CIs is, unfortunately, sparse and experiments, where a CI (or a replica) is intentionally harmed, are highly complicated to perform. This means that modeling approaches often represent the only viable way to gain high-resolution estimates of the system KPIs for encompassing sets of starting conditions and disturbances. In recent years, several modeling frameworks were developed based on different approaches (Ouyang, 2014), e.g., graph-based (Buldyrev et al., 2010), flow-based (Rosato et al., 2008), agent-based as well as combinations thereof (Tootaghaj et al., 2017).

Still, to the knowledge of the authors, most approaches are targeted to specific CIs and the dynamic aspects, i.e., damage cascades, are most often not considered. This severely limits the possibilities to model and analyze the mutual interdependencies of CIs and the temporal evolution of disturbances, highly important aspects when quantifying the resilience of the individual infrastructure.

The graph-based modeling approach presented in this paper targets this gap. It has the goal to understand and quantify failure cascades and restoration periods of interdependent CIs after a power outage. Therefore, the different infrastructures, e.g. power, water, medical emergency treatment, that are identified as critical are represented as nodes and dependencies are depicted as connecting edges. Sections 2 and 3 show how the numerous interdependencies of a diverse set of CIs are abstracted to a set of network edges and how it is evaluated if a specific node provides the necessary service to another node or not. Damage cascades (as well as repair processes) are estimated based on both life- and repair times. Although the developed model has a clear focus on the understanding of the effects of power outages, it is generic enough to also study other threats by extending the model straightforwardly. Data from OpenStreetMap is used to construct an exemplary grid for the medium-sized city of Freiburg, Germany. Here, the local population and local enterprises are depicted as well, in order to be able to assess the direct impact of power outages on both groups. To show exemplary modeling results, a complete blackout of the full power grid is simulated and the resulting predictions for the damage cascade are presented in Section 4.

2. Modeled critical infrastructures

As the first step of the generation of the network model, it is necessary to define which facilities and services should be depicted. The answer to the question of whether an entity is part of the critical infrastructure (CI) is often debatable and depends on the used definition for the term ‘critical’. The European Commission defines a CI as ‘an asset or system which is essential for the maintenance of vital societal functions’ where damages ‘may have a significant negative impact for the security of the EU and the well-being of its citizens’ (European Commission, 2023). Based on this definition, the European Commission lists the following CI sectors (European Commission, 2005):

- Energy: oil and gas production, refining, treatment, storage, transmission and distribution, electricity generation, transmission and distribution;
- Transport: road transport, rail transport, air traffic, inland waterways transport, ocean and short-sea shipping;
- Information/communication technologies: information systems and network protection, instrumentation automation and control systems, internet, fixed and mobile communication, radio communication and navigation, satellite communication and broadcasting;
- Water: provision of drinking water, control of water quality, stemming and control of water quantity;
- Food: provision of food and safeguarding food safety and security;
- Health: medical and hospital care, medical serums, vaccines and pharmaceuticals, bio-laboratories and bio-agents;
- Financial: payment service/payment structures (private), government financial assignment;
- Public and legal order and safety: maintaining public and legal order, safety, and security, administration of justice and detention;
- Civil administration: government functions, armed forces, civil administration services, emergency services, postal and courier services;
- Chemical and nuclear industry: production/storage/processing of chemical and nuclear substances, pipelines of dangerous goods, i.e., chemical substances;
- Space and research.

Based on these categories the facilities and services shown in Table 1 were selected. However, before having a closer look at this selection in Subsection 2.2, the next subsection discusses the main characteristics assigned to each CI depicted in the network model.

2.1. Lifetimes and repair times

The network model presented in this paper aims to understand damage cascades caused by any loss of the supply of electrical power. In principle, all facilities/services which can be labelled as CI should either be able to operate for a significant time without power (such as policemen who can continue to work even without power at the police station) or they should be equipped with emergency power capabilities (such as hospitals that are required to have emergency power generators). But this does not indicate that a CI can operate infinitely long without external power supply. Instead, it can be expected that the critical facility/service will successively lose its different functions up to a point where it becomes dysfunctional. To model this complicated and highly individual behavior in a simplified way, the network model in this paper assigns a 'lifetime' $t_{L,i}$ to every CI node i, which quantifies the durability of the node when losing the external power supply. The gradual breakdown of its functionality is simplified to a binary state where the node is either operative or dysfunctional.

Once the breakdown of a CI component has occurred, it cannot be expected that it will start to work again immediately once the power supply is restored. The staff needs to return to their workplaces, stocks need to be refilled and equipment such as computers need to be repaired or restarted. In consequence, the network model constructed below assigns a 'repair time' $t_{R,i}$ to every CI node i. This time needs to pass after the power supply (and possibly other necessary services from other CIs) of a dysfunctional CI node is restored before it becomes operative again.

The combination of $t_{L,i}$ and $t_{R,i}$ enables the model presented below to capture all relevant processes which follow on an outage. Starting with the intact network, first facilities fail directly after the outage, followed by facilities with $t_{L,i} > 0$ until the power outage is over and repair processes start, leading to the successive restoration of the dysfunctional critical services. Still, to yield realistic results, $t_{L,i}$ as well as $t_{R,i}$ need to be set cautiously by acknowledging inherent uncertainties. Given that Europe only rarely experiences large-scale, long-lasting disturbances of the power supply, there are no (or only limited) practical experiences considering the performance of the CIs when cut from power supply. In addition, every disturbance is different in terms of disturbance cause (storm, earthquake, human attack) and side effects (e.g., earthquakes also damage hospitals while storms might be unproblematic), which complicates a general estimation of $t_{L,i}$ and $t_{R,i}$ even further. To tackle these challenges regarding the generalizability of the specification of model parameters, this paper makes three assumptions:

- It is reasonable to define fundamental $t_{L,i}$ and $t_{R,i}$ values for any critical facility/service. These time values describe the resistance and repair capabilities of the facilities in case services, on which the facilities depend, are not provided but the facilities themselves are not directly harmed. It is assumed that the values are independent of the specific reason for the supply loss. This indicates that, e.g., a hospital will react in the same way to a loss of power due to storm damages as it will react to a loss of power caused by a human attack on power transmission lines;
- In case that $t_{L,i}$ and/or $t_{R,i}$ of a given CI node deviates from these fundamental times, this deviation is only caused directly by an adverse event damaging the system. This means that, e.g., an earthquake might damage both, the power grid as well as hospital a, i.e., it might set $t_{L,i} = 0$ for them, but the failure of the power grid does not alter $t_{L,i}$ of another hospital b, which is connected to the power grid but unaffected by the earthquake;
- To account for the inherent uncertainty of $t_{L,i}$ and $t_{R,i}$, both can be defined in terms of stochastic distributions. Individual values are drawn when setting up a grid for simulation, see Subsection 2.3. In this paper, Gaussian distributions are used at this point, see Table 1 to find means and standard deviations of different CIs.

Using stochastic distributions to account for the inherent uncertainties of $t_{L,i}$ and $t_{R,i}$ allows to estimate the influence of this lack of knowledge on the system performance by resimulating the same adverse event, using different realizations of the network under study, i.e., different sets of $t_{L,i}$ and $t_{R,i}$.

Now, after defining the critical sectors of interest and after clarifying the two times which characterize the different critical assets, the next subsection specifies the selection of CIs depicted in the network model, as well as the motivation for the individual choices of the different $t_{L,i}$ and $t_{R,i}$ distributions.

2.2. Selected critical infrastructure

The specification of the different $t_{L,i}$ can be understood as the quantification of the infrastructure vulnerability (Münzberger et al., 2017; Pescaroli and Alexander, 2016) against long-lasting undersupply. In this paper, a technology assessment ordered by the German parliament was consulted since it provides a unified perspective by discussing the expected effects of a large-scale and long-lasting power outage on various CIs (Petermann et al., 2011). Since such a long-lasting outage never happened in Germany, the described decay processes need to be understood as educated guesses. Nevertheless, they allow to estimate realistic timescales of failure cascades following the loss of power supply. The estimation of the various $t_{R,i}$ values is even more complicated since the repair processes need to be considered under the assumption that a severe power outage took place, triggering multiple different (interdependent) damage cascades, which directly impact the viability of system restoration. In this paper the various $t_{R,i}$ values were assumed to be of the same order as the $t_{L,i}$. Since it cannot be expected that two infrastructures of the same type, say hospital a and hospital b, have exactly the same life- and repair times and to account for the inherent uncertainty of both times, the individual $t_{L,i}$ and $t_{R,i}$ were drawn from Gaussian distributions when setting up one realization of the network model (as described in Subsection 2.1).

Table 1. CIs depicted in the network model, their respective sector and specifications of model parameters.

ID	Infrastructure	sector	n_{Fr}	Dependencies	$t_{L,i}$ [h]	$t_{R,i}$ [h]	mns_i
1	EHV productions	Energy	5	none	0	0	0
2	EHV import/export	Energy	1	none	0	0	0
3	EHV grid	Energy	1	**1**, 2	0	0	2
4	HV productions	Energy	3	none	0	0	0
5	HV grids	Energy	1	3, **4**	0	0	1
6	MV grids	Energy	6	5	0	0	1
7	MV district distributions	Energy	42	6	0	0	1
8	LV grids	Energy	286	7	0	0	1
9	Metro/Tram network	Transport	1	**5**, 10	0	4 ± 0.5	1
10	Traffic management system	Transport	1	**7**	0	0	1
11	Harbors	Transport	-	5	0	6 ± 1	1
12	Power grid, train	Transport	1	**5**	0	0	1
13	Power grid, rail network	Transport	1	**5**	72 ± 12	48 ± 12	1
14	Fuel stations	Transport	35	8	0	0	1
16	Mobile communication	Communication	1	**8**	0	0	# LV nodes/2
17	Radio/Press	Communication	1	**5**	240 ± 12	72 ± 12	1
18	Water distributions	Water	4	7	72 ± 12	72 ± 12	1
19	Food stores	Food	80	8	96 ± 12	36 ± 6	1
21	Hospitals	Health	8	8, 18	168 ± 12	72 ± 6	2
22	Ambulance services	Health	8	21, 16	120 ± 6	48 ± 6	2
23	Resident doctors	Health	118	8, 21	48 ± 12	24 ± 6	2
24	Nursing homes	Health	6	8, 21	48 ± 12	48 ± 6	1
25	ATMs	Financial	33	8	0	0	1
26	Bank branches	Financial	50	8	72 ± 12	28 ± 12	1
27	Fire brigades	Public order/safety	15	16, 18, 22	120 ± 6	48 ± 6	3
28	Police stations	Public order/safety	18	16, 22, 27	120 ± 6	48 ± 6	3
29	Prisons	Public order/safety	1	7, **28**	240 ± 24	120 ± 12	1

In addition to the two times, it needs to be defined which interdependencies between the CIs should be considered. Those interdependencies are subsumed under the 'minimal necessary supply' mns_i variable, which represents the vulnerability of individual infrastructure components to supply losses and is used in the damage propagation logic of the network model (see below). If, for example, node j of the network model has two connections to other nodes and it also needs both of them for proper operation, $mns_j = 2$ is set, i.e., there is no redundancy at all. If the node would only need one connection, i.e., $mns_j = 1$, it would be less likely that it becomes dysfunctional in case of (local) damages of the network.

Table 1 summarizes the mns_j of the different CIs considered in the network model, as well as the parameters defining $t_{L,i}$ and $t_{R,i}$. The listed infrastructure encompasses the first eight sectors specified in Subsection 2.1. Several critical services/facilities are subsumed into a single node, e.g., the metro/tram network. The column 'n_{Fr}' lists the number of nodes per CI for the network of Freiburg introduced in Subsection 2.3. Most infrastructures depend on the supply from other infrastructures (column 'dependencies', the listed numbers refer to the column 'ID'). Bold numbers indicate that the infrastructure can be connected to several members of the other infrastructure type. Besides the telecommunication node (described below), $mns_j < 4$ holds due to the fact that conditions, like the possible need of hospital a for two power connections or the possible need of ambulance service b for two different operative hospitals, are not considered. In other words, the model assumes that a single connection to another node type suffices to fulfill the dependency.

The power grid is separated into four levels, extra high voltage (EHV), high voltage (HV), medium voltage (MV), MV district distribution and low voltage (LV) to allow for the specification of power outages which target different voltage levels. Please note that not all non-power CIs are attached to the LV level of the power grid, i.e., many facilities are immune to power outages at the lowest voltage level. A few services, e.g., fire brigades, have no direct dependence on the power grid so that outages can only affect them indirectly. The nonexistent lifetimes of the infrastructures representing the power grid are based on the fact that, in general, the different voltage levels collapse instantaneously once not enough power is provided by the overlaying grid level. The $t_{L,i}$ of other CIs are typically in the orders of days, like for hospitals, but can also be zero in some cases. Fuel stations, for example, depend on the power grid to keep their pumps running and the metro or tram stops moving once the electrical power is gone. Mobile communication is modelled by a single node and its failure is, due to batteries and other long-lasting emergency power measures, not directly related to the loss of power supply. Instead, an overload caused by communication attempts of the local population is expected to be the dominating cause of failure once a severe outage occurs (Petermann et al., 2011). It is assumed that the loss of half of the LV grids is sufficient to trigger this overloading (column 'mns_i'). The addition of ATMs and bank branches to the list of CIs is motivated by the fact that power outages disable all options for electronic payments, i.e., the affected population has to rely on cash to make their daily transactions. Therefore, the availability of ATMs and bank branches becomes very relevant to restock the cash reserves. While ATMs are instantaneously disabled once the power outage happens, banks can still operate (in emergency mode) by recording money withdrawals on paper, i.e., the loss of computer systems might harm the service but does not block it completely (Petermann et al., 2011).

In addition to the critical facilities listed in Table 1, the network model also contains nodes representing the population and local enterprises which depend on the LV power supply. Table 2 lists the specification of these nodes. Other dependencies, like the fact that the population depends on operative hospitals, are neglected. This limitation will be addressed in further developments of the model. Still, the node setup in Table 2 allows for the determination of the direct effects of power outages on the 'average' consumers.

Table 2. Nodes of the network model representing population and local enterprises.

ID	Consumers	sector	n_{Fr}	Dependencies	$t_{L,i}$ [h]	$t_{R,i}$ [h]	mns_i
30	Population nodes	Consumer	286	8	0	0	1
31	Local enterprises	Consumer	286	8	0	0	1

Having defined all node types entering the network model, the next section discusses the setup of the exemplary grid for the City of Freiburg, Germany.

2.3. Network model for Freiburg, Germany

To construct the network model for the medium-sized city of Freiburg in Germany with its 230.000 inhabitants, the various infrastructures in Table 1 (column 'n_{Fr}') were successively added as network nodes. Its respective dependencies were represented by network edges. To get realistic estimates for the number of nodes in the different categories, information from OpenStreetMap was used by employing Overpass turbo (Raifer, 2023). Besides getting realistic numbers, this approach has the added benefit that geocoordinates can be collected, i.e., it is possible to reproduce the geographic distribution of the different CIs. Though some parts of the network were set by hand. This concerns the EHV and HV layers of the power grid as well as nodes which subsume different services, i.e., the tram network, the traffic management system, the power grids for trains and railways, the mobile communication and radio/press. Edges, i.e., dependencies, were mostly defined by proximity, e.g., individual food stores were linked to the closest node representing a LV grid.

Based on this approach the network was set up in the following way. First, five EHV production nodes, one EHV import/export node and one EHV grid node were placed, followed by three HV production nodes and one HV grid node. Then, six MV grid nodes, based on data from OpenStreetMap, were attached to the HV grid node, followed by 42 MV district distribution nodes located at the center of the districts of Freiburg. 286 LV grid nodes were attached to the MV district distribution nodes. After finishing the representation of the power grid, 35 fuel station nodes, four water distribution nodes and 80 food store nodes were added. To cover the health sector, 8 hospitals with 8 emergency services, 118 resident doctors and six nursing homes were attached. 32 ATMs and 50 bank branches represent the financial sector. To include public order and safety, 15 fire brigades, 18 police stations and one prison were added. Finally, the remaining infrastructure from Table 1 was attached with the

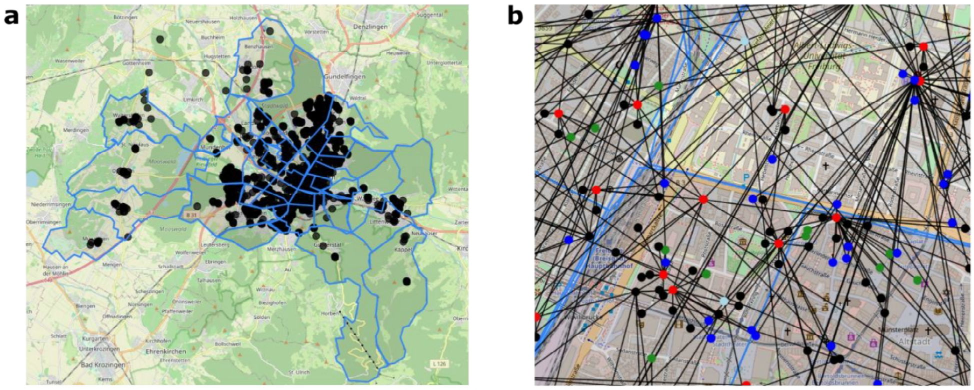

Fig. 1. Exemplary network model for the city of Freiburg, Germany. (a) The black dots represent the nodes of the network, edges have been omitted for clarity. The blue polygons represent the districts of Freiburg. (b) Looking closer, this image shows nodes representing the power grid in red, water nodes and food stores in green, hospitals, doctors and nursing homes in blue, and fire brigades as well as police stations in light blue. Black dots represent the other node types, black lines represent the network edges and blue lines show district borders.

single exception of the harbor (ID 11) due to the simple fact that Freiburg has none. To incorporate population and local enterprises (see Table 2), one population node and one node representing the enterprises were attached to each LV grid node. Based on data from the city administration, providing numbers for inhabitants and enterprises per district (Freiburg City, 2023), every population node got a number assigned, which represents the sum of people associated with the respective node. Here, the population of each district was equally distributed over all population nodes found in the respective district. Enterprises were treated similarly. As final openly available information, the number of hospital beds for all hospitals depicted in the network was collected. This information is used to assess the relevance of the different hospital nodes when simulating the effects of a power outage.

In total, the final network model consists of 1299 nodes and 1811 edges; Figure 1 presents a visualization of the node distribution. Having constructed the network of CIs, the next section presents how damage cascades are estimated to predict the system response to a power outage.

3. Modeling damage cascades

To simulate the temporal evolution of a disturbance affecting the network of CIs, an enhanced simulation setup was applied. This simulation environment, called CaESAR (Fraunhofer EMI, 2023), is based on an iterative algorithm that checks and adapts the states of all nodes (and edges) of the network in each timestep. Here, three main ingredients are necessary to perform simulations of damage cascades:

- The node list specifying the elements of the network under study. The Subsections 2.2 and 2.3 described in detail how the node list was constructed for this paper. The columns 'ID', 'Infrastructure', 'Sector', '$t_{L,i}$', '$t_{R,i}$' and 'mns_i' of Table 1 can be understood as a representation of the node list. In general, every CaESAR-node can have more attributes to account for other propagation logics than the one used in this paper, making the framework highly flexible;
- The edge list specifying the interdependencies of the network. Again, the Subsections 2.2 and 2.3 described in detail how the edges were set. The column 'Dependencies' in Table 1 can be seen as representation of the edge list;
- The definition of the threat which damages the network. It specifies which nodes or edges of the network are targeted by the initial adverse event. The threat can either damage nodes based on their name, sector or any other attribute found in the node list. It is also possible to define a geographical region where the threat is applied in order to account for localized events like storms. It is possible to specify a certain damaging probability for the threat. This allows to simulate probabilistic events where only a subset of the selected nodes is affected, such that the strength of the damaging event can be modulated.

Having defined the node list, the edge list and the threat, the simulation starts by applying the threat to the network to determine the initial damage event. Typically, the threat overwrites the $t_{R,i}$ of the affected nodes to account for physical damages caused by, e.g., a storm. This initial system state is then propagated over time to assess the temporal response of the network to the initial damage. In each timestep, the simulation determines if the damage is propagated via the edges to dependent nodes following the approach described in the next subsection.

3.1. Damage propagation

The logic used for damage propagation and repair progress is based on the interdependencies, i.e., the network edges, the times $t_{L,i}$ and $t_{R,i}$ and the different mns_i specified in the node list. After the initial damage is applied, the simulation starts to iterate over the timesteps by performing the following checks.

- For every node it is checked how many supplying nodes are still operative. In case this number falls below the node-specific mns_i, it remains operative as long as $t_{L,i} > 0$. However, from now on it is recorded how long the node was not sufficiently supplied;
- In case it is observed that a node was not sufficiently supplied for the time $t = t_{L,i}$, the node becomes dysfunctional, i.e., the damage propagates deeper into the network. In consequence, the node stops to supply nodes which depend on it;
- Once it is observed that a dysfunctional node is sufficiently supplied again, it becomes operative again, i.e., it is repaired as long as $t_{R,i} = 0$ holds. If $t_{R,i} > 0$, the simulation starts to record how long the dysfunctional node was sufficiently supplied;
- In case a node with $t_{R,i} > 0$ was sufficiently supplied for a cumulated time of $t = t_{R,i}$, the node becomes operative again. This means that it restarts to supply nodes which are dependent on it so that the repair of the network progresses.

Figure 2 presents a visualization of the damage propagation concept. By iterating the network in time based on the described logic, the simulation produces a trajectory of snapshots of the network state for each timestep. This provides a possibility to calculate the performance of the whole system, a quantity which represents a natural KPI in resilience studies.

Fig. 2. Concept of the damage propagation based on the minimal necessary supply (mns). (a) The node 'EHV grid' with $t_L = 0$ h and $mns = 2$ does not become dysfunctional if two of its supplying nodes are dysfunctional (indicated by the color red) since the remaining three supplying nodes are still operative and provide sufficient supply (indicated by the number one at the edges). (b) If four of the supplying nodes become dysfunctional, the mns of 'EHV grid' is not met, it immediately becomes dysfunctional ($t_L = 0$) and the damage propagates to the next node, 'HV grid' which also becomes dysfunctional.

4. Simulation of the effects of a large-scale, long-lasting power outage

To demonstrate an exemplary application of the concept outlined in the sections above, the following study inspects the model predictions for the worst-case scenario, i.e., the full, long-lasting blackout of the (European) EHV power grid. The network model of Freiburg introduced in Section 2 is analyzed. The threat definition (used to mimic the blackout) targets all EHV production nodes as well as the EHV import/export node (ID 1 and 2 in Table 1). All those nodes become dysfunctional at $t = 0$, triggering the collapse of the full power grid and all other nodes without lifetime ($t_{L,i} = 0$), like ATMs. It is assumed that the threat damages the targeted nodes for a whole week, which is sufficient to observe the successive decay of all different CIs over time. Figure 3 visualizes the system decay by depicting the percentage of operative nodes for the different infrastructure categories over time. Please note that the exact shape of the observed evolution depends on the used sets of $t_{L,i}$ and $t_{R,i}$. To get an impression of the influence of the uncertainty of both timesets, two different sets where drawn from the Gaussian distributions defined in Table 1. The solid lines in Figure 3 represent the first set of times, the dashed lines show the results for the second set. It can be seen that the uncertainty of the times leads to uncertainties regarding the system decay following the outage as well as regarding the evolution of the system repair. Please note that the curves for operative hospital beds represent the hospital nodes of the network weighted by the number of beds. When comparing the different infrastructures, it can be observed that the fuel stations fail at first, due to $t_{L,i} = 0$, followed by the resident doctors, banks, the water grid, food stores and police stations and fire brigades. The hospitals survive the longest, some of them become dysfunctional only after the power supply is restored again. This failure is due to the fact that hospitals depend on both power and water, to stay operative. This means that the restoration of the power supply is not sufficient to either prevent the failing or to start the repair of the hospital nodes, the water nodes need to be back as well. This dependency on the water nodes is also the reason why the hospitals, together with the fire brigades, are the last infrastructures which fully recover, i.e., their repair only starts once the water supply is restored at around $t = 240$ h.

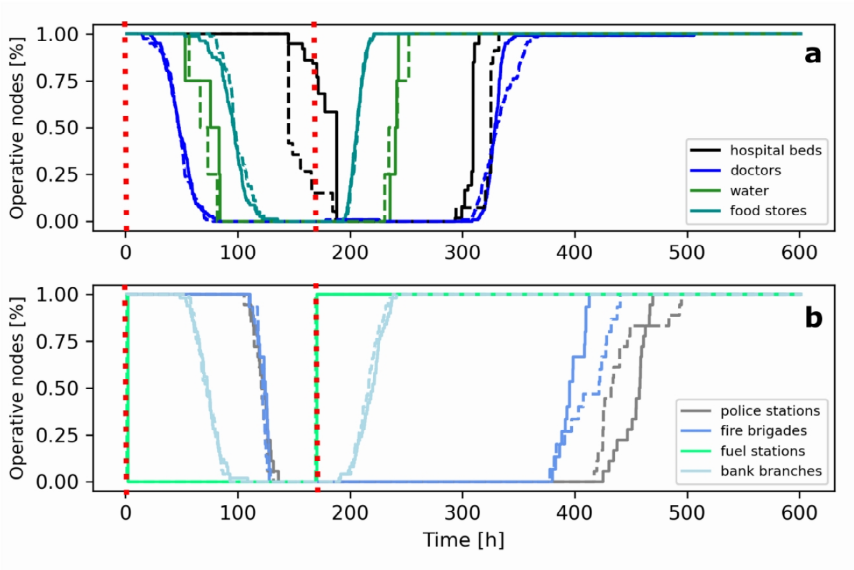

Fig. 3. Breakdown of the network of CIs for a full blackout of the EHV grid lasting for one week. (a) and (b) depict different infrastructures, the dotted red lines represent start and end of the loss of the EHV power supply.
Solid and dashed lines distinguish the results for two sets of $t_{L,i}$ and $t_{R,i}$ drawn from the Gaussian distributions defined in Table 1.
Please note that, having life- and repair times of zero, the curves for the fuel stations do not differ.

The curves in Figure 3 represent typical KPIs to assess resilience as described in the introduction. The longer the decline of the performance curve after an adverse event is delayed, or the sharper it rises back to 100 % during the repair phase, the more resilient the infrastructure is against the modeled damaging event. It is possible to define bounding conditions when calculating KPI curves, e.g., one might assume that some hospital beds are redundant so that the KPI for the hospital beds only decays once the number of lost beds exceeds this redundancy. The curves can also be used to quantify the influence of mitigation measures, which aim for the reduction of the system vulnerability to the studied disturbance.

As an example, Figure 4 shows the curves resulting from the assumption that all hospital nodes have $mns_i = 1$ instead of $mns_i = 2$, i.e., they can either compensate the loss of power or water. This change drastically improves the resilience of the complete grid of CIs for both sets of $t_{L,i}$ and $t_{R,i}$. First of all, the hospitals do not become dysfunctional because the restoration of the power supply is enough to prevent the failure of the hospitals. This has the consequence that the nodes representing ambulance services (depending on working hospitals and working communication) and resident doctors are repaired earlier since they do not have to wait for the repair of the hospitals. This effect also accelerates the repair of nodes representing the fire brigades, which are assumed to depend on working ambulance services for proper operation (see Table 1). This again speeds up the repair of the police nodes, which depend on the operating fire brigades. So, the change in the mns_i of hospital nodes triggers an improvement of the resilience of several other CIs against the blackout event.

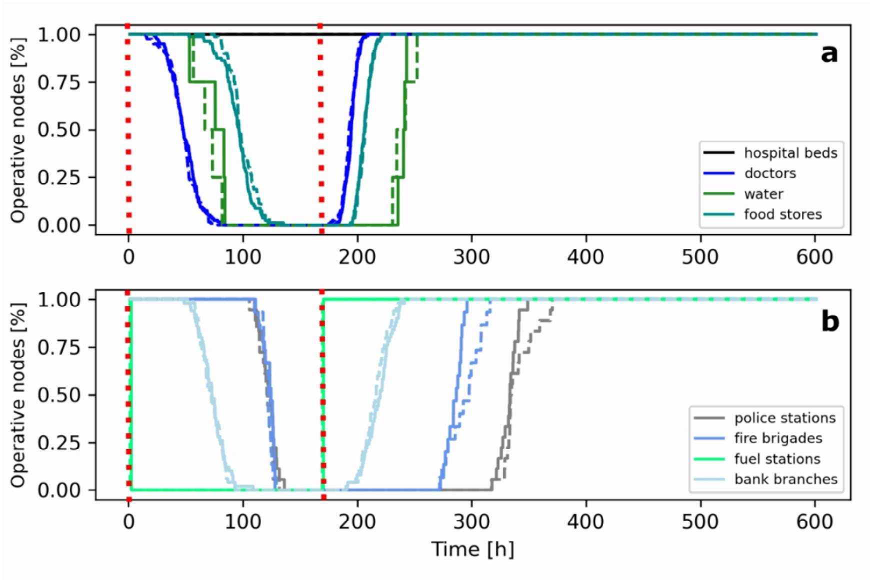

Fig. 4. Breakdown of the network of CIs for a full blackout of the EHV grid lasting for one week.
Compared to Figure 3, the model assumes that all hospital nodes have $mns_i = 1$ instead of $mns_i = 2$.
(a) and (b) depict different infrastructures, the dotted red lines represent start and end of the loss of the EHV power supply.

Summary

This paper presents a network modeling approach to assess the resilience of a grid of diverse, interdependent CIs. The numerous dependencies between the considered CIs are a priori very different, i.e., the dependency of an ATM on a functioning power supply is conceptually very dissimilar from the dependency of ambulance services on operative hospitals. Still, it is necessary to combine those dependencies in a single model in order to be able to understand vulnerabilities of modern societies depending on the complicated grid of CIs. The modeling approach of this paper aims exactly at such a unified description of the dependencies. To test this approach, the effects of a large-scale, long-lasting power outage are inspected. Lifetimes are defined to account for emergency measures, like emergency power generation, and repair times are assigned to cover delays in repair processes following such a severe event. Both times are defined in terms of Gaussian distributions to account for individual differences between different infrastructures of the same types, as well as for the inherent uncertainties regarding the estimation of those times.

Further studies need to improve the level of detail of the network, e.g., the mobile communication needs to be fleshed out. In addition, the predictions for other scenarios, e.g., cyber-attacks targeting correspondingly vulnerable nodes, need to be analysed to detect possible shortcomings of the current modeling framework. Additionally, the logic defining the failure cascades need to be revisited. The current implementation, based on the minimal needed supply mns_i, has the shortcoming that different dependencies are treated interchangeably, e.g., for $mns_i = 1$ hospital nodes do not care if the water or the power supply is operative. Currently it is planned to replace the single number mns_i by a list of 'mandatory supplies' indicating how many supplying connections to the different other infrastructures need to be operative to prevent the failure of node i.

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