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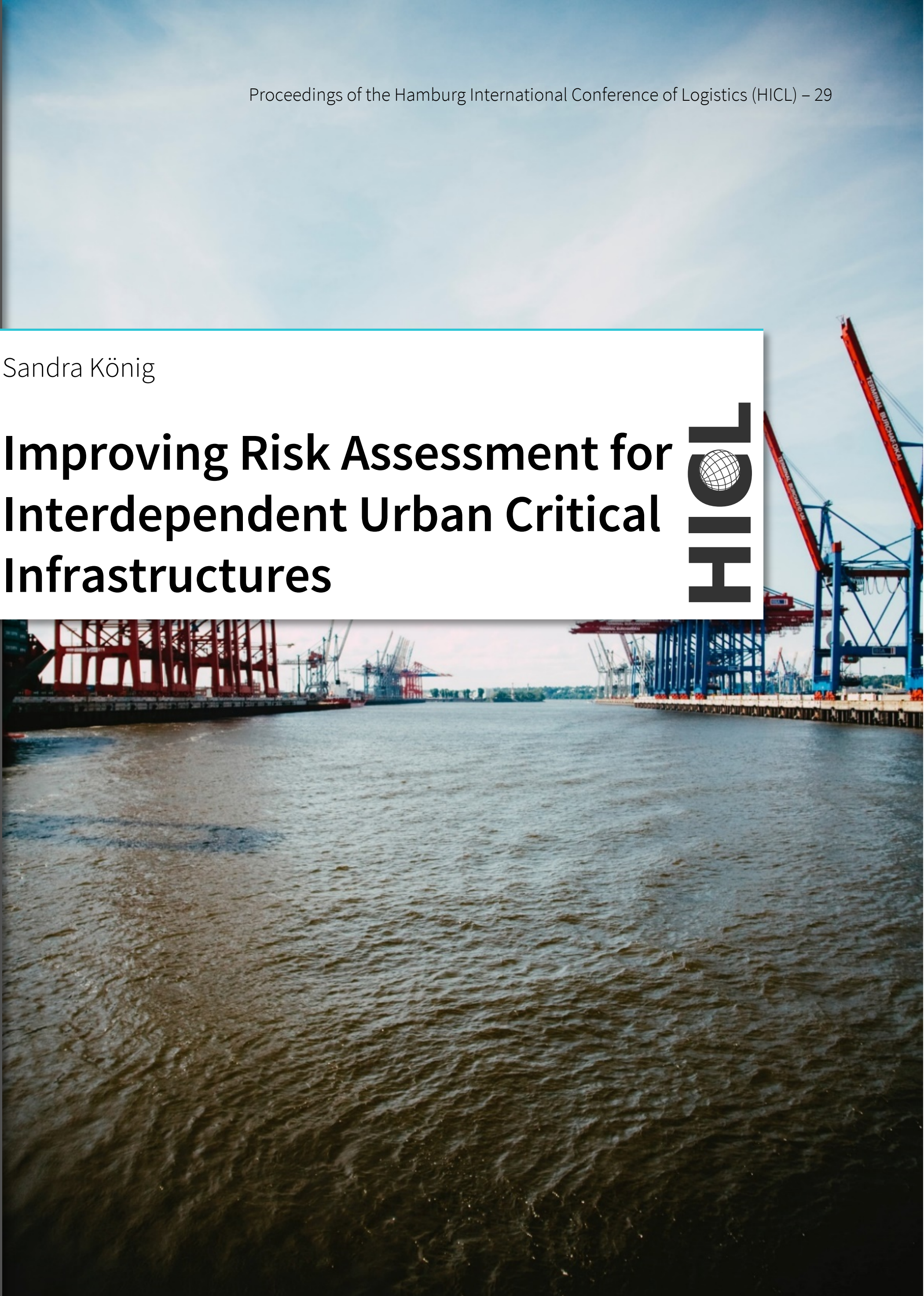

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Improving Risk Assessment for Interdependent Urban Critical Infrastructures

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Purpose: Urban critical infrastructures are highly interdependent not only due to their vicinity but also due to the increasing digitalization. In case of a security incident, both the dynamics inside each infrastructure and interdependencies between them need to be considered to estimate the overall impact on a city.
Methodology: An existing high-level model of dependencies between critical infrastructures is extended by incorporating more details on the individual infrastructure's behavior. To this end, a literature review on existing models for specific sectors is conducted with a special focus on machine learning models such as neural networks.
Findings: Existing models for the dynamics of specific urban infrastructures are reviewed and integration in an existing dependency model is discussed. A special focus lies on simulation models since the extended model should be used to evaluate consequences of a security incident in a city.
Originality: Existing risk assessment approaches typically focus on one type of critical infrastructures rather than on an entire network of interdependent infrastructures. However due to the increasing number of interdependencies, a more holistic view is necessary while the dynamics inside each infrastructure should also be considered.

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1 Introduction

The benefit of models and simulation in systems of critical infrastructures in security has long been recognized (McLean et al., 2011). Existing simulation approaches may support risk assessment of interconnected critical infrastructures, as in an urban environment. Any holistic risk assessment of urban critical infrastructures should comprise two major parts: a model of all involved infrastructures and a description of the interdependencies between them. The latter is typically an abstract high-level model, e.g., a representation of the network of critical infrastructures as a graph where the critical infrastructures are represented as nodes and the interdependencies as edges. The description of the individual infrastructures depends on the amount of available information. In the simplest case, the functionality is measured on a qualitative scale. The dynamics that yield to changes of the functionality need to be investigated for each infrastructure individually and thus the specific infrastructure models require detailed information and domain knowledge. Risk managers rarely have both a good overview and a deep knowledge of all relevant processes in different infrastructures. One way to approach this problem is to integrate existing simulation models into the high-level dependency model, which is the topic of this article. The proposed method uses neural networks imitating existing domain-specific simulations to enable, or at least simplify, combination of the local views to a simulation model for the entire network of infrastructures.

2 Domain-Specific Simulation Models

This section provides a short overview on domain-specific simulation models that might be integrated into a high-level model of interdependent critical infrastructures. The focus is on transport, energy and water, where a lot of research has already been done, but also food and media are investigated considered relevant when analyzing security of urban infrastructures. Details can be found in the cited papers.

2.1 Transport

Simulation tools for specific transportation systems have been developed and used during the last decades, e.g. for railway, underground and roads. The increased use of traffic simulation has led to guidelines on their application (Olstam and Tapani, 2011).

The network simulation tool OpenPowerNet (Institute of Railway Technology, 2020) focuses on railway power supply networks. It allows simulation of common power supply systems while taking into account the electrical network structure (Stephan, Jacob and Scheiner, 2008). In the UK, railway simulation modeling software has been applied to design baggage transfer (Yeung and Marinov, 2017).

The open source package SUMO (Simulation of Urban MObility) allows simulation of traffic in large scale networks. An overview on recent developments and application of the tool is given in (Lopez et al., 2018).

A model similar to the one we propose here for general infrastructures already exists for the transportation domain: artificial neural networks are used to forecast onboard passenger flows on metro lines and support control and management strategies on transportation systems (Gallo et al., 2019). The model describes the passenger flows as a function of the number of passengers at stations, counted at turnstiles. Training data for the neural network are gained from existing simulation data of a dynamic loading procedure or the rail line.

2.2 Energy Sector

A powerful simulation environment is Gridlab-D (Chassin, Schneider and Gerkensmeyer, 2008; GridLAB-D Wiki, 2020), which is especially applicable to smart grids. Further notable simulation tools include MYNTS (Fraunhofer SCAI, 2020), an extension to the network simulator ns-3 (Wu, Nabar and Poovendran, 2011) or the combined simulation framework for energy and gas systems (Erdener et al., 2014).

An overview on simulation tools for smart grid is given in (Bindner and Marinelli, 2013) and a review of modelling tools for energy and electricity systems with a focus on renewables is provided in (Ringkjøb, Haugan and Solbrekke, 2018).

Interactions between power systems and ICT are investigated in (Müller et al., 2018), models for electricity and gas systems in (Erdener et al., 2014).

2.3 Water

Simulation models are applied in many different parts of water utilities, ranging from water quality (Ziemińska-Stolarska and Skrzypski, 2012) to water distribution systems (Paluszczyszyn, Skworcow and Ulanicki, 2015). Simulation models of urban water management are reviewed in (Peña-Guzmán et al., 2017) and an overview on water resource software is discussed in (Borden, Gaur and Singh, 2016).

2.4 Food

The use of simulation in the area of food supply is relatively new. A discrete event simulation has been used to investigate sustainable delivery of food (Leithner and Fikar, 2019) und simulations have been used to optimized the economic effect of producers (Tundys and Wiśniewski, 2020) and both approaches are particularly paying attention to the supply chain for organic products. Agent-based models may be used for efficient crop production supply chain redesign (Borodin et al., 2014) to simulate agri-food supply chains (Utomo, Onggo and Eldridge, 2018).

2.5 Media

Some countries such as Germany specify media as crucial for society and thus put effort in protecting it (Federal Ministry of the Interior, 2009). Especially social media have the potential to significantly influence consequences of events or attacks such as the one in Munich in 2016 (the local, 2016). Numerous simulation models exist for spreading of rumors through twitter (Serrano, Iglesias and Garijo, 2015).

3 Interdependent Urban Critical Infrastructures

A network of interdependent critical infrastructure is conveniently described by a two-layer model - a high-level "outer" model describing the interdependencies and more detailed "inner" models of the different infrastructure nodes. The interdependencies are vividly representable by a directed graph where nodes represent critical infrastructures and edges correspond to dependencies. Dependencies of any kind should be taken into account, ranging from physical or logical dependencies to geographic proximity, which is an essential factor in urban infrastructures.

A core part of risk assessment in infrastructure networks is risk evolution, i.e., understanding impacts of reduced availability of one or more infrastructure on the others. In alignment with the recommendation of a qualitative risk management (Münch, 2012) it is useful to represent the level of functionality of each infrastructure on a finite scale, e.g., ranging from 1 (properly working) to 5 (not working). How a critical infrastructure changes from one state to another depends on its neighbors, e.g. a hospital might be affected by limited availability of power, as well as on the internal dynamics of the infrastructure, e.g., the number of available emergency generators. Manifold methods exist to describe the dynamics inside the critical infrastructures. The actual model choice is strongly influenced by the availability of information on the individual infrastructure. If a conditional likelihood for each change can be assigned, a Markov model might be used for a conservative estimation of the overall functionality (König and Rass, 2018). If the reactions to an external incident can be described more explicitly, automata models can be used (König et al., 2019). In both cases, data from simulations or from domain experts can support statistical estimation

of respective parameters; it is even possible to use machine learning to train other machine learning models (Rass and Schauer, 2019).
Training such models is not always possible due to limited data. Individual models for the various domains often exist but are typically not compatible. One way to integrate existing simulation methods, as presented in the last section, is to mimic their behavior by re-modelling them as neural networks. The various nets can then be connected in order to simulate the entire network. The remainder of this section describes the integration into the high-level network model. The approach is illustrated in Figure 1.

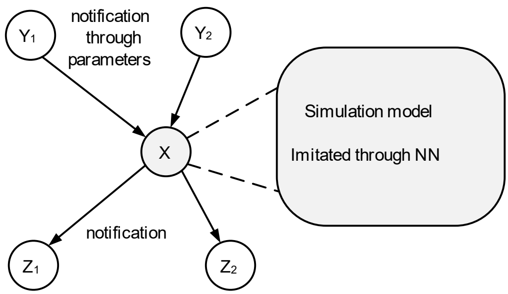

Figure 1: High-level view of dependency model

The main challenge is the combination of potentially many different infrastructure models. One approach is to allow edges of the dependency graph to be used for communication between nodes, transmitting two pieces of information: (a) the current state of a CI, and (b) parameters refining this risk situation (these will determine the reaction of the dependent CIs). For example, if a power supplier CI reports a state "problem" (represented by 2) to a water provider, this information is extended by information on the current (reduced) level of energy supply, which causes the pumps of the water supplier to run at lower performance. In the dependency graph the edge from the power supply to the water provider signalizes the level of functionality and augments this information with data relevant for the dependent CI. The simulation model of the water provider will in turn be used under an adapted setting due to the messages from the energy provider. Such communication between components works best when the components are represented by homogeneous models. To that end, machine learning techniques may be applied to mimic the behavior of a CI, i.e., machine learning systems such as (deep) neural networks may be trained with data from the identified simulation models. Connecting these digital twins into an overall co-simulation model is then a matter of "connecting" software modules accordingly, that is, the output parameters of one deep neural network are input to the neural network.

4 Conclusion

Integrating existing simulation models of critical infrastructures into a dependency model is one way to support risk assessment of interdependent urban critical infrastructures. The main issues to be investigated in future work are the choice of suitable simulations methods and details on the co-simulation, e.g. avoiding oscillation in the network.
While assemble existing software pieces may be challenging, artificial intelligence (AI) and machine learning may be an alternative, e.g. when used in a heterogeneous co-simulation environment. Their high flexibility enables cross-domain co-simulation and incorporation of existing simulation methods. It overcomes the shortcomings of most machine learning techniques, namely the huge amount of training data and the missing expalinability. Training data are generated by the underlying simulation models and these models provide, to some extent, knowledge about the specific domain, i.e., the domain knowledge may help explaining the internal behavior. Further, the proposed method allows cause analysis in the big picture, i.e., identification of infrastructures that may trigger cascading effects. Overall, the combination of AI and simulation for risk management appears as a promising direction of further research.

Acknowledgement

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