Strengthening Resilience in Critical Infrastructure Systems: A Deep Learning Approach for Smart Early Warning of Critical States

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Systems of critical infrastructures are characterized by strong interdependencies and the developments of urban areas towards Smart Cities even increase the underlying complexity due to growing automation and interconnectedness. A system of highly cross-linked components is especially prone to systemic risks making concepts of resilience accordingly important. One way for being able to withstand in times of stress, maintain security of supply, and promote adaptive and anticipative capabilities, is to establish early warning capabilities. As cities are complex and rather chaotic socio-technical systems reigned by randomness, the caused parametric uncertainties challenge modeling approaches that are intended to support robust decision-making. Sophisticated methods based on artificial intelligence can play an essential role in this case, as they perform well on highly complex environments and large data set. To study resilience, the urban area is split into zones where the city's state is determined by the states of these zones and the state of a zone is characterized by the criticalities of infrastructures accommodated there. Considering criticality as an atomic building block for urban performance assessments, this paper proposes a zone-based state forecast methodology by applying deep convolutional neural networks for learning state evolution that is influenced by non-linear demand dynamics. Furthermore, a case study is presented that applies agent-based simulations and underlines the relevance of deep learning approaches for Smart City early warning systems.

Keywords: smart crisis management, resilience, security of supply, forecasting, agent-based modeling, performance metrics, deep learning.

1. Introduction

The functioning of critical infrastructures (CIs) is essential for the well-being of our modern society. In each of them, there are several processes that require in-flows of specific resources for performing tasks, for offering services, or producing new resources to be consumed by other entities. A high quality of service relies on a timely and comprehensive availability of specific resources. The direct and indirect consequences of the current Covid-19 pandemic especially reveal the vulnerability of critical supply systems e.g. a sudden increase in purchasing behavior, triggered by political announcements such as movement restrictions, led to shortages of specific consumer items and consequently to uncertainties among the population (Keane & Neal, 2021). CI systems are systems of highly interconnected components and are especially prone to systemic risks and cascading failures (Buldyrev et al., 2010) making concepts of resilience accordingly important (Arafah et al., 2018; Hickford et al., 2018). Developments towards Smart Cities (SCs) even increase their complexity due to growing automation and interconnectedness. Here, information and communication technology (ICT) plays an essential role to achieve a sustainable development pervading other CIs. One way for enhancing resilience is to strengthen crisis management. Especially, improved situational awareness and assessment on possible future developments and CI states certainly help decision-makers to identify appropriate management strategies. Whilst research on CI resilience is continuously growing, approaches taking into account different hazards, cascading effects, dynamics, or uncertain information need to be further elaborated (Curt & Tacnet, 2018). Especially, against the background of future digitalized infrastructures, combining continuous monitoring with learning techniques is promising for performance prognoses of critical entities. This paper presents a smart resilience engineering approach for measuring and forecasting the state of CI systems by means of deep learning. The focus is on short-term

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forecasts. Urban areas are split into zones whose states are reflected by the criticalities of the CIs accommodated there. The forecast methodology is zone-based and applies a deep convolutional neural network (CNN) for learning state evolution that is influenced by demand dynamics. Learning particularly includes experiences made with deviations from usual states. The goal is to enhance crisis management and prevention capabilities and secure the supply of critical resources to the population in the face of occurring and impending shortage or bottleneck situations.

This paper is structured as follows: Section 2 discusses the notion of resilience and presents related work. Section 3 introduces our smart resilience engineering approach and clarifies technological requirements. Section 4 presents a case study applying agent-based simulations and emphasizing the relevance of deep learning approaches for SC early warning systems. The paper concludes with a discussion and directions for future work in Section 5.

2. Resilient Smart Cities

Enhancing the resilience of urban areas has become of major interest in the last years, both for academics and practitioners (Meerow et al., 2016). Managing infrastructure dependencies and hence preventing and preparing for failures is regarded as a basic requirement for resilient societies (Monstadt & Schmidt, 2019).

2.1. *The notion of resilience*

Resilience is defined in terms of three stages: the ability of a system to reduce the probability of an adverse event, to absorb the shock if the adverse event occurs, and to quickly re-establish normal operating conditions. Thus, resilience encompasses the four following characteristics: robustness, redundancy, resourcefulness, and rapidity (Bruneau et al., 2003). It is the intrinsic ability of an organization (system) to maintain or regain a dynamically stable state allowing to continue operations after a major mishap and/or in the presence of a continuous stress (Hollnagel, 2006). In particular, SC developments need to address resilient city concepts (Arafah et al., 2018). Cities in general are examples of complex systems and are extremely vulnerable to diverse threats making initiatives for enhancing resilience of utmost importance (Godschalk, 2003). Building resilient cities requires flexible planning to keep up with changing dynamics in the environment, designing adaptable artefacts being able to withstand and reconfigure in times of stress, and agile managing to sense changes in the environment and act anticipatively and proactively (Desouza & Flanery, 2013). Hence, SC developments must include and strengthen smart crisis management, which is seriously challenged by possible new and unforeseen disruptions and the range and severity of their cascading effects. Improved anticipation capabilities of CI states through, e.g., early warnings surely contribute to maintain the functioning of critical urban services and hence enhanced crisis management capabilities (Woods, 2006). Here, the less the performance of critical services drops and the faster it returns to one hundred percent, the better resilience is. SCs open up advanced data collection capabilities that could support performance forecasts.

2.2. *Related work*

Research in the field of resilient SCs is broad comprising different frameworks helping to understand, assess, and improve resilience of urban areas (Dhar & Khirfan, 2017) or advanced IoT architectures (Abreu et al., 2017). SCs are equipped with a dense network of smart devices and sensors, where massive amounts of data are produced constantly. Key areas of research are dedicated to collecting, managing, and evaluating this data for providing decision support in various often critical segments. Predicting traffic flow, air quality, power generation, or electricity consumption are some important research fields, e.g. with the help of machine learning (Bomfim, 2020). Disaster management especially benefits from smart technological solutions (Ragia & Antoniou, 2020) providing decision-makers with condensed information from different data sources. Here, Big Data analytics plays a leading role (Shah et al., 2019) being highly important for e.g. improving situation awareness or developing predictive capabilities in the framework of crowd management and evacuation plans (Yang et al., 2017). Real-time data can also be combined with simulations for identifying the occurrence of an emergency, mapping the current state, and simulating its progress in real-time (Lacinák & Ristvej, 2017). Furthermore, the ICT infrastructure of SCs and advanced analysis techniques can be used to improve the information exchange between first responders, public authorities, and citizens (Bartoli et al., 2015). Sensors are also combined with social networks where e.g. people have the role of sensing and event detection (Crooks et al., 2013).

SC developments pave the way for handling growing urbanization issues. However, to best of the authors' knowledge, there is a lack of supporting solutions for crisis management that help decision-makers to maintain critical urban services and especially the supply of important resources in times of occurring and impending bottleneck situations. To fill this gap, this paper proposes a forecasting methodology that focuses on the performance of critical entities, which is co-determined by corresponding service demands and coping capacities of the according entities. The forecasted performance values enhance early warning capabilities and can serve as basis to e.g. potentially initiate a re-allocation of critical resources.

3. Forecasting States of Critical Infrastructure Systems

For studying capabilities and potentials of learning mechanisms for SC early warning systems, some assumptions on the technological reality are made. Furthermore, an agent-based simulation framework that integrates a deep learning module is set up to conduct corresponding investigations.

3.1. *Technological framework*

We assume that a city can be divided into zones, with each zone accommodating different CI entities. The city's state is then determined by the states of these zones. Motivated by the current Covid-19 pandemic, the concept of the 15-Minute City (de Valderrama, N. M. F. Luque-Valdivia, J. Aseguinolaza-Braga, 2020) is highlighted enabling all citizens an immediate and safe access to all essential i.e. critical urban services within a 15-minute walk or bike trip. One can consider this as an innovative and sustainable approach for increasing the resilience of urban societies. Cities as Paris or Melbourne are pioneers in elaborating the operationalization of this concept of self-sufficient walk- and bikeable neighborhoods. In the spirit of this concept and in the context of SCs, we assume the existence of such or similar supply zones and consider them as smart environments forming a basis for assessing the performance of a city, thereby referring to critical services. An ICT infrastructure containing neighborhood- and wide area networks (NAN, WAN) enable CI entities to transfer their state data and possibly further relevant information to a SC crisis management unit (SC-CMU), where the states of the various zones are calculated. The internal state of a service provider can be expressed by a dynamic criticality value reflecting the current quality of service in view of current and expected demands and is further enriched by information on current and anticipated states of up-stream supply chains. Additionally, an SC-CMU can collect information describing current boundary conditions with regard to, e.g. climate or politics, which may influence the demand dynamics. Forecasts are possible by an accordingly integrated module.

3.2. *Research methodology*

The critical facilities under investigation are represented in an agent-based framework for capturing the relevant processes as well as the required and offered resources for running their services. The term resource is used as a placeholder for anything that can be spatially shifted, including materials, power, and water as well as information bits and human beings. Zone agents mark specific areas of a city and collect the performance values of the CIs they enclose. Furthermore, the entities that demand the resources offered by the CI agents are modeled as agents as well. Each entity has several processes requiring an in-flow of specific resources to be consumed when performing its tasks. The entity possibly might produce new resources consumed by other agents. Initial configuration values are stored in a database. These concern the processes of the CIs, polygon shapes of city zones as well as a basic demand behavior that is varied for each entity and during the simulation to ensure diversity.

In view of the huge complexity of SCs and the stochastic nature of cascading effects or feed-back loops caused by certain triggering events and possibly amplified by autonomous decision-making through a vast number of components or individuals, learning components need to play an integral part in smart crisis management solutions. In the proposed framework, a specific learning agent governs the transfer of appropriate zone state data to the learning module. Table 1 illustrates the type of agents modeled and the ordered tasks of the regarded processes within a given time step. For convenience only, demands are generated zone-wise by the corresponding zone agents and the CI agents update the status of the demand agents based on whether their demands are met or not. In case the demand is met, the corresponding agent is deleted. Otherwise, alternative options are determined which e.g. may lead to accumulated demands. The tasks repeat according to defined time steps and during the simulation run.

Table 1. Tasks of the regarded processes of the modeled agents within a time step.

Task	Demand agent	CI agent	Zone agent	Learning agent
1			Generate demand	Check current time
2	Move towards the next CI agent	Update resource container		
3		Update data container of zone agent		
4			Transfer data to learning agent	
5		Update demand agent's status & own resource container		
6				Generate data for learning module

Agent-based modeling distinguishes from other modeling approaches by its scalability and simple adaptability of specific models and parameters (Wooldridge, 2009). Besides a flexible integration of new agents, further preferences can be included on an agent-specific level and calibrated depending on the agent's main state variables, which are determined by environmental and internal conditions, but also on forecasts in conjunction with the agent's targets and the associated resource requirements. These possibilities are comfortable for studying the consequences of disruptions that may concern the offering as well as demanding agents. A way of characterizing resilience is to analyze the supply performance or quality before and after some disruptions have occurred, where the driving factor for this are current and expected demands for critical services. Understanding the dynamics of demands for various urban services, which themselves may be interdependent, is quite difficult in general, all the more during exceptional phases. However, indicators in terms of varying state variables such as criticality of CI entities, can be applied as building blocks for both, measuring the current states of the supply zones and the state of the overall performance of the city. Criticality is a time-dependent measurement, reflecting the severity of the consequences a failure of a CI has to the overall security of supply. Criticality is a demand-driven concept and result from socio-political processes (Ottenburger et al., 2018). Zone agents aggregate the corresponding criticality values of the CIs. The underlying performance metrics can be constructed as weighted sums of critical services' criticalities, where the weighing factor is specified by the SC-CMU. Knowing state changes in advance enables an SC-CMU to make decisions to mitigate supply shortages.

3.2.1. *Forecast model for zone supply states via Convolutional Neural Networks*

The aforementioned indicators and the knowledge on boundary conditions being continuously collected by the SC-CMU form a basis for the forecast model for future supply states of the zones, which can be considered as a grid-like parquetting of the urban area. Depending on urban planning issues, this zone segmentation might be quite regular containing rectangular geometries but it is not limited to it and could be more complicated. However, knowing all neighboring zones of any given zone, gives rise to a matrix-like cluster model using the proximity between zones, i.e. adjacent zones correspond to adjacent matrix elements, which themselves characterize a state. For the sake of simplicity, in this paper, we neglect the inclusion of boundary conditions into the prediction model and rather focus on the very basic criticality-based state model, where adding boundary conditions to this basic model can be considered as some sort of matrix extension (current and on-going research). Empirically, proximity plays a crucial role to understand how demands evolve, shift, and accumulate within an urban system. The matrix representation of the zones naturally invites to consider the matrix and its elements as a first structured layer of a deep CNN (Simard et al., 2003) to apply 'Tensor Flow' (Zaccone, 2016), by making use of the spatial structure of the input data. Besides the input and output layers, the topology of such deep CNNs is basically determined by hidden convolutional and fully connected dense layers. Convolutional layers emerge from so called filters of kernel size such as 2×2, which shift across the input matrix by given step sizes, e.g. one. Furthermore, we chose the sigmoid function as activation function. As explained in Section 3.1, criticality values of various critical service providers are transferred to a SC-CMU, where they are assigned to the corresponding zones. After having specified the prediction horizon, the output of the input/output-tuple for training the CNN for zone states is again a matrix, containing the future states associated to the states of the input measurement.

4. Case Study

For studying deep learning approaches for SC early warning systems, we have implemented a set of according agents exemplarily for the city of Karlsruhe in Germany. For the sake of simplicity, we have considered a single CI to rather focus on the capabilities of learning. Nevertheless, the approach is not limited to a specific CI and the framework enables to make corresponding extensions. Measuring states of all urban supply systems similar to the approach we describe here has the potential to implicitly detect interdependent phenomena.

4.1 *General framework*

The city area was segmented into a grid of 25 zones. Supermarkets constitute CI agents and the resources investigated are two basic foodstuffs that in principal can be substituted by each other. Each supermarket has food stocks that are filled each morning. Agents are generated in each zone during the day demanding a certain amount of these foodstuffs. For demand generation, we distinguish between three population groups with different purchasing behavior – according to purchasing time and quantities. The first group concentrates their purchasing to the morning hours, the second to the evening hours, and the third group distributes their purchases flexibly over the day. We further assume criticality factors that reflect the willingness to seek further supermarkets if the demand is not met. In addition, there is a specific substitution factor per population category and foodstuff that reflects preferences for a specific item. Values for purchasing behavior, criticality, and substitution are stored per population group in a database. For generating a concrete demand agent, these values are uniformly randomized within the given parameters. Furthermore, the demand agents are randomly distributed in each zone. Also, as the simulation progresses, the criticality increases if the demand is not satisfied and the agent has to look for an alternative supermarket. With regard to shortage scenarios, this may be interpreted as growing panic if the demand agent finds itself in front of empty shelves. Furthermore, in this initial approach we assume that the demand agent looks for the nearest supermarket based on its current location. We further assume a certain speed of movement, which is set individually for each demand agent and which is based on a random transport mean (vehicle, foot, bicycle, or public transport). Depending on the current food stock and the demands, a supermarket calculates its criticality and forwards it to the corresponding zone agent. In our simulation, these criticality values are determined once per time step, per supermarket, and per foodstuff according to function $c\colon \mathbb{N} \times \mathbb{N} \times \mathbb{N}^{+} \to [0,1]$ with

$$c_{CA}(x, r, \bar{t}) = \begin{cases} g(x, r, \bar{t}), & r \leq CA \\ f_{CA}(x, r), & otherwise \end{cases} \quad (1)$$

where for a specific foodstuff, CA denotes the critical amount of storage, r the current amount available, and x the current demand. For this case study, we have chosen

$$g(x, r, \bar{t}) = \begin{cases} \rho + (1-\rho) * (x/r)^{1/\bar{t}}, & x < r \\ 1, & otherwise \end{cases} \quad (2)$$

with $\bar{t}$ denoting the remaining time steps until closure time and ρ the minimum criticality value for the case that the current available stock is smaller than the critical amount of storage but the demand can be fulfilled by the stock available. Emptying stocks may be regarded as less critical towards the end of the day. For the case study, we exemplarily set $\rho = 0.9$. In general, the bigger the criticality value is, the more critical the state is. Furthermore, we have set

$$f_{CA}(x, r) = \min\left(\frac{x}{r}, 1\right) \tag{3}$$

as a first approach. The zone agent can be interpreted as a data collector or technical component within the NAN or WAN of that respective zone, relaying the collected data to the SC-CMU. For the sake of simplicity, we have chosen a very strict zone performance metric, namely the maximum of all criticalities of supermarkets lying in the respective zone, which is used by the learning component of the SC-CMU as the input. The output is determined according to the prediction horizon for the corresponding time step in a same way but with the following difference: instead of applying the original range of values from the state assessment, we map these to three states respectively colors – 5, 10, 15 respectively green, yellow, and red indicating the state of the zone in a simplistic way. Green corresponds to the value sub-range [0,0.3), yellow to the value sub-range [0.3,0.6), and red to the value sub-range [0.6,1.0]. The reasons for this mapping are twofold: Firstly, decision makers in the SC-CMU need clear and unambiguous information on state changes. Secondly, training is expected to be more successful the less classification clusters there are. In our case study, the prediction horizon and the simulation time step were chosen to be 30 minutes. The scenarios on which this case study focuses are disrupted supply chains affecting the daily stock replenishment of selected supermarkets according to an increasing disruption rate in the following sense: Every fifth working day some randomly selected supermarkets are affected by a failure of a daily delivery of goods. The number of these supermarkets is determined by a failure rate, starting at 6%, which increases by 3% every 250th day. This means that within the first 250th simulated working days, on every fifth day, 6% of all supermarkets are impaired by a one-day lasting delivery disruption. Within the 251st and 500th simulated working day such disruptions occur with a disruption rate of 9% and so on. Based on the agent simulation framework described above, a training data set consisting of 115.000 input/output tuples corresponding to 5000 working days, was generated in a single simulation run.

4.2 ***CNN: Topology and results***

The input and output neurons are given by 5×5 matrices, where the input matrix contains values lying in the interval [0,1] and an element of the output matrix is either 5 (green), 10 (yellow), or 15 (red) – the bigger these values are the more critical the state is. The CNN design approach we chose uses the Keras-Phython-libraries[a] for TensorFlow: The first and only convolutional layer is determined by one 2×2-filter with step-size 1. A further hidden layer is a dense layer with 300 neurons, followed by a further dense layer with 100 neurons and a dense layer with 25 neurons for the output. The error function for applying gradient descent in the back propagation is simply the mean absolute percentage error. The metric for assessing the quality of the classification results is as follows:

$$MAPE := \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(x_{i,true} - x_{i,model})}{x_{i,model}}\right| \cdot 100\% \tag{4}$$

The aforementioned set of training data consisting of 115.000 input/output tuples was subdivided into 75% training data and 25 % validation data and after 1000 iterations steps the state forecasting accuracy lies above 99,5%. In the following, we give a description of a short but representative extract of our results: Nine supermarkets located in zones B2, C1, C2, C5, and D2, are affected by supply chains interruptions. Two supermarkets lie in zone C1 and four supermarkets in zone C2. The other mentioned zones accommodate one supermarket, respectively. Changes according to the generated demand agents during the day are illustrated in Fig. 1 comprising newly generated agents as well as agents whose demands are not met.

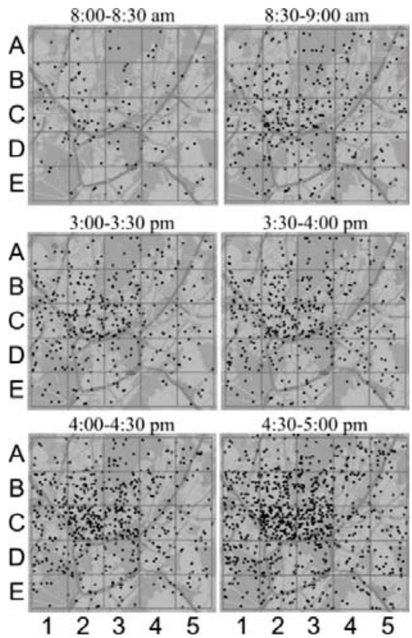

Fig. 1 Generated demand agents for different time slots. Zones C1 and C2 experience state deteriorations during the day.

Table 2 shows the observed and predicted state values for different time slots. Although several supermarkets are affected by supply disruptions, demands can be met in the morning, which can be explained as follows: (i) demand agents potentially change the zone and search for other supermarkets, such as in zone B2 and zone D2. These zones are neighboring zones of zones with a high density of supermarkets; (ii) the supermarket density in a zone is per se high, such as in zone C1 and C2. The stocks of basic

[a] https://keras.io/

goods are sufficient to satisfy the demands in the morning; (iii) the number of demanding agents is low due to a smaller population density, such as in zone C5. During the day the situations gets tenser. Again, observed and predicted state values are compared. Zone C1 and C2 experience deteriorating states. Increasing demands in the zone during the day as well as additional agents from the neighboring zones potentially contribute to the deteriorating situation (Fig. 1). States for zone C1 are not correctly predicted as can also be seen in Fig. 2. However, the tendencies predicted are correct. The state of zone C1 improves between 4:00 and 4:30 pm, which is potentially owed to a relaxed demand situation. This excerpt further shows how the functions (1), (2) and (3) work. In addition, critical amounts of storage are not fallen below and the criticality is mainly determined by the quantity of demand and current amount of foodstuff available.

The study emphasizes the added value of this forecasting approach: improved situational awareness also with regard to future states, especially with the possibilities to consider diverse drivers of state changes and to learn from deviations. Conceivable scenarios are manifold ranging from service disruptions to sudden increase in demands, where particularly patterns of demand flows can be learned. It is important to note that detailed person-specific data on consumer behavior or data of service providers are not required. For conducting this study, demand is generated under certain assumptions. However, the learning module does not depend on these configurations. Our implementation further shows possibilities of visual support helping to interpret the forecasted values, which is certainly subject of further improvements as well.

Table 2. Observed (obs.) and predicted (pred.) state values. Green (g) corresponds to [0,0.3), yellow (y) to [0.3,0.6), and red (r) to [0.6,1.0]. The cells highlighted in grey show status deteriorations during the day.

	8:00-8:30 am	8:30-9:00 am		3:00-3:30 pm	3:30-4:00 pm		4:00-4:30 pm		4:30-5:00 pm	
Zone	Obs.	Obs.	Pre.	Obs.	Obs.	Pre.	Obs.	Pre.	Obs.	Pre.
A1	0.025	0.0	g	0.004	0.014	g	0.017	g	0.019	g
A2	0.003	0.003	g	0.004	0.011	g	0.021	g	0.023	g
A3	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
A4	0.003	0.003	g	0.02	0.041	g	0.03	g	0.038	g
A5	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
B1	0.002	0.003	g	0.006	0.014	g	0.014	g	0.014	g
B2	0.002	0.005	g	0.014	0.039	g	0.038	g	0.041	g
B3	0.004	0.004	g	0.016	0.035	g	0.039	g	0.045	g
B4	0.033	0.003	g	0.006	0.006	g	0.013	g	0.017	g
B5	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
C1	0.002	0.033	g	0.532	0.547	r	0.035	g	0.53	r
C2	0.011	0.023	g	0.05	0.188	g	0.5	y	0.5	y
C3	0.001	0.008	g	0.031	0.017	g	0.027	g	0.037	g
C4	0.005	0.002	g	0.008	0.013	g	0.013	g	0.03	g
C5	0.002	0.005	g	0.006	0.011	g	0.015	g	0.022	g
D1	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
D2	0.004	0.004	g	0.018	0.02	g	0.045	g	0.059	g
D3	0.001	0.003	g	0.001	0.009	g	0.011	g	0.012	g
D4	0.005	0.008	g	0.013	0.008	g	0.015	g	0.031	g
D5	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
E1	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
E2	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g
E3	0.007	0.003	g	0.021	0.034	g	0.033	g	0.055	g
E4	0.002	0.004	g	0.006	0.014	g	0.015	g	0.018	g
E5	0.0	0.0	g	0.0	0.0	g	0.0	g	0.0	g

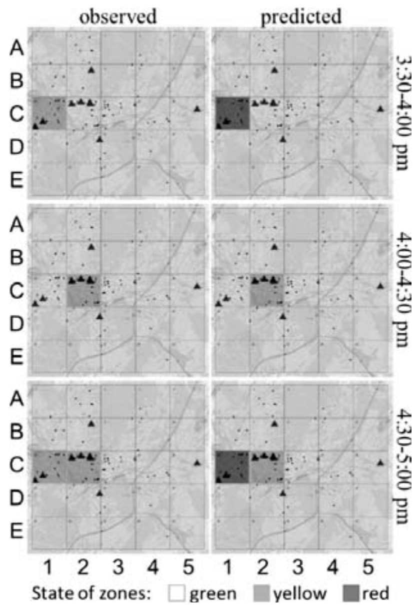

Fig. 2. Observed vs. predicted states. The triangles illustrate disrupted service providers, the circles non-disrupted providers.

5. Discussion and Future Research

Driven by growing urbanization issues, SC developments mainly settle around sustainability and digitalization for improving comfort and quality of life for the city's citizens. Yet, urban resilience considerations are often not adequately addressed. Enhancing urban resilience means to target at concrete improvement aspects, such as to consider building redundancies, to strengthen organizational and management units, and to harden infrastructure. This research emphasizes the need for integrating urban resilience into SCs in terms of smart crisis management capabilities and is motivated by the fact of increasing interconnectedness and automation of various critical segments. A single failure (accident, component failure, intended harm) can potentially lead to adverse cascading effects deteriorating security of supply or the city's performance. The complexity of SCs, their different states, the innumerous amount of crisis scenarios are hard to be described in terms of models alone. A big advantage of continuously collecting and evaluating data of all entities and system states, where the latter is expressed by certain performance indicators, is to improve forecasting these states, through machine learning techniques as e.g. neural networks or predictive analytics. This becomes in particular interesting for decision-making in the context of unprecedented disruptions. The presented approach can be tailored to strategic and city specific configurations respecting preferences of the decision-makers concerned.

The following aspects need to be examined in more detail in future research: (i) The agent-based model provides means to generate data that is assumed to be available in the context of a SC – criticality values of entities that are based on e.g. current demand and available stocks. The SC-CMU and forecasting module, respectively, would process criticality values solely and directly. Hence, the technological innovation is only dependent on a city-based zone model, a learning component, and ICT for transferring criticality values. However, since disruptions normally occur infrequently, generating synthetic data, e.g. for different types of disruption scenarios, via multi agent-based simulation models is a promising approach. For the purpose of this research, we made assumptions on citizens' demand and the replenishment of stocks. Realistic data would certainly improve the agent-based based models as well as the insights on actual demand dynamics. In turn this requires consequent updating of models and parameters as well as deep understanding of behavioral aspects. We have chosen a microscopic demand model since macroscopic models covering various boundary conditions, socio-economic factors, and randomness in individual decision-making do not exist a priori and if so, adapting them to specific urban environments would be too complicated. Hence, a first approach for uncovering the dynamics in demands is to analyze variations of certain demand related state variables on a semi-aggregated and zone-based level, respectively. Future work particularly aims at extending the deep learning mechanism by considering various boundary or environmental conditions for implicitly revealing spatially and temporally 'moving' demands on an urban scale in a semi-aggregated sense. Especially, if the prediction horizon is larger than chosen in this paper, certainly more information has to be included in the prediction model. Furthermore, the deep learning mechanism must be able to continuously learn and future research is dedicated to building a kind of memory as well; (ii) In real world environments, the time horizon for collecting training data needs to be reduced. The learning component as part of an early warning system should be able to give valuable information within a much smaller training time frame than 5000 days as well as evaluation time-steps and should be continuously improved through further learning. Since disruptions occur infrequently, small time horizons would probably not be sufficient. In this context, it is important to cover a sufficient amount of diverse disruptions scenarios and the SC-CMU conducting SC crisis exercises as well as improving the agent-based approach to generate synthetic data may help to overcome this issue. Improving models of urban demands w.r.t. certain goods can be based on studies and continuous surveys – understanding generation patterns, which normally, as we assume, reveal some regular structures, depending e.g. on socio-economic factors. Furthermore, the proposed technological innovation can also be used to measure fine temporal resolved customer flows at individual service providers, creating a base for further model improvements. (iii) This approach assumes CIs to share their criticality values with the SC-CMU. These values aggregate information on demand and internal processes. Hence, this approach tries to strike a balance between processing very sensitive information that potentially would yield to more precise forecasting results and non-sensitive information limiting the predictive value.

Criticality associated with a resource transferred to a crisis management in a secure way would be a minimum consensus of sharing data – sharing not with potential competitors but with an authority, which e.g. would be in line with the German fundamental obligations for CI operators. (iv) For applying this approach to multiple CIs, the entries of the matrices for training the CNN could be accordingly enhanced comprising current and future states for diverse CIs and different zones. Interdependent phenomena may be implicitly detected as current combinations of CI criticalities may yield to specific forecasted zone states. Although working with this zone abstraction, computational complexity and dimensionality can get very large, therefore designing feasible deep learning models is subject of current research.

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