Improving the Resilience of Socio-technical Urban Critical Infrastructures with Digital Twins: Challenges, Concepts, and Modeling

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Abstract

The increasing number of crises, including natural disasters and military conflicts, underscores the importance of resilient critical infrastructures (CIs), especially for urban areas. However, current approaches for CI modeling, monitoring, and resilience assessment are lacking a holistic view of cities as complex, interconnected, and socio-technical systems. This paper explores the application of the Digital Twin (DT) concept as a promising tool to assess and improve the resilience of urban CIs in light of various hazards. DTs are virtual real-time representations of a physical system that can be used to perform real-time analysis, simulate what-if scenarios, and provide decision support, during crises and normal operations. To this end, we identify and discuss key challenges for the development of Urban Digital Twins (UDTs), including data management, technical and social modeling of CIs, integrated CI co-simulations, model validation, and resilience assessment. To address the complex nature of urban areas as systems-of-systems, we present overarching modeling concepts by considering CI interdependencies and socio-technical interactions, resulting in the concept of the Socio-technical Digital Twin (STDT). Beside incorporating agent-based modeling, we discuss the issue of demand synchronization and propose the concepts of model selection and model transfer to facilitate the modeling process for UDTs. Furthermore, a multi-layered modeling framework for interdependent urban CIs is presented, where the proposed concepts are integrated and an overview and discussion of the technical and social modeling of CIs is provided, with a particular focus on the power, water, and transportation domain. Finally, we deal with the quantitative resilience assessment for interconnected CIs and discuss ways of integrating these methodologies in DTs. Our approach frames CIs as socio-technical systems and integrates the human perspective into the modeling process and resilience assessment. The presented modeling framework can be used to simulate various scenarios for analyzing their consequences in advance and measuring resilience in a holistic context. Moreover, the proposed concepts and modeling approaches can support future developments towards UDTs for crisis management.

Keywords: Urban digital twins, Critical infrastructures, Infrastructure resilience, Socio-technical systems, Crisis management, Resilience assessment

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Contents

Acronyms

ABM Agent-based Modeling.

CI Critical Infrastructure.

DT Digital Twin.

STDT Socio-technical Digital Twin.

STS Socio-technical System.

UCI Urban Critical Infrastructure.

UDT Urban Digital Twin.

1. Introduction

In the contemporary era, the omnipresent threat of crises, appearing in the form of pandemics, natural disasters, and military conflicts, can profoundly impact peoples' lives. In 2021, historic flash floods devastated parts of Western Europe, causing dozens of deaths. The disaster revealed the missing awareness and anticipation of such events, gaps in disaster response planning and communication, and rudimentary coordination between institutions [1]. Moreover, the Pakistan floods of 2022 affected over 33 million people with over 1700 deaths and estimated economic losses of over $30 billion [2]. In addition, the Ukraine-Russia and Israeli-Palestinian conflicts further emphasize the high reliance of humans on continuous access to essential services, specifically *critical infrastructures* (CIs). These catastrophic events demonstrate the emergence of unforeseen cascading effects, created by *interdependencies*, which are "invisible" during normal operation. Furthermore, the COVID-19 pandemic highlighted, that even without physical damage, human behavior in crisis situations can have significant, unexpected impacts on CIs, e.g. logistics [3]. Despite the distinct nature of these crises, they highlight the urgent need for novel approaches to ensure the reliability and security of CIs. To deal with future scenarios, innovative methods are needed to identify, predict, and analyze potential events, support crisis management, and formulate effective solutions.

Urban areas are particularly vulnerable to crisis situations due to their high density of population, infrastructures, and built environment. In fact, urban areas are highly complex, dynamic, and self-organized systems [4]. Moreover, cities and infrastructures have to be considered and analyzed as *socio-technical systems* (STS) [5]. The interplay of humans, infrastructures, and the environment creates a complex web of dependencies, interactions, and vulnerabilities. *Urban critical infrastructures* (UCIs), such as power distribution systems, water supply, transportation systems, information and communication technologies, healthcare systems, and more, provide vital services to citizens and represent the foundation of modern society.

For these reasons, ensuring the *resilience* of UCIs is a crucial task for mitigating the impact of disasters on urban populations. Resilience is a key concept in disaster risk management and refers to the ability of a system to withstand and recover from (potentially unexpected) disruptions while ensuring a certain level of functional operation. Although there are several definitions of resilience, most of them agree on a timeline of four common phases [6], as shown in Figure 1. In particular, the *plan* phase involves proactive identification and preparation for potential threats, while the *absorb* phase deals with the rapid response to a disruptive event, aiming to minimize the initial impact. Subsequently, the *recover* phase focuses on the restoration and returning to normalcy after the initial shock has been absorbed. Finally, the *adapt* phase concerns learning from experience and making long-term adjustments to enhance system capabilities against future incidents.

To enhance the resilience of UCIs, resilience needs to be defined and assessed in an objective and holistic manner. However, no standardized methodologies for resilience assessment of UCIs exist, especially when multiple domains are considered [7]. Moreover, resilience implies to consider various scenarios that may not have occurred yet and for which no empirical data are available. As a consequence, there is a need for comprehensive *simulations* of the system. Thereby, a holistic approach is necessary since CIs exhibit interdependencies between various systems, as highlighted by the mentioned examples, ultimately resulting in cascade effects [8, 9]. However, the simulation of interdependent CIs is computationally and conceptually challenging and only few works exist [10, 7]. Furthermore, the role of human behavior on CI resilience is rarely considered in the literature and lacking research [11, 12].

The *Digital Twin* (DT) concept is a promising approach to overcome the aforementioned issues. A DT can be viewed as a virtual replica of a physical system, such as a city and its CIs, that can be used to model and simulate the behavior of the physical system in real-time [13]. In turn, the DT can be used to perform actions on the real system. DTs are considered a key enabler for the digital transformation [14].

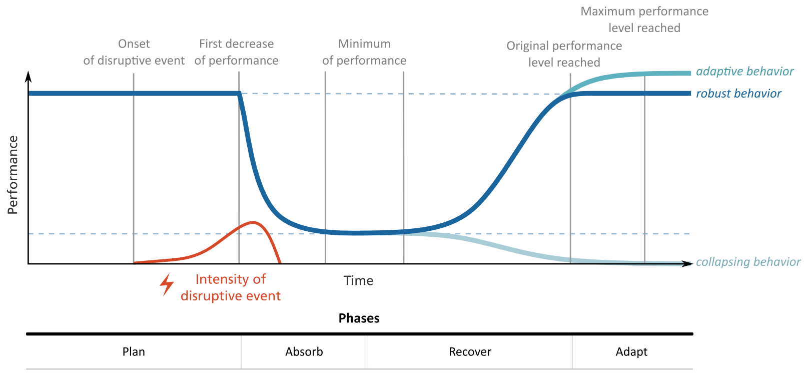

Figure 1: Illustration of the resilience cycle, adapted from [6], used under CC BY 4.0

In the context of CIs, DTs can establish real-time analysis, allow for the simulation of "what-if" scenarios in a virtual environment, provide decision support during normal operation as well as during a crisis, and thus increase the resilience of UCIs [13]. Additionally, the simulation capabilities of DTs can be used for resilience assessment, for example to study system behavior for different scenarios, compare infrastructure improvements, or test different control strategies. However, while the body of research on the technology is growing, DTs have not yet become widely established in the context of UCIs. Until now, *Urban Digital Twins* (UDTs) have mostly been used for urban planning [15, 16, 17]. Despite the potential, the adoption of UDTs for disaster risk management is still in its infancy [18].

This paper aims to contribute to the understanding of improving and assessing the resilience of socio-technical UCIs with the help of DTs. We discuss how the DT concept can be applied to UCIs and which challenges in the employment of UDTs arise. To leverage UDTs for crisis management, we consider UCIs as STSs by including the human influence throughout the modeling process. Thereby, three key CI domains are investigated in more depth: power systems, water distribution systems, and transportation infrastructures. We emphasize the importance of a holistic view by explicitly modeling technical and social interdependencies under various crisis scenarios, allowing for a deeper understanding of interconnected UCIs and urban systems as a whole. On this basis, we explore and discuss challenges, concepts, modeling, and resilience assessment in the context of UDTs:

- **Challenges Identification**: Several conceptual and technical challenges impede the development and application of DTs for urban areas. We discuss challenges regarding the acquisition, transmission, and processing of data, which are significant in the context of CIs and crises, compared to other DT applications. Moreover, the technical and social modeling of UCIs is discussed, highlighting general limitations and principles. We present the role of simulations within DTs and summarize major challenges for interconnected CI simulations. The validation of socio-technical models and the DT itself presents another significant challenge. We further discuss current issues in resilience management and assessment and point out the lack of holistic approaches.

- **Concepts Definition**: In this work, we present six overarching concepts for the modeling and design process for UDTs. The concepts address several of the identified challenges, for example by considering different kinds of CI interdependencies and socio-technical dependencies. Building on the DT paradigm, we introduce the new concept of the *Socio-technical Digital Twin*. Moreover, agent-based modeling is applied as a bottom-up approach to address the complexity of the system. We then investigate the synchronization of infrastructure demands, possibly leading to overloads, especially during crises. Moreover, the selection and transfer of models are essential concepts for DTs to deal with data scarcity and model uncertainty. The proposed concepts can aid future modeling approaches of UCIs and developments of UDTs.

- **Modeling Approach**: We propose a holistic modeling framework for UCIs and their simulation for the employment in DTs and other applications. The framework integrates the proposed concepts and consists of the layers *technical system*, *social system*, and *environment*. By understanding CIs as services for the population, our human-centered modeling design provides a new approach for improving resilience from a human perspective. To address the complex nature of CIs and enable the discovery of emergent effects, we combine agent-based modeling with network-based simulation approaches. The framework uses a multi-layered graph-based representation of CIs and accounts for physical and geographical interdependencies. While the framework can be applied to UCIs in general, we provide a special focus on power, water, and transportation infrastructures by presenting modeling approaches for the technical and social system for each domain and evaluating their use for the application in DTs. The integrated modeling of the STS and CI dependencies leverages the evaluation of UCIs under various disaster events, providing an all-hazards framework for measuring and improving the resilience of cities in a holistic way.

- **Resilience Assessment**: Finally, the quantitative resilience assessment for UCIs on the basis of the proposed modeling framework is examined by providing an overview of resilience metrics, including general definitions and domain-specific examples. We provide important considerations and approaches for assessing UCI resilience in a holistic way by addressing the interconnectedness of the systems and uncertainties. This includes the integrated assessment across multiple CI domains and hazard types. We discuss how the concept of resilience can be integrated into the DT paradigm and how resilience assessment can be leveraged by DTs for the real-time monitoring of UCIs.

The remainder of the paper is structured as follows. In Section 2, existing works on UDTs are reviewed. Section 3 provides a deep discussion on challenges involved in the development of UDTs. In Section 4, we present major concepts relevant for UDTs and the modeling and analysis of UCIs. Section 5 presents our holistic modeling framework and discusses the modeling of UCIs and the integration of the concepts. Section 6 deals with the resilience assessment for UCIs in DTs. Finally, conclusions and practical implications of the proposed framework are drawn up in Section 7.

2. Related Work on Urban Digital Twins

The idea of the DT is attributed to Michael Grieves, who described this concept in 2002 [19]. A DT is conceived as a virtual representation of an object, process, or system and its real-time connection to the physical counterpart. DTs are often realized using data and information to perform simulations and analyses, even in real time, and are typically used to improve performance and support decision-making processes. With the advancement of digital technologies, the Internet of Things (IoT) [20], and data analytics, the idea of DTs has been increasingly considered in the recent years in various disciplines, e.g. manufacturing, building information modeling (BIM), smart cities, energy, transportation.

For example, the authors in [28] have conducted a comprehensive exploration for novel opportunities applying the DT concept within the sector of water resources management. An in-depth analysis of the main challenges inherent in the establishment and continuous upkeep of DTs was carried out, and finally a set of strategic recommendations designed to advance the integration and application of DTs in the field of water infrastructure management have been proposed. Instead, the research in [25], [26], and [27] was primarily dedicated to the investigation of DTs in the transportation domain. On the one hand, in [25], a simulation approach was used to study the urban environment of Barcelona by integrating mobility data sets obtained from mobile devices with traditional urban network data extracted from OpenStreetMap, thus enhancing insights into the dynamics of urban mobility. On the other hand, in [26], the authors introduced a new approach for modeling motorway traffic and showcased it by applying a continuously synchronized DT model of the Geneva motorway, while in [27] the paper focuses on the exploitation of a DT using traffic data to deal with evacuation scenarios. Moreover, the authors of [24] focused on smart cities and proposed a life-cycle model for UDTs, distinguishing between reactive, predictive and forecasting functionalities. In [13], particular attention was paid to the application of DTs in the field of CIs and crisis management. More specifically, starting from potential hazards to infrastructures and on the basis of the analysis of requirements related to infrastructure characteristics, a conceptual framework to support the improvement

Table 1: Comparison and positioning of the current work with respect to the related works on UDTs

Paper	**Context**	**Infrastructure Domains**	**CI System Modeling**	**Human Behavior Modeling**	**Focus on crisis events**	**CI Interdependencies modeling**
Dembski et al. [15]	Collaborative urban planning	Transportation	yes	no	no	no
Schrotter et al. [16]	Urban planning, 3D model	general	no	no	no	no
Hämäläinen et al. [17]	Urban planning, 3D model	general	no	no	no	no
Herzog [21]	Urban planning	general	no	yes	no	no
Ruohomäki et al. [22]	3D model	Energy	no	no	no	no
Nochta et al. [23]	Sustainability	Energy, Transport	no	yes	no	no
Bauer et al. [24]	Smart city, IoT	general	no	no	no	no
Sánchez-Vaquerizo et al. [25]	Urban traffic micro-simulation	Transportation	yes	no	no	no
Kušić et al. [26]	Motorway traffic micro-simulation	Transportation	yes	no	no	no
Rundel et al. [27]	Evacuation, Visualization	Transportation	yes	no	yes	no
Berglund et al. [28]	Optimization, Monitoring	Water distribution	yes	no	no	no
Pedersen et al. [29]	Error diagnosis, Monitoring	Water distribution	yes	no	no	no
Xu et al. [30]	Energy management, Optimization	Energy	yes	no	no	no
Meuser et al. [31]	Disaster Communication	Communication system	yes	yes	yes	no
Ford et al. [32]	Crisis Management	general	no	yes	yes	no
Fan et al. [33]	Crisis Management	general	no	yes	yes	no
Brucherseifer et al. [13]	Crisis Management	general	no	no	yes	no
Current work	Crisis management, Resilience assessment	Power, Water, Transportation	yes	yes	yes	yes

of the resilience of infrastructures has been proposed. In addition, the subject of disaster management has received considerable attention in the research described in [33]. Here, DTs have been elaborated as a paradigm for enabling four interdisciplinary areas concerning multi-data sensing for data collection, data integration and analysis, multi-actor game-theoretic decision-making, and dynamic network analysis for dealing with disaster response and emergency management. Further research in this direction has recently been presented in [18] with reference to the potential of DTs as a combination of digital-based intelligence technologies, by distinguishing between four different levels (Digital Twin Prototype, Digital Twin Instance, and Digital Twin Environment, the latter divided into Adaptive and Intelligent).

To summarize the overview of the related work, Table 1 compares our work with the related works on UDTs. Most developments in the field of UDTs focus on urban planning, where city development, citizen participation, and sustainability are the major objectives. Among CIs, the transportation domain was most commonly considered. DT applications in the water and energy domain exist as well, however they are mostly concerned with system optimization and monitoring. A holistic perspective on urban areas, considering multiple CIs and their interdependencies, is missing. Moreover, in the mentioned contexts, the focus is usually on the normal operation and not on crisis scenarios and critical events. In addition, the consideration of human behavior is often lacking, but is crucial in the context of crisis management. Furthermore, only few works exist that connect DTs with the concept of resilience [13]. Although UDTs are recently also considered in the field of crisis management, most of this work does not deal with CIs in detail.

Our work aims to fill the described research gap by connecting UCI modeling with the idea of DTs and the concept of resilience. In contrast to related works dealing with domain-isolated approaches, we consider multiple, interdependent CIs, with a focus on power systems, water distribution systems, and transportation infrastructures. In this context, we investigate the application of UDTs for smart cities, thereby integrating human behavior modeling, contributing novel approaches for resilience assessment and crisis management.

Further related work on specific aspects of UDTs will be discussed throughout the following sections. In the next section, we discuss in more detail the main challenges that need to be addressed in the development and application of a UDT in the context of smart cities and crisis management.

3. Challenges

As has emerged from the previous sections, the DT concept is a promising tool for improving the resilience of UCIs. However, several conceptual and technical challenges impede the development and application of DTs for urban areas.

This section aims to highlight those challenges in the development of UDTs, especially in the context of UCIs and crisis management. Section 3.1 presents challenges related to the acquisition, transmission, and processing of data, which is the foundation of a DT. Since modeling is an essential task towards the creation of a DT, Section 3.2 and Section 3.3 highlight challenges regarding the modeling of UCIs from a technical and social perspective. The potentials and challenges of simulations within DTs are presented in Section 3.4. The validation of models and simulations presents an additional challenge, outlined in Section 3.5. Incorporating the concept of resilience into the DT paradigm, assessing the resilience of UCIs, and the associated challenges are discussed in Section 3.6. Section 3.7 deals with domain-specific challenges for energy, water, and transportation infrastructures.

3.1. Data Provision and Management

The foundation of a DT is a well-established database that provides all necessary information for the DT functionalities at the required level of detail. A UDT requires a solid technical infrastructure to manage data acquisition, transmission, processing, and storage. In the context of CIs, this results in various challenges.

A main challenge for UDTs is the acquisition of data from CIs. Compared to DTs for industrial processes that are typically applied in a closed physical and technical environment, access to CI data, both static and real-time data, presents several difficulties. Access is often hampered by security concerns from CI operators or a limited knowledge about construction details of the built environment. While the former issue requires both technical solutions and political commitment by accounting for several stakeholders, the latter problem needs significant technical commitment to be resolved [34]. Topological reconstruction approaches for underground infrastructure based on open data might provide approximate information [35]. Nevertheless, the existing limitations result in *data scarcity* for UCIs, hindering the development of UDTs.

UDTs are closely related to the idea of smart cities, as they aim to accelerate the digital transformation, provide a data platform for different stakeholders, and improve urban processes [18]. Thus, smart city data platforms could serve as a starting point for UDTs by providing various data from the city, such as IoT sensor data, and data catalogs for historical data [22]. Existing UDT projects, like those in Wellington, New Zealand [36], Zurich, Switzerland [16], and Helsinki, Finland [17], currently aid urban planning procedures and rely on many different data sources. Thereby, the improvement of data acquisition and processing is a key research question in creating a comprehensive UDT [37].

Moreover, data from urban areas is highly heterogeneous and data representations from different CI domains can vary significantly between different systems. Hence, the fusion of various data sources and types requires a common ontology description to enable the usage of the data in further UDT functionalities, e.g. cross-domain simulations. Although smart city ontologies have been developed, they may not cover the extent of the intended DT application, requiring the adaption or development of a customized ontology. Moreover, there is a lack of common data models and standardizations for DTs [38].

Since DTs are a real-time representation of the real world, they need to fulfill real-time requirements. In order to update the virtual replica of DTs with the latest information, sensor data needs to be filtered, combined, and processed with regard to the corresponding virtual objects. On a citywide scale, processing and extracting information in a timely manner is a significant challenge. The efficient and automatic processing of data from varying input sources is an open research question [33]. Furthermore, uncertainties in the information extraction present a challenge that must be accounted for in the system estimation and simulation of CIs.

Table 2: Examples and Classification of Data Types for UDTs

Data	**Category**	**Domain**
Topography	static	Environment
Land usage	static	Environment
Time and date	dynamic	Environment
Temperature	dynamic	Environment
Humidity	dynamic	Environment
Socio-economic status	static	Population
Population movement	dynamic	Population
Residential buildings	semi-static	Civil infrastructure
Public buildings	semi-static	Civil infrastructure
Bridges	semi-static	Civil infrastructure
Power grid	semi-static	Energy
Power demand	dynamic	Energy
Water network	semi-static	Water
Water demand	dynamic	Water
Road infrastructure	semi-static	Transportation
Traffic	dynamic	Transportation

Table 2 shows a collection of the most relevant data in the context of UCIs and their classification. Data used in DTs can typically be categorized as static or dynamic [39]. Static data refers to information that persists for a longer time horizon than the time frame being analyzed. In contrast, dynamic data changes within the observation time of the DT and requires regular updates of their state. During crisis situations, objects that are normally considered as static can change unexpectedly, requiring the new category of *semi-static* data. One example of this third category is the sudden destruction of roads because of an earthquake. This aspect needs to be taken into account for DTs used for crisis management.

Representing crisis situations in UDTs presents further complexities. To deal with semi-static data, information that is not collected on a regular basis, e.g. network topology and parameters, needs to be verified. Accordingly updating semi-static data has to be considered in the data management of the DT, which complicates technical designs. Furthermore, in crisis situations, many data sources might not be available and may need to be replaced with other sources. The data available under such circumstances may significantly differ from the data used in the normal operation, resulting in a even more diverse set of data inputs. Remote sensing, social sensing, and crowd-sourced data can be used to gather necessary information in crisis situations [33, 40]. However, this is only possible to a limited degree and the fusion of these data into the database of a DT requires new technologies.

The link between data transmission and communication infrastructures creates additional challenges for DTs in crisis situations. Disasters might affect various CIs, including communication and information infrastructure. Specifically, the loss or limitation of data transmission from sensors and other sources could have an impact on the data available in the DT, and thus the DT functionalities. Hence, DTs need to be designed in a way to deal with data loss and the resulting uncertainty, and further make it transparent to the user. The impact of data losses can be limited by the use of alternate communication channels, which are not dependent on central infrastructure [41]. However, decentralized communication infrastructures are still in the research stage and existing infrastructures are optimized for centralized data processing.

3.2. Modeling of Urban Critical Infrastructures

Models play a fundamental role in the DT concept because they form the basis for simulations, system estimation, and analysis. The first step towards creating a DT is the initialization of the *virtual replica* which contains a virtual, always up-to-date representation of the real system in form of models and data [13]. The contained models can be categorized into structural models, describing the composition of real-world components, and behavioral models that describe their dynamics [13]. The specific approach to modeling can vary significantly based on the intended application and context of the DT.

For DTs in general, both data-driven (black-box) and physical (white-box) modeling is possible, as well as hybrid approaches [42]. When ample data is available and physical modeling is difficult, machine learning techniques can be applied effectively [43]. However, in situations of data scarcity, physical modeling becomes essential. As discussed in the previous section, the availability of data depends on the environment and application for the DT and is especially challenging in the context of CIs. Moreover, the effectiveness of data-driven models is usually limited by the range of operating states in the training data, which typically reflects only the normal operation. Combining physical and data-driven modeling in DTs might be promising for achieving increased performance but involves several challenges.

The multitude of potential modeling approaches and available models highlights an essential question for scientific reasoning: the selection of models. Choosing the right model means to decide which assumptions about the real system should be included to facilitate the understanding of the real world. A general design principle in this context is the *principle of parsimony*, also known as Occam's razor. This principle states that each model should be as simple as possible while describing all relevant features of the real world. The term "relevance" needs to be clearly defined, as one can always argue that an additional or different assumption would potentially increase the understanding of the real system. However, if the number of assumptions is increased excessively, the model's usefulness and comprehensibility can decrease. Therefore, the choice of adequate assumptions and models remains a considerable challenge for UDTs.

CIs can be seen as a collection of manifold interacting components that can change their properties and adapt their behavior, and can therefore be characterized as *complex adaptive systems* [8, 44]. Since the term "critical infrastructures" encompasses several sectors, UCIs have to be considered and modeled as a *system-of-systems*. In the normal operation, CIs appear to be isolated systems that do not interact with each other. However, they exhibit hidden interdependencies, which can lead to critical cascade effects [9, 45]. Therefore, it is crucial to consider these interdependencies between CI sectors in modeling and simulations for the DT to aid in the comprehension and forecasting of these critical effects.

Prior to modeling, CI interdependencies have to be identified, which represents a challenge itself. Due to their "invisibility" during normal operations, the dependencies between the multitude of systems and components are not obvious. Domain knowledge from experts and empirical data from past incidents and disasters can be used to identify interdependencies, although this process involves extensive manual work [46].

3.3. Social Modeling

Critical infrastructures are deeply interconnected with the behavior of people. The entirety of influences of human behavior on a superordinate system is often called *human factors*. Human factors include the influence of a single human's behavior on a system, as well as the combined interactive behavior of groups of people, also called social behavior.

The nature and extent of human factors in the context of infrastructures have been described by [5], highlighting that infrastructures should be considered as a *socio-technical system* (STS). An important connection between citizens and infrastructures is that the demand of infrastructure users constitutes the load placed on an infrastructure, e.g. the burden of traffic on roads or the energy and water demanded from a distribution grid. However, this demand is also influenced by the availability of the infrastructure, e.g., users might adjust their demand behavior to traffic jams or low water pressure.

Additional interdependencies arise since legal, political, and societal expectations shape the development of infrastructures. For example, the availability of a technology shapes the expectation of citizens on the infrastructure and thereby the infrastructure's development. These expectations include minimum acceptable standards for the infrastructure, but also limit the development of the infrastructure to the technologies considered in the regulatory framework for the development of the infrastructure. For example, the road infrastructure is typically built by considering existing cars, while cars are also built to fit into the infrastructure. The traffic laws that govern the use of these cars are further developed for the existing cars and infrastructure, again shaping which technical features are built into newly developed cars.

While this socio-technical perspective is frequently discussed in the literature on UCIs, socio-technical interdependence is less incorporated in DT research [13]. This is because initial DT concepts are centered around the modeling of purely technical systems, such as machines or production systems [19]. The socio-technical perspective has recently received attention in the context of UDTs in [23], although the primary focus was on the role of DTs as a tool for communication and decision support in social systems. The integrated modeling of social and technical systems remains an open issue.

The interconnectedness of social and technical systems raises key issues that we will highlight in the following. The first two issues concern the modeling of individual and collective behavior of humans, the third and forth issue concern two key capabilities of DTs: sensing variables from and act upon the real system.

Individual behavior involves decision-making, which is rarely rational, but rather depends on cognitive and emotional factors [47, 48]. In the last century, various theories have been proposed to quantitatively describe this behavior, e.g. the theory of bounded rationality [49] and the prospect theory [50]. Bounded rationality describes the fact that human decisions are always dependent on incomplete knowledge of the world and finite cognitive abilities to process information. In addition, the prospect theory highlights that the context plays an important role in human behavior and decision-making, especially in decisions under uncertainty and decisions that are subject to risks. This irrationality of individual behavior has been shown to be highly relevant for the understanding and management of disasters [51].

Collective behavior, i.e. the behavior of groups of people, inherits and extends the complexity of individual behavior [52]. Especially in times of crises, human relationships and the resulting collective behavior can lead to emergent behavior. Such emergent behavior is usually dominated by controlled, prosocial decisions and contrary to popular belief, panic rarely occurs [53]. Moreover, prosocial collective behavior can be seen as a potential key strength of cities in overcoming challenges beyond the capabilities of purely technical solutions [54]. However, emergent behavior can also be associated with a high degree of improvisation and creativity [55], resulting in unexpected responses, and further increasing complexity and uncertainty in social systems.

Sensing of social behavioral variables is limited by practical, legal, and ethical constraints. It is obvious that accurately measuring certain human traits, such as emotional states or intentions, is not feasible. Moreover, potential approaches for the sensing of human factors are often restricted by privacy and data protection laws [56].

Acting capabilities of DTs for STSs should be considered a challenge. One promise of DTs is the aided or automated action on and control of the real-world system. For STSs however, this concept can only be applied to the technical components and only to a limited degree, as the complex nature and potentially high impact of decisions typically raises concerns about the automated action when social systems are involved. Furthermore, any action within the social system is itself subject to the political, legal, and institutional context of society. In the case of urban crises, this includes the responsibilities and lines of command of local institutions as well as the applicable laws in the affected city.

In summary, the inclusion of socio-technical perspectives in the DT paradigm raises a number of challenges to consider for future UDTs. The *uncertainty* and *complexity* of human behavior and the planning of societal interventions, have led to the term *wicked problems* [57]. This term essentially embodies the notion that no singular and definite "solution" can be found for such societal problems. The long-standing discourse of the social and human sciences on the intricacy of these challenges further underscores the improbability of definitive solutions. However, it is essential to take the complexity into consideration when building systems aimed at alleviating issues of STSs. This is especially pressing, as solutions solely focusing on technical aspects might underutilize the smart capabilities urban spaces inherit from their citizens [54].

3.4. Simulations in Digital Twins

Simulations are a highly important tool in the context of critical infrastructures, as real experiments are mostly infeasible, due to practical and ethical reasons. Nowadays, simulations of CI systems are typically used within the scope of single CI sectors for different objectives, such as system estimation, prediction, and infrastructure planning. Developing simulation models and keeping them up-to-date with the real system is a laborious task.

In the DT concept, the use of simulations is a key feature that allows for the analysis of various scenarios and the exploration of potential consequences. This encompasses simulations for all considered sub-systems, their connections, and environmental conditions. Models and simulations can be employed in the DT framework in three different functionalities:

- **System estimation**: The virtual replica is continuously receiving raw data, which need to be processed before it can be used for further applications. The received data usually represent only a partial picture of the real system as not every UCI component might be equipped with sensors. As the virtual replica should contain a complete copy of its real counterpart at any time, the state of components, for which no direct measurements exist, needs to be estimated. For this task, a model that describes the system dynamics pertaining to the according CI domain is required.

  Since the implementation needs to fulfill real-time requirements, the computational complexity of the state estimation method needs to be regarded carefully. Analytical approaches might be infeasible for systems that contain many variables, e.g., a large number of traffic participants might be present in a transportation network. In this case, other approaches for determining the state of hidden variables need to be considered, for example Approximate Bayesian computation.

- **What-if (Ad-hoc) simulation**: In the context of crises or critical situations, the quick analysis of potential countermeasures is essential. Often, a decision must be made between alternative actions under time pressure and extensive studies to find the optimal solution are not possible. Therefore, these decisions have to be made heuristically by the involvement of experts and empirical knowledge, which can lead to suboptimal results.

The DT concept addresses this issue with Ad-hoc and fast-forward simulations. As the virtual replica of the DT always represents the current state of the real system, simulations can be conducted on the basis of the current situation. So-called *virtual clones* can be instantiated from the virtual replica to provide a safe environment for experiments [13]. This can offer comprehensive forecasts of the system behavior as a firm basis for timely decision-making.

Because the simulation results should be available as fast as possible, the simulation speed of the fast-forward simulation is required to be much faster than real-time. Moreover, the level of detail of the models and thus their computational effort needs to be chosen carefully. However, since the aim of the "what-if" analysis is to predict non-obvious, emergent effects, a certain minimum of detail is required. In particular, the modeling of interdependencies is essential for this task to assess potential wide-spread consequences. The parallel execution of multiple what-if simulations with different levels of detail and durations is conceivable.

- **Scenario simulation**: To assess the impact of various crisis events on UCIs, scenarios can be defined, e.g. floods, earthquakes, or an explosion. With these scenarios, resilience assessment can be conducted by simulating the consequences on the entire system. A scenario could be simulated under different configurations to compare system performance, e.g. comparing infrastructure modifications or restoration strategies. Potential scenarios can either be defined from scratch or with the use of recorded data from the DT. In particular, a past real incident could be analyzed in retrospective and alternative response measures could be simulated to learn and adapt from crises. *Multiverse Simulations* could be used to analyze alternative outcomes after a point of divergence [58].

  Scenario simulations can be performed offline to thoroughly assess and prepare for these events. For this case, more detailed simulation models with longer execution duration can be used. Additionally, software-in-the-loop or hardware-in-the-loop testing could be performed for more advanced analysis, which is not possible for fast-forward simulations.

During the implementation of a DT, the different requirements and the reuse of simulation models in several functionalities of the DT should be considered for its design architecture.

The modeling of interdependencies and the holistic assessment of the system necessitates an integrated simulation of the complete system. However, the *co-simulation* of multiple CIs, i.e. the synchronized execution of all sub-system simulations, brings additional challenges compared to a simulation in a single domain [10]. We identify the following main technical challenges for CI co-simulations:

- **Modularization**: Simulators for different CI domains, which might have different system, platform, and hardware requirements, have to be brought together to run in a common software environment. Federated simulation approaches have been proposed for the handling of multi-domain CI systems [59, 60]. For example, each of the sub-systems (e.g. power grid, communication network, etc.) can be run in parallel in a dedicated environment with specifically allocated computational resources. However, the construction of a simulation platform requires sophisticated software designs to handle the communication between the sub-systems.

- **Simulation Time Synchronization**: In a co-simulation, it is essential to "orchestrate" the execution of sub-system simulations in a way that their respective outputs and other events can be exchanged in time by considering causality and determinism [61]. As most existing simulation tools are optimized to run as standalone solution, many of them are not prepared for dynamic interactions *during* the simulation. Therefore, they may have to be adjusted for the use in co-simulations or new tools with suitable interfaces need to be developed.

- **Different Time Scales**: The time scales of dynamic behavior differ significantly among CI domains. For example, power systems contain relevant dynamics in the range of milliseconds, while traffic systems show dynamics that occur in the range of hours. Building an efficient architecture that synchronizes the simulation of different CIs despite their different time scales presents a major challenge [62]. For example, using equidistant time steps would be inefficient since small time steps required to capture the dynamics of the fastest CI system produce unnecessary computational overhead for other simulators. Discrete event simulations can be used to handle the management of events with variable simulation time steps, but involve challenging design efforts [58].

- **Event Management**: As external events may influence every sub-system, these events have to be defined in a common format, transmitted to every affected sub-system, and processed by the respective sub-systems [61]. This event management requires a sophisticated software architecture to ensure that all events are transmitted and processed in time before the simulation continues.

- **Deployment**: The management of several software applications and packages for the simulators is not trivial. Software dependencies, updates, and IT security need to be considered for reliable IT-based solutions. Containerization tools, e.g. Docker, may simplify this process. However, licensing issues and missing interfaces of commercial simulations can complicate the deployment in different environments.

3.5. Validation

In scientific and commercial endeavors alike, the question "Is our result *good*?" is highly relevant. In this context, the term *validation* is often mentioned. Colloquially, the term *validation* is often associated with the question whether the *right system was built*. The IEEE Standard for System, Software, and Hardware Verification and Validation 1012 [63] defines validation more precisely as the evaluation whether a system satisfies specified requirements, solves the right problem, and satisfies user needs. However, the application of this definition to the context of DTs is not trivial.

As the definition of validation relies heavily on the definition of requirements, the validation of a DT as a whole depends on the intended use of the DT. Therefore, the validation of a DT would provide evidence for the question "Did the DT solve the problem, that it was intended to solve?". If the purpose of the DT is to assess and enhance the resilience of UCIs, this includes to help in a crisis or assess the system in all phases of resilience. Therefore, validation would answer the question "Did the DT help in the planning for, absorption of, recovery from, or adaption to a crisis?".

It is obvious that these questions can only be answered after the implementation and thorough long-term review of DTs. If validation is intended before such a long-term review, it should assess whether the DT provides services that are *assumed* to aid the aforementioned goals. This question then resorts to the validation of functions or sub-systems of the DT for a specific application. In particular, validation questions for sub-systems or functions of a DT could be:

- **Data acquisition:** "Does the measured data correctly represent the physical system's state?"
- **State estimation:** "Are the unmeasured state variables of the physical system correctly estimated?"
- **Monitoring:** "Does the overall picture correctly and continuously represent the physical system's state?"
- **Simulation models:** "Do the simulated models correctly represent the physical system's behavior?"
- **Decision Support:** "Can conclusions and decisions be drawn from the provided information?"
- **Actuation:** "Are the actions on the physical system performed as intended?"

Each of these questions is part of the respective research field that investigates the methods and technologies used for these functions or sub-systems. As these research areas encompass a multitude of scientific fields, we will highlight challenges on the validation of simulating socio-technical models with a focus on crisis situations. The validation of simulated computer models is a broad field that is in depth discussed in [64]. For the context of crises and resilience of UCIs, we want to highlight three challenges: facets of data scarcity, limitations of validation methods, and the increased role of uncertainty.

In classic engineering and natural sciences, validation of models is typically performed through the comparison of model outputs to a set of data from the real system. This data can be generated through experiments, simulations of other previously validated models, or sufficient observation of the real system. However, as highlighted in Section 3.1, data from experiments, previous observations, and other validated models for UCIs are typically considered unavailable for crises, especially if they are unprecedented.

Additionally, the validation methods of classical engineering typically use statistical hypothesis testing, such as t-tests. These tests typically assume a number of strong assumptions that are rarely justified in the context of crises. One example is that the most common tests for validation assume statistical properties, such as normality of error distributions, or seek to fit expected values of statistical models. However, non-normality and unexpected dependencies can become an issue in the context of rare, critical events.

Lastly, typical approaches for validation assume that it is possible to fit a model to data in a way that the model output errors are sufficiently small, so that the predictions of a model can be utilized for further actions on the system. However, as discussed in Section 3.3, the uncertainty of STSs makes it virtually impossible to make accurate predictions. Therefore, the arising uncertainty in model assumptions and outputs leads to potentially unreliable predictions, even if the governing behavior of the system was correctly characterized in the model.

As the above challenges highlight, the validation of DTs in general and socio-technical models in particular is complex and multifaceted. Nonetheless, ascertaining validity is crucial for both research and application, highlighting the relevance of this aspect. Subsequently, a discussion is required on the reasonable expectations and applicable methods for validating socio-technical models.

3.6. Resilience Management and Assessment

The concept of resilience receives increasing attention and has been used in many different research fields, such as economics, psychology, and ecology [11]. In the context of CIs and crisis management, resilience-related terms are frequently used [6]. The various research fields have adapted the resilience concept to their domain contexts and considered diverse scenarios [6, 7]. This however, complicates a general, interdisciplinary definition of resilience. Even for particular domain contexts, a formal definition and quantification has been elusive and there are no universally recognized standards.

The concept of resilience is connected to DTs in three different ways. First, DTs provide extensive simulation tools to assess the consequences of potential scenarios for UCIs and the population [13]. Within these simulations, performance measures can be evaluated in order to assess the resilience of the system. This assessment can be conducted in a short-term context, for example for decision-making during crisis events, or in a long-term context for infrastructure planning to evaluate different options for hardening the infrastructure. Second, the practical application of a UDT in a smart city would improve the resilience of the real UCIs in the future. The UDT could provide improved decision support with reduced time for sense-making processes, which would lead to quicker and more effective disaster response, thus increasing resilience [13]. Last, the DT itself and the platform it is running on need to be constructed in a resilient manner [13, 18].

Resilience management can be seen as an addition to traditional risk management in the operation of CIs [6, 11, 65]. While risk management mostly focuses on known hazards, their likelihood, and prevention, incorporating the concept of resilience means to consider unexpected events and assessing and improving the resilience of the system. Like the DT, resilience management encompasses all phases of the resilience cycle, mostly monitoring and adaption [6]. However, the different and partially conflicting understandings of resilience and its analysis hinder a broad and effective integration of resilience-based measures and standards in the planning and management of CIs in the near future. Resilience management is generally applied separately in different CI domains. Hence, bringing the resilience management of different CI sectors together is a major challenge for DTs.

To evaluate the resilience (improvement) of UCIs in an objective manner, a quantification of resilience is required. However, no universal method for resilience assessment that could represent a comprehensive picture of multiple UCIs exists [7, 12]. Therefore, the selection, combination, or creation of suitable metrics that capture resilience across several CI domains poses a significant challenge. Additionally, while traditional risk-oriented assessment methods usually focus only on the failure of components or the immediate impact of an event on the system, resilience assessment implies considering all resilience phases, which is rarely done at once in the literature [65]. For example, the system recovery and the time needed for the repair of infrastructure components are of relevance for assessing resilience. However, for simulations, this requires the modeling of the system restoration, often including uncertainties and several assumptions. Moreover, following the concept of *general* and *specified resilience* [6], assessing the general resilience of a system, i.e. the behavior to any kind of (unknown) hazard, is much more difficult and rarely discussed in the literature than assessing resilience against a specific type of hazard.

As pointed out in Section 3.3, CIs are deeply interconnected with the behavior of people and need to be considered as STSs. However, the role of societies and human behavior on CI resilience is rarely considered and lacking research [11, 12].

3.7. Domain-specific Challenges

Here, we identify domain-specific challenges to consider towards DT applications that are particularly relevant in the CI domains of energy, water, and transportation infrastructure.

3.7.1. Energy Infrastructures

Although this work focuses on power systems as the most vital and fundamental energy infrastructure, gas networks and heating grids belong to the category of energy infrastructures, too. However, their technical characteristics and challenges are more similar to those of water networks, as they transport fluids.

Compared to other types of infrastructures, power systems are highly dynamic systems, i.e., they can change their state in a very short time. This is emphasized, for instance, by the event of abrupt frequency drops in the European interconnected transmission grid that resulted in a highly critical system separation in 2021 [66]. This event further demonstrates that (intra-domain) cascade effects within the power system can occur when power flows are shifted to other lines due to a failure. This fact makes the right selection of models representing all effects relevant for DTs at different timescales important. Therefore, model reduction and system identification (e.g. due to aging) remain open challenges [67].

While transmission grids are often well-equipped with sensor and control infrastructure, distribution grids at urban scales typically lack real-time measurements, particularly in the medium and low-voltage grid. The unavailability of data or limited time resolution has to be considered for the application of sensing and state estimation within the DT.

Many systems and devices rely on power systems nowadays and almost every other CI system depends on power in some way. With the trend to an "all electric society", these dependencies are becoming even more important. Therefore, this overarching dependency needs to be taken into account in modeling.

3.7.2. Water Infrastructures

Water infrastructures consist of many distinct and technically heterogeneous types of systems. These systems include water potabilization and treatment plants, water distribution systems for potable water, waste water systems, water irrigation systems, and open bodies of water used for multiple causes like water supply, waste disposal, and transportation. Each of these types of infrastructures presents specific challenges, for which DTs have been proposed as a viable tool [28, 68, 69]. Our work focuses on water distribution systems for potable water, as access to drinking water is crucial to human survival.

A growing number of DT applications in the domain of water distribution systems have been discussed in literature. A recent review of the key approaches and challenges highlights the lacking capabilities of models to include continuous updating through data in a DT [28]. Furthermore, limitations are highlighted regarding the high uncertainty of system parameters, e.g. roughness of pipes, and uncertainty in real-time data, e.g. positions of manually operated valves.

3.7.3. Transportation Infrastructures

Transportation infrastructures provide the service of mobility, which plays a highly relevant role for modern society, as it enables people to efficiently travel between their locations of interest, e.g. their residence or workplace. This leads to a firm linkage between the dynamics of urban transportation systems and the daily routine of the citizens. Urban transportation systems consist of different sub-systems for different transportation modes and numerous technical structures, such as traffic lights, streets, or rail systems, and are complemented by the travelers. As these components are interconnected, the transportation system itself forms a system-of-systems.

Moreover, the travelers within this system-of-systems interact with each other, e.g. in a congestion or overloaded public transportation, and mutually influence their mobility behavior and decisions. This results in complex relationships that are hard to account for when modeling transportation systems. In addition, travelers have a plethora of choices, ranging from the selection of transportation mode to individual routing decisions. As the decisions of individual travelers cannot always be assumed to be rational [47, 70], the representation of the current state of urban transportation systems faces a high degree of uncertainty.

Furthermore, creating a multimodal model of urban mobility and keeping the model up-to-date with its real counterpart poses the challenge of fusing multiple heterogeneous data sources. As transportation systems comprise different sub-systems and numerous technical components, a variety of different sources of mobility data is available, including traffic counting sensor networks, mobile GPS trackers, and LiDAR sensors. However, fusing such data to create a holistic model is challenging and an active field of research [71].

4. Concepts

To address the aforementioned and discussed challenges, this section presents conceptual approaches for the design process of UDTs and the modeling of UCIs. We identify and discuss six overarching concepts that are relevant in the realm of DTs and can aid future development for UDTs. In particular, we discuss:

1. the prevalence of interdependencies in UCIs,
2. how the socio-technical nature of UCIs can be incorporated in DTs,
3. how agent-based modeling can be applied for the context of UCIs,
4. the cause and risk of the synchronization of CI demands,
5. the selection of models to reduce uncertainty,
6. and how data scarcity can be addressed through model transfer.

4.1. Interdependencies

As mentioned in Section 3.2, interdependencies between CIs are barely visible, but can lead to unforeseen critical effects, e.g. cascade effects in disasters. Because CI interdependencies play a minor role during normal operations, they are often not considered, let alone modeled or simulated. While the isolated modeling of CI domains might be viable for UDTs designed for urban planning, the modeling of interdependencies is indispensable for UDTs in the context of resilient UCIs to take critical failures into account.

We consider a unidirectional relation between two systems as *dependency*, whereas mutually dependent relationships can be classified as *interdependencies*, as shown in Figure 2. Although there may be dependencies between components within one CI system (intra-domain dependencies), we use this term only to refer to dependencies between two components from different CI systems (inter-domain dependencies).

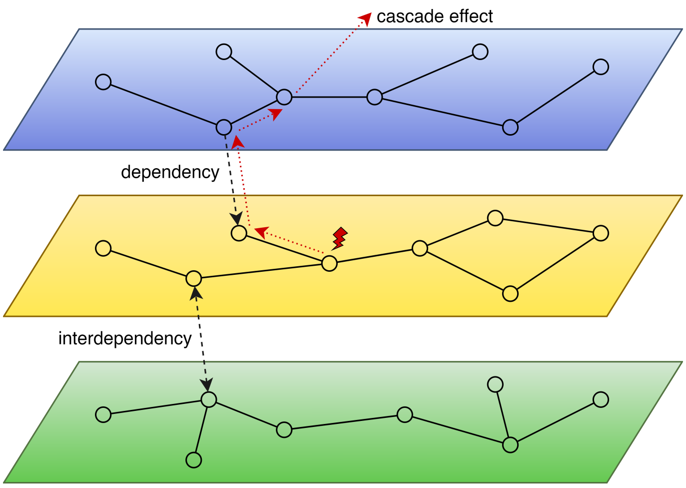

Figure 2: Illustration of CI layers (e.g. water, power, and transportation system) and dependencies between each other

Interdependencies can be classified into the following types: physical, cyber, geographic, and logical [8, 10]. For example, the reliance of many systems on power supply can be considered as a physical dependency. Cyber interdependencies are created through the involvement of communication systems and data collection, transmission, and processing. Geographic dependencies are created by the vicinity of UCI components to each other and the geographic scope of external impacts. The different types of interdependencies need to be addressed by using specific modeling approaches.

The effect of interdependencies varies in the temporal and spatial extent. For example, while the dependence on power comes immediately into effect, the dependence of fossil power plants on functioning transportation infrastructures is only relevant at much longer timescales, due to storages [72]. Moreover, dependencies may exist beyond the scope of urban areas. This has to be considered for the modeling of dependencies.

Dependencies can further be categorized into their relevance during different resilience phases. During normal operations, they usually play a minor role, e.g. for planning maintenance works and billing. In the case of a failure, certain dependencies might propagate a malfunction to other systems, thus amplifying the original impact during the absorption phase. During the recovery, additional dependencies might come into play, e.g. the restoration of power systems relies on access to streets, which might be destroyed due to an earthquake. Furthermore, resources for the restoration process might be limited across all CIs, creating *resource-sharing interdependencies* [73].

The existence of CI interdependencies is often regarded in a negative light because they increase the risk of failures and cascade effects. However, dependencies can also be utilized in a positive manner if well managed, for example by using synergies between power and water networks during grid restoration [74].

While the concept of CI interdependencies is widely accepted, simulations of interconnected UCIs are rare, especially for more than two domains [7]. The consideration of interdependencies necessitates sophisticated design concepts for the modeling and simulation of UCIs. In order to simulate all effects that could potentially affect every other system, the simulations of different CI systems need to be performed simultaneously (co-simulation). Alternatively, in the case that all dependencies are assigned in the same direction, the simulations could also be performed consecutively, e.g. if the power network would have an influence on the communication system, but not vice versa, the power network could be simulated beforehand.

Beside the dependencies within CIs, *external dependencies* represent influences of the environment on UCIs, such as time of day or temperature. As discussed in Section 3.3, the influence of human behavior can also be seen as a mutual dependency, which we call *socio-technical interdependencies* and is analyzed in the following.

4.2. Socio-technical Digital Twin

As discussed in Section 3.3, influences of human factors on technical systems are pivotal in the modeling of UCIs. To accurately represent socio-technical UCIs, the socio-technical interactions need to be considered. Therefore, we propose to include socio-technical models in DTs, leading to the concept of the *Socio-technical Digital Twin* (STDT), which is depicted in Figure 3. This approach extends concepts of existing DTs by including models of the social sub-systems in the virtual replica.

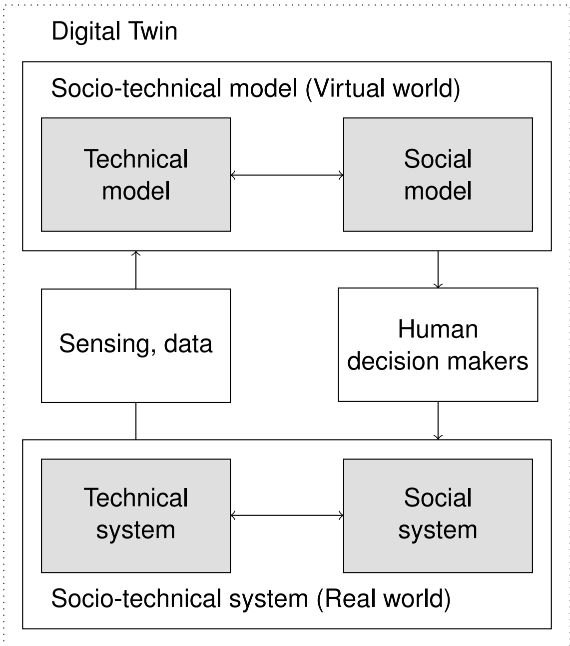

Figure 3: Concept of the STDT. While sensing and data collection will typically be based on the technical system, actions are made by human decision makers on the basis of the integrated socio-technical model and can be directed at both the social and the technical system.

To facilitate the inclusion of models of human behavior, the challenges of acting and sensing discussed in Section 3.3 have to be addressed. The most common approach is to sense human impact on an infrastructure directly, e.g. measuring power and water demand through smart meters, or indirectly, e.g. monitoring people movements through traffic sensors and estimating their impact on other infrastructures. Another opportunity for sensing in social systems is the analysis of data generated by the widespread use of smart technologies by citizens. For example, the analysis of smartphone locations or social media data might be used to estimate the number of people in an affected area during a crisis or to gauge the sentiment of people towards current events [75].

Acting in a STDT could be facilitated either by automated actions within the technical system, as is the case for closed-loop control of technical systems, or by using the DT as a tool for human decision makers. On the one hand, including socio-technical models in the DT could help to improve the precision of automated control of the technical systems by reducing uncertainty of model outputs. On the other hand, the STDT could offer support for human decision makers, in particular for crisis management. STDTs could be used to increase the understanding of the underlying dynamics in UCI systems and highlight potential effects of interventions. In this context, the concept of the human-in-the-loop in decision-making processes plays a major role [13].

The STDT concept opens up new possibilities for UDTs by allowing to include knowledge about human behavior and promises to strengthen DT capabilities. While models of human behavior are limited in their accuracy, as discussed in Section 3.3, the STDT approach of sensing and integrating data into the STSs could help to address the issues regarding validation, highlighted in Section 3.5.

4.3. Agent-based Modeling

UCIs are socio-technical systems-of-systems, which can be modeled through a spectrum of approaches. These approaches can be segmented into "top-down" and "bottom-up" approaches, differing in their perspectives and methodologies. In "top-down" modeling, the focus is primarily set on observing and understanding the system's behavior at an aggregate level. This approach treats the system as a whole, often relying on high-level abstractions and overarching principles to describe its behavior. In contrast, "bottom-up" modeling takes a more granular perspective by dissecting the system into its constituent parts. In this approach, the aggregate behavior of the system is not assumed but is derived from the results of the behavior and relations of its entities.

Agent-based modeling (ABM) is a prominent bottom-up modeling paradigm that can be used to deal with the nature of complex systems [44]. Since urban areas and UCIs must be considered as complex systems that can show emergent behavior, ABM appears to be a suitable modeling choice for UCIs. A variety of entity types within the STS of UCIs could be represented as agents. Primarily, humans that make decisions can be considered as agents, but also CI facilities, such as hospitals, or components with which humans interact, can be treated as agents. As ABM is a widely adopted approach for modeling various systems, this section will only give a brief overview of the method. For an in-depth presentation of ABM, the reader is referred to [76] or [77] for a general overview, and to [78] for the context of STSs and CIs.

ABM represents actors or sub-systems as individual entities, called agents. An agent can represent a human or a technical component capable of making decisions or an abstract entity, such as a corporation, government, or association. Each agent contains its specific traits as parameters and its behavior as functions. The agents interact with one another, allowing for the emergence of the aggregate system's behavior. Agent-based models further incorporate an environment representing components and constraints of the system that influence the agents but are not considered autonomous actors. The interactions of agents can either be direct, i.e., the function of one agent can manipulate the parameters of itself or of another agent, or indirect, i.e., the agent's function manipulates an environment variable that then influences the behavior of other agents. An example of the ABM concept and the structure of an agent is shown in Figure 4.

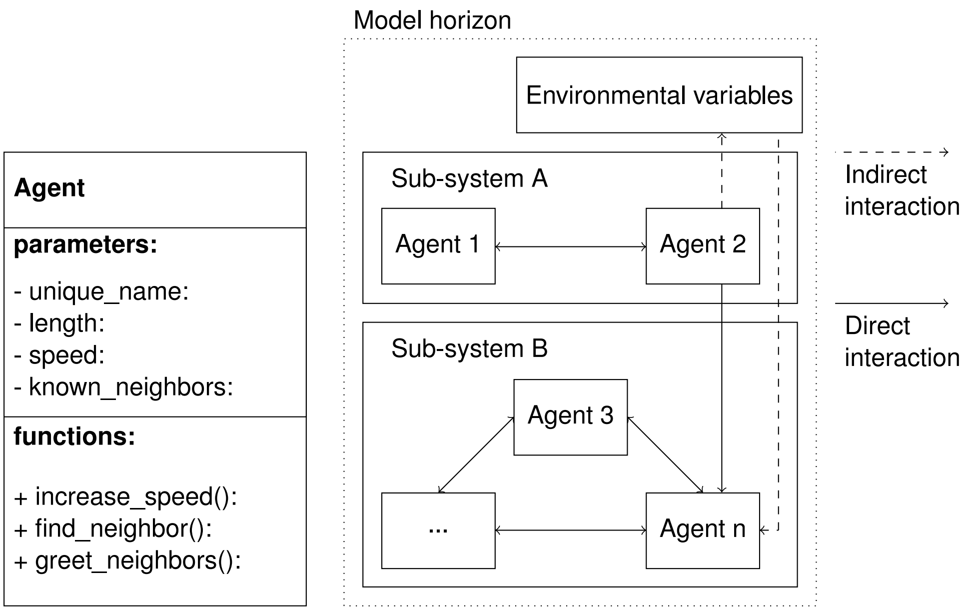

Figure 4: Agents (left) are represented as programming objects that carry traits as parameters and action capabilities as functions. The nested structure (right) allows the modeling of sub-systems as groups of agents and the direct interaction between agents and indirect interactions through the environment.

The advantages of employing ABM for modeling UCIs are multifaceted. First, ABM is typically driven by assumptions about the lower system levels, i.e. the agents, rather than assumptions about the aggregate system. This renders ABM particularly suitable for situations where comprehensive knowledge about the aggregate system is lacking. Requiring little assumptions on the aggregate system makes ABM especially promising for the modeling of crisis situations, since empirical data on crisis is rare. In this context, ABM can enable investigations of the aggregate system's behavior based on assumptions about individual behavior, without requiring prior knowledge of the aggregate system in an unprecedented situation.

Second, ABM provides a flexible framework to explore different scenarios and the result of potential variations in agent behavior. This can help to explore a multitude of potential future outcomes in a crisis situation under differing assumptions about the reactions of citizens.

Moreover, ABM excels in modeling spatial relationships and is consequently well-suited for systems with spatially distributed components, such as UCIs. In this regard, combining ABM with the topological modeling of CIs is key for modeling geographical interdependencies.

Finally, the alignment of agents with easy to recognize real world entities facilitates communication and understanding of the modeling process and simulation results, making ABM a valuable tool for stakeholders and decision makers. This is particularly advantageous for policy and management planning in the context of resilience for UCIs because the processes and the rationales of decision-making must be made transparent to stakeholders.

4.4. Demand Synchronization

The synchronization of infrastructure demands is a phenomenon within the social system of UCIs, created by the collective behavior of people. The effect of spontaneous synchronization has been discovered in biological, physical, and social systems, and has been studied in the context of complex networks [79]. However, in the context of infrastructures, the effect of synchronization is rarely considered, since people and their activities are independent from each other most of the time. In the sense of the central limit theorem, which states that the sum of independent, identically distributed random variables converges to a normal distribution whose relative standard deviation decreases with a higher number of variables, this means that individual actions, e.g. demand, cancel out, leading to a smooth course of aggregated variables. However, synchronization invalidates the assumption of independence.

If human behavior synchronizes, significant consequences can arise, especially when linked to CIs. For instance, during the coronavirus pandemic, self-increased panic buying of disinfectants and toilet paper caused a strain on logistics [3]. Furthermore, citizens in the UK are synchronized by the TV program on a regular basis, which can create immense surges in the power grid due to the simultaneous use of water kettles [80]. These examples show the relevance of demand synchronization in the context of CIs and emphasize the importance of analyzing, understanding, and predicting synchronized behavior.

Synchronization can be critical for an infrastructure system in two different ways. First, the synchronization of demand behavior can lead to high aggregated demand if many individual demands are high at the same point in time. Most infrastructures are not designed to supply all customers with high demand simultaneously because this situation is very rare and statistically unlikely. Therefore, synchronization can lead to exceeding capacity limits. Second, spontaneous demand synchronization can lead to sudden, unexpected changes for the aggregated demand, which can be critical for the system's stability. A sudden change would create a mismatch of demand and supply, which can destabilize the system. This effect is more critical if the demand shift is unexpected.

Demand synchronization is particularly relevant for power systems. Compared to other networks, the synchronization of power demand can have much more severe consequences. For example, in the water distribution grid, high demand would cause a temporary drop in water pressure, which would not directly endanger the stability of the system. If the internet traffic is overloaded, this would lead to increased waiting times but not to any damage of the physical infrastructure. However, in the power grid, overvoltage and overloads can damage certain parts of the power infrastructure, such as power lines and transformers. For this reason, protection mechanisms will usually trip, causing temporary and local outages. For distribution grids, however, these protections devices often need to be manually reactivated, resulting in significant power outages. Moreover, in crisis situations, when infrastructure is already damaged or service personnel are stretched to the limit, the duration of households without power can be even longer. The synchronization of high power demand therefore represents a significant threat for supply reliability that must be anticipated and mitigated.

The origin of synchronization can be divided into two categories [81]. *External* influences, such as daytime, season, or weather, affect people and their demand behavior in the same way, thus constitute synchronization. As these exogenous variables can be directly observed, their influence on the demand can be estimated in advance. Contrastingly, *internal* dynamics within the social part of the system, e.g. the spreading of fake news over social media, can also lead to synchronized behavior of people and possibly their use of infrastructure services. These internal effects can hardly be predicted or observed directly, as discussed in Section 3.3. The modeling and analysis of such internal dynamics could help in understanding and predicting irregular demand changes, reducing the risk of such critical scenarios.

4.5. Selection of Models

While the aforementioned concepts can aid the development of models, the challenge of model selection mentioned in Section 3.2 remains. This challenge is deeply interconnected with the challenge of validation, outlined in Section 3.5, as both essentially address the question, which assumptions about the real world are correct, i.e. useful for the goal of the model. While validations aim to assess the overall correctness of a model, this section focuses on how to decide which assumptions to include in a model.

To address the challenge of model selection, a novel framework for choosing models in the context of STSs was recently presented [82]. The approach takes an instrumental stand on the aim of modeling by assuming that a model's goal is not primarily to understand the world, but its primary focus is to provide insights as basis for actions and decisions. Thus, an assumption is only relevant with regard to the overall modeling objective. In the context of this work, model details and assumptions are evaluated based on their contribution to enhancing the resilience of UCIs and providing insights through the DT. To test this approach, the framework utilizes statistical hypothesis testing and technical requirement analysis to verify the relevance of different levels of detail in social models in regard to critical behavior in the technical system.

First, technical requirement analysis is used to identify, which functions of a UCI are critical, i.e., are necessary to sufficiently serve citizen's demands. Second, system states that could impede these supply objectives are identified, e.g., which loads or dynamics might negatively impact the infrastructure's physical integrity.

As an example, the requirements can be derived from technical standards, as they specify the expectations of stakeholders in a legal context [82]. The results of the requirements analysis are then used to assess whether a difference in model details is significant for the relevant system properties. The significance can be assessed through statistical hypothesis testing. The hypothesis tests evaluate whether the model's predictions show statistically significant differences in the distributions of the model's output values.

This approach of model selection could help to avoid unnecessary modeling details, thereby reducing model uncertainty. The approach could further be used to aid in the selection of competing modeling structures and support efforts of validation.

4.6. *Transfer of Models*

The system of UCIs, including the social behavior within this system, exhibits a high degree of complexity, as elaborated in Section 3. Therefore, sufficient data is needed to accurately predict various dynamics of UCIs in different situations. However, Section 3.1 revealed that data of UCIs is usually scarce, especially for crisis events. Moreover, the availability of empirical data sources varies widely between different cities and existing data sets are naturally limited to their context, e.g. the specific disaster, location, or historical situation. This fact limits the applicability of machine learning methods as they rely on extensive amounts of empirical data.

In fact, most machine learning models share the problem that they generalize poorly to unseen domains, i.e. data distributions that are not represented in the training data. Typically, such models are trained on massive amounts of data for a specific, defined task and context, in which they may achieve tremendous accuracy. However, when the context changes, the models may yield imprecise results. For example, machine learning models trained on data from the normal operation of UCIs may fail when applied to rare events. Within the last years, notable improvements of the generalization properties of machine learning models trained on heterogeneous data from different but related domains have been achieved [83]. In terms of urban areas, this may refer to training a model with data from different cities, aiming to generalize to unseen cities. While the growing amount of data, e.g. on urban mobility, may facilitate to train such a model for regular operation, the scarcity of data for rare events complicates such a procedure for crises.

For instance, estimating human responses to an earthquake that has not yet occurred in a specific urban area faces a lack of data to support modeling assumptions about human behavior in this case. This implies the need for methods specialized for domain adaptation, enabling predictions of human reactions and behavior in contexts when high-quality and adequate data is not available. In particular, overcoming contextual limitations may enable models that can predict human crisis behavior in new contexts. This would be a tremendous achievement to support crisis management. The concept of model transfer, depicted in Figure 5, consists of learning general spatio-temporal behavioral patterns and adapting them to a novel context, e.g. a crisis or a new city, to overcome data scarcity. In the above example, this refers to using existing data on earthquakes from other urban areas to estimate the human behavior in the area of concern. However, further investigation is needed to explore model transfer within the context of UCI [84].

In machine learning, transfer learning specifically seeks to perform such a task. In transfer learning, a model is usually trained on data from a source domain before being refined to a target domain. In the

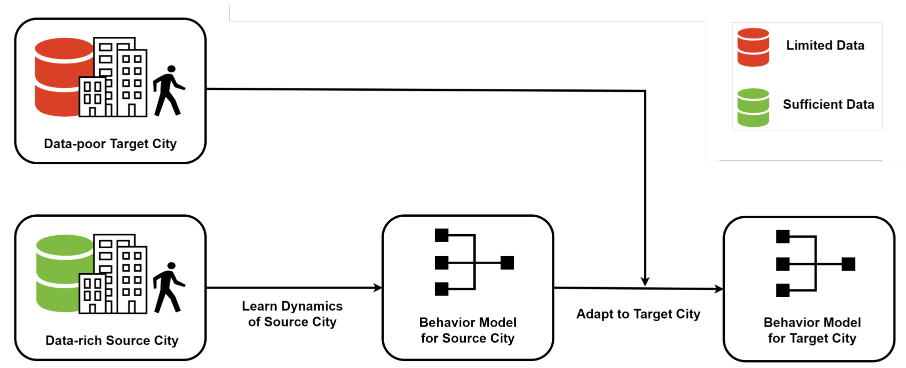

Figure 5: Concept of model transfer: The large amount of data from the *source city* is used to train a model, which is then adapted to fit the *target city*, based on limited data. This results in a model for the target city.

context of urban areas, a data-rich area may serve as the source domain, while a data-poor area usually is the target domain. For example, recent works investigated the prediction of citywide mobility by using transfer learning [85, 86]. A model is trained on human behavior and environment data from the source city to learn behavioral patterns within the source city first, such as movement patterns between its regions. This model is then either fine-tuned with limited data from the target domain or applied directly to predict the according behavior in the target city. Refinement approaches in transfer learning range from freezing certain layers of a pre-trained neural network and retraining the others to using a pre-trained model for feature extraction for re-using previously learned data representations [87].

For urban mobility, there are two highly relevant applications for the transfer of models. One of them concerns the transfer between urban areas. As previously stated, this involves training on data about the source city with the goal of generalizing movement patterns as a product of environmental influences. The trained model can then be used to predict the spatial mobility patterns in the target city, with or without further fine-tuning.

The second application is a transfer between two different events, e.g. disasters, such as floods and earthquakes, or regular situations as well. Here, the source and target domain represent the same urban area, but the environment changes, influencing the behavioral patterns within the system. This is reflected by pre-training a model with sufficient data, e.g. on regular situations, and refining the model with limited data on crisis behavior.

Combining transfers between urban areas and between events is a promising approach to estimate the impact of crises on human behavior in an entirely new urban area. Nevertheless, further investigation of the transfer of models as a particular task of domain adaptation is needed to aid future crisis behavior models.

5. Modeling

This section deals with the modeling of UCIs in the context of UDTs and integrates the concepts introduced in Section 4. We present and discuss general modeling aspects, such as ABM, interdependencies, and synchronization, as well as the modeling of CI systems, in particular, power systems, water distribution systems, and transportation systems.

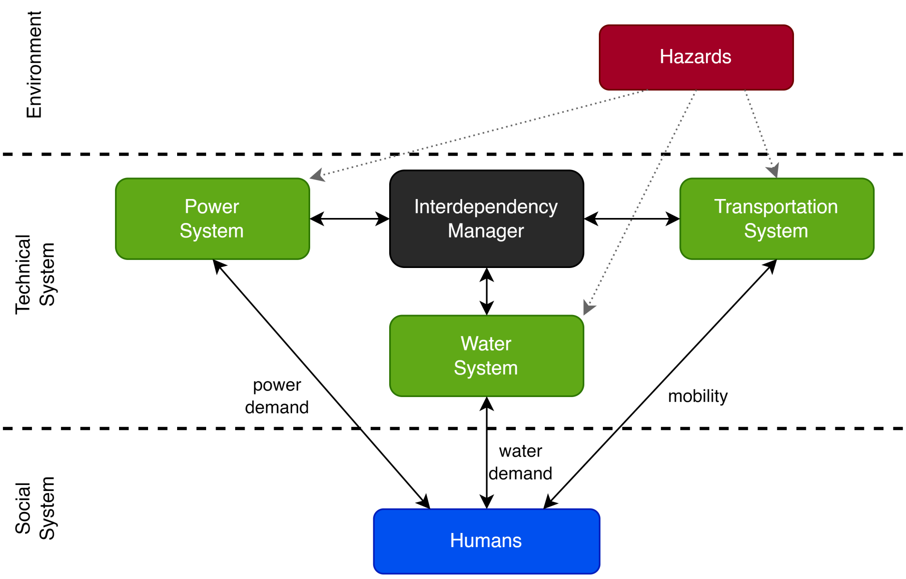

Figure 6: Modeling framework for UCI simulations within UDTs

The models presented can be embedded in a superordinate modeling framework shown in Figure 6. This framework can form the basis for co-simulations within a UDT. Following the concept of STSs, the modeling approach can be divided into three main parts:

- **Technical System**: This encompasses the physical modeling of all technical components of the UCIs. The CI systems are modeled and simulated in separated modules. The interdependency manager handles the dependencies between the systems.

  For the physical models, many established simulation tools exist that can be used or adapted. However, as discussed in Section 3.4, they have to be adjusted for additional interfaces to be used within the integrated simulation platform.

- **Social System**: Humans are part of the STS of UCIs. Since they interact with infrastructures in both ways, they are considered as agents that can affect every technical UCI system. This approach puts the human perspective and human needs at the center, understanding infrastructures as services to the population.

  The social and human behavior can be modeled in many different ways. The interface to the technical system needs to be defined. The absence of readily available implementations complicates the process of including social behavior into the modeling for DTs.

- **Environment**: The environment represents all external influences on the system that originate beyond the system boundary of the UCIs of a city and its residents. This includes exogenous variables and external impact events such as disasters. The specific impact needs to be modeled individually and depends on the type of hazard, the affected area, and the vulnerability of components.

To address the nature of CIs as complex adaptive systems, we combine agent-based modeling with network-based simulation approaches. The modeling approach can be seen as a bottom-up simulation that considers all individual components and sub-systems. We consider physical components of infrastructures as *entities* and humans as *agents* of the system. The integrated modeling of the STS enables the holistic assessment of the system and the discovery of emergent effects, created for example by geographic or socio-technical interdependencies.

We are solely concentrating on physics-based (white-box) modeling. In the context of resilience, which considers rare and unknown events, physics-based modeling appears to be the more suitable approach compared to black-box modeling because it allows the simulation of situations that have never occurred in the real system. Thus, physics-based modeling can be expected to provide more useful outcomes and a better understanding of the complex system of UCIs, especially for situations outside the normal operation.

The selection of models is a vital process that needs to take the specific requirements and goals of a UDT into account. In general, it can be said that due to the holistic approach of UDTs and the challenges arising in the coordinated simulation of UCIs (see Section 3.4), the level of detail in the models used may be lower compared to domain-specific analyses. They should however be detailed enough to capture all relevant behavior that impacts the overall system significantly, i.e. the main functionality of components and the relationships between system domains. For example, the failure of a power device due to undervoltage and its consequences presents an essential characteristic that should be included in the model for a UDT, while non-critical power quality features, such as harmonics in the voltage frequency, may only be relevant for the power grid operator.

5.1. Technical System

This section focuses on the modeling of the technical part of the UCI systems. We introduce the structural modeling of UCIs and their interdependencies as a graph-based representation. Then, we present and discuss different approaches that can be used for modeling the physical behavior of UCIs, in particular, power grids, water distribution systems, and transportation infrastructure.

5.1.1. Modeling UCIs

Infrastructures are systems that consist of technical or organizational components that are connected between each other and provide a service. The modeling of CIs encompasses the description of their components, their behavior, and the interfaces to the infrastructure users and the environment.

Many CI systems can be modeled with graphs to describe their structural composition [88, 10]. Table 3 exemplifies that several UCI entities can be represented as nodes and edges. Often, the nodes can be associated with a demand of infrastructure services, while the edges contain information of flows. Most of the physical entities can be assumed static in their location.

We therefore model UCIs as graphs, constituting a set of *layers*, as depicted in Figure 2. Each CI system $k \in \{1, \ldots, K\}$ is represented as a graph

$$G_k = (V_k, E_k) \tag{1}$$

with nodes V_k and (intra-layer) edges E_k that are associated to the CI domain k.

Although the graph representation provides structural insights into the system, the system's topology alone is not able to predict the state and behavior of the system under different conditions. In addition, the modeling of dynamic behavior within CI domains is required to simulate state variables over time, e.g. flows. For example, while purely topology-based models can estimate the immediate impact of spatial events on adjacent nodes, simulations are still necessary to assess the degree of resulting service operation and consequences to the entire system.

Compared to models that are created for a specific application and known environment, models for the use in UDTs for crisis management must be able to deal with uncertainties, created for example by missing

Table 3: Examples of UCI Entities that can be represented as Nodes and Edges

Infrastructure	Node-like entities	Edge-like entities
Power	Busses, Consumers, Generators, Transformers, Substations, Switches	Overhead lines, Underground cables
Water	Junctions, Consumers, Pumps, Reservoirs	Pipes, Sewer lines
Transportation	Crossings, Stations, Transfer hubs	Roads, Rail lines, Public transportation connections
Communication	Sensors, Data centers, Routers, Mobile base stations	Communication cables, Wireless communication channels
Logistics	Warehouses, Distribution centers	Shipping routes, Supply chains
Healthcare	Hospitals	Medical pathways, Information flow
Finance	Banks, Cash machines	Transactions, Payment networks
Emergency Services	Fire stations, Police stations	Emergency response routes, Emergency Communication

data, model uncertainty, or abnormal operation modes. While many existing models are only useful in a predefined operation point (e.g. due to linearization), models in UDTs should be designed in a way that they are still useful in unusual situations to provide an informative value.

5.1.2. Interdependencies

Different approaches for the modeling and simulation of CI interdependencies exist. System dynamics and input–output approaches analyze the system and its interdependencies in a top-down perspective by describing the system with stocks, flows, and feedback loops. The dynamics can often be modeled with differential equations, which eases the analysis and simulation. However, top-down approaches are limited by the explicit modeling of interdependencies based on existing knowledge, required calibration of system parameters with data, and their inflexibility to topology changes [10].

To analyze interdependent CI systems at a component level, bottom-up approaches are required. Network-based approaches address the graph-like nature of UCIs and can be divided into topology-based and flow-based. Topology-based methods benefit from computational speed but cannot provide sufficient information about the internal states of CIs [10, 89]. Flow-based methods, on the other hand, provide a high level of detail and represent the dynamics of the system, which comes with increased computational cost, especially when the system is large [10, 89]. Furthermore, network-based approaches are able to consider all types of interdependencies (physical, cyber, geographic, and logical) [10].

Using the graph-based representation of UCIs, where every domain itself is represented by the graph G_k, dependencies can be defined as directed or bidirectional edge between two nodes of different domains [88]. The *dependency network DN* describes dependencies as a directed graph [58]

$$DN = (V, D) \tag{2}$$

that connects the set V of all nodes of the disjoint graphs G_k by the set of inter-layer edges

$$D = \{(n_o, n_d) \,|\, n_o \in V_i, n_d \in V_j\}, \tag{3}$$

where n_o represents a node in domain i that is dependent on node n_d in domain j. Extended formulations to describe node-edge or edge-edge dependencies are possible.

The dependency network can model physical dependencies by using edge weights for the inter-layer edges. For example, an inter-layer edge, pointing from a pump node in the water network to the node within the power network from where it is supplied with power, could contain the information of the required amount of power. Cyber dependencies can be incorporated by assigning sensor nodes within the communication network to the entities from which measurement values about their current state are transmitted. To consider geographic interdependencies, the entities of all networks are provided with spatial information, which can be used to model impacts from the environment.

5.1.3. Ontology Description

As discussed in Section 3.1, the use of an ontology description is necessary for modeling all UCI entities with a common data model. Many smart city ontologies have been developed, but most of them are designed for sector-specific applications, such as the energy sector, smart homes, and urban planning [90]. For the context of UDTs, we identified the following ontologies being particularly useful.

CityGML is a widely used standard by the Open Geospatial Consortium (OGC) for representing and exchanging 3D city models [91]. It provides a comprehensive ontology for urban environments, including buildings, roads, and other infrastructure. However, CityGML appears to be mainly used for 3D models and is not so widely used for network-based representations of infrastructures.

SAREF (Smart Appliances Reference Ontology) is an ontology developed by the European Commission for describing smart appliances and their capabilities [92]. The focus is to improve the interoperability of smart appliances, however, it could be extended to cover broader aspects of smart cities.

FIWARE NGSI-LD is an open standard developed by the FIWARE community for representing and exchanging information about entities in a smart city context [93]. It is designed to support real-time data exchange and integration, which plays a crucial role for DTs. Furthermore, the use of FIWARE has been proven useful for UDTs [24].

Due to its openness, flexibility, and adaptability, we consider the FIWARE standard suitable as an ontology description of UCIs. There exist developments that are centered on smart city applications, such as the "Smart Data Models" [94]. Nonetheless, the ontology may need to be adjusted to the specific DT application. Furthermore, adapters for the interoperability with the used simulators are required.

5.1.4. Power System

Three-phase alternating current (AC) has prevailed for the transmission and distribution of power worldwide. Transformers can convert AC voltage to different voltage levels. The modeling of power systems is often simplified by considering just one phase under the assumption of symmetric operation.

There are different models for power systems that can represent the electrical behavior at different levels of detail. In the simplest case, the loads at nodes, e.g. buildings, are aggregated as the sum of active power. However, this model neglects reactive power, line losses, and the network topology.

The consideration of sinusoidal voltages and currents leads to the AC power-flow model [95]. In contrast, the so-called "DC power-flow" uses approximations that lead to linear equations, which can be handled more easily from a computational point of view. However, these assumptions are more justified for high-voltage networks and not for urban distribution systems. Moreover, the linearized model is only appropriate for normal operation conditions, when the system state is close to the according operating point. If the objective includes representing critical situations, the selected model should yield accurate results also for unusual system states, where the system might operate at limiting conditions.

The power-flow model is a steady-state model that can for example calculate the new resulting steady state due to a component's failure. However, it is not able to represent transient effects, i.e. trajectories between steady states at short timescales. For this, the differential equations of electrical circuits must be considered. However, their simulation increases computational efforts and simulation time significantly, which would complicate their use in UDTs. While transient effects might be relevant for system stability in transmission grids [96], they could be negligible for urban distribution systems. Thus, the AC power-flow model might be sufficient for capturing the main effects in the context of hazard impacts on interdependent UCIs.

For the implementation of the power system model, many commercial and open-source tools exist. *Pandapower* [97] is an open-source Python package for simulating electrical power systems with a focus on static and quasi-static analysis and provides solvers for the AC power-flow model. The tool has been used in other cross-domain simulations [60] and is known for its flexible interface and great performance.

5.1.5. Water Distribution System

As with any system, the level of detail in a water distribution model must be selected based on the desired insights. For DTs this means, that depending on the physical variables of interest and the available sensors, different models might be chosen.

For a simple estimation of water availability and the usage of water tanks, simple models, such as the flow balance in tanks and main pumps, might be sufficient. Such models are extensively utilized in socio-technical models of water systems [98] but are typically insufficient if spatially distributed insights into the dynamics of water distribution systems are of interest.

Most current applications of DTs in the realm of urban water distribution systems utilize more extensive models [28]. In addition to the balance of mass, these models use the topology of the water distribution system as a graph and assumptions of friction in the pipes to model the water pressure available at each junction of the water distribution system, i.e. the locations of water demand.

Finally, more extensive models of water distribution systems could be considered for DTs, as there is a rich literature on models of piped fluid systems [99]. These models could be used to simulate transient effects in the system, e.g. pressure surges. While these models could merit benefits for highly dynamic situations, the increased need for data and computational resources makes it hard to employ such models for large scale systems like urban water distribution systems.

A widely used simulator for water distribution systems is the *Water Network Tool for Resilience (WNTR)* [100]. WNTR is an extension of a prior network simulator (EPANET) and is especially useful for resilience analysis, as it provides built-in capabilities for the analysis of water distribution systems on the basis of resilience metrics and pressure drops. The tool has been used in other cross-domain simulations [60].

5.1.6. Transportation System

As pointed out in Section 3.7.3, the transportation system consists of multiple sub-systems, serving different modes of transportation. The vehicles of different transportation modes either share transportation networks, e.g. cars and buses share streets, or rely on their own networks, such as trains. Each of these networks can be modeled individually as part of a multi-layer network.

Transportation networks exhibit a graph-like structure consisting of nodes, such as junctions or stations, and links between the nodes, such as streets or rails. Hence, the individual networks are typically modeled as graphs. In addition to these intra-layer links, multi-layer networks are equipped with inter-layer links between the different layers within the transport domain, representing transfer hubs that provide the possibility to change the mode of transportation.

To create detailed graph-based models for transportation networks, publicly available data, e.g. from OpenStreetMap, can be leveraged. There are several works that exploit such data sources. For example, the author of [101] created a repository of street network models based on OpenStreetMap data for every urban area in the world. Such street network models have been used for a variety of tasks, ranging from routing [102, 103] over traffic analysis [104] to machine learning applications [105]. Furthermore, OpenStreetMap data plays a significant role in traffic network modeling for traffic simulations. Several simulators, such as SUMO ("Simulation of Urban MObility") [106] and MATSim ("Multi-Agent Transport Simulation") [107], provide the possibility to automatically generate a transportation network model based on OpenStreetMap data.

These automatically created transportation network models have been proven to serve as a basis for modeling transportation systems within DTs [26]. Moreover, SUMO comes with a tool to intervene the simulation, which allows to calibrate the traffic situation with real data and modify the system, providing interfaces that can be used to model interactions with other CI systems. Thus, simulators equipped with such interfaces seem promising for the application in UDTs to simulate scenarios with disruption events and test different traffic control strategies.

5.2. Social System

As discussed in Section 3.3, human behavior significantly impacts the state of UCIs. On the one hand, the operational load of infrastructures is generated by the actions of its users, e.g. the amount of power or water that is consumed. On the other hand, CIs are operated and maintained by humans to ensure the functional operation, which is especially relevant during a crisis, e.g. for restoration. To estimate the state of a technical infrastructure system or simulate its behavior in a scenario, assumptions about the behavior of humans are necessary. While both mentioned socio-technical perspectives are highly relevant in the context of crises, this section focuses on the modeling of user behavior and infrastructure demands. The output of such demand models represents the input for the models of the technical systems.

Simple demand models include for example the assumption of constant demands or standardized demand patterns. Moreover, if sufficient sensors are available, real-time demand data on infrastructure demands can be streamed into the technical models. However, those approaches are limited in simulating crisis scenarios, as these methods do not allow forecasting for unprecedented situations. Therefore, more advanced demand models have to be considered as well to provide a deeper understanding of user behavior.

The following subsections give a brief overview how demand behavior can be modeled in the context of UCIs. For this, we first outline how the concepts of ABM and synchronization can be leveraged for modeling CI demands. Followingly, examples of behavior models used in the CI domains of power, water, and transportation infrastructure are presented and discussed.

5.2.1. Agent-based Modeling

ABM has been used for a variety of tasks related to urban areas, infrastructure systems, and crises, as discussed in Section 4.3. Especially the modeling of human behavior is a highly relevant application for the STDT, as detailed behavior patterns improve the understanding of urban dynamics.

Many works have used ABM for social models that solely concentrate on modeling human behavior. For instance, agent-based models of mobility patterns and mobility demand [108, 109, 110] or energy demand [111] address human interactions with UCIs. Modeling such demands on the microscopic level of citizens can generate detailed representations of dynamic loads on infrastructures. This enables models of infrastructures that represent human needs and behavior patterns.

Moreover, several mobility simulation software, such as SUMO [106] or MATSim [107] model traffic as the aggregated traveling of individual agents. These simulators have been used in several microscopic models of transportation infrastructure, for instance in a DT of the transportation network in Barcelona [25], a DT of a highway segment near Geneva [26], or a model of the pedestrian traffic flow in Salzburg [112]. Such agent-based mobility models can introduce spatial dynamics in microscopic infrastructure demand models, creating spatio-temporal loads for the infrastructures. Moreover, ABM has been deployed to model the behavior and evacuation efforts of people exposed to natural disasters, such as hurricanes [113] and earthquakes [114], demonstrating the applicability of agent-based behavioral models also for rare events.

These models for infrastructure demand and behavior patterns can serve as a basis for modeling infrastructures as STSs. In fact, human behavior has not only been modeled in isolation, but also embedded in models of infrastructure systems. In [115], human behavior is integrated in a model of power, water, and transportation network by ABM to analyze the effects of seismic events. Moreover, in [116], agents have been used to model households and businesses and their respective consumption and production in an interdependent infrastructure model. Such socio-technical agent-based models are particularly suitable for investigating emergent effects in social systems and analyzing their impact on UCIs.

As a modeling paradigm that is closely related to simulation, the potential of ABM for STDTs lies especially in the use of scenario simulations and Ad-Hoc simulations (see Section 3.4). For this purpose, ABM has been explored in the context of DTs for urban social systems [21].

While these examples showcase the benefits of ABM for modeling UCIs, a drawback of ABM lies in the high number of variables due to the disaggregated structure of agent-based models. Therefore, ABM simulations may require extensive implementation and tend to be computationally expensive [10]. Furthermore, the large number of variables increases the uncertainty of model inputs.

One approach to address model uncertainty is model validation, which we discussed in Section 3.5. This aspect has been highlighted as especially relevant for ABM [117]. The goal of validation in this context would be to reduce uncertainty by establishing trust in the model assumptions based on measurement data. Furthermore, model uncertainty can be decreased through methods of model selection (see Section 4.5). Similarly, model selection aims to reduce model uncertainty either by selecting models that fit the observational data or by reducing model complexity, i.e. getting rid of unnecessary assumptions. One facet of data-driven model selection can be the instantiation of the model, i.e. the estimation of a system's initial state as starting point for the simulation.

5.2.2. Synchronization

The concept of demand synchronization, as described in Section 4.4, can be modeled by building on ABM. In ABM, agents may influence each other's behavior, but often maintain independent, individual actions. In the case of synchronization, the agent's actions become synchronized, which can have significant implications on the overall system behavior.

Synchronization can be modeled in different ways. For example, the *Kuramoto model* [118] is a popular mathematical description of synchronizing coupled oscillators. It has been extended to more advanced formulations and has been examined under various configurations. However, it has been applied mostly for problems which involve oscillating variables, which is not the case for infrastructure demand. Synchronization has also been studied in the context of multi-agent systems with a focus on system control [119].

By understanding synchronization as correlation between the individual properties, e.g. power demand, synchronization can be modeled with random variables, which exhibit dependencies. Copulas provide a flexible way of modeling dependencies between random variables by separating the modeling of marginal distributions from the dependence structure [120]. Copulas have been used in finance, risk management, and engineering to model dependencies. In the context of demand modeling, copulas have been used to model correlated stochastic electricity demands with a normalized parameter [81]. This approach can be used to generate synthetic demands given a synchronization parameter, as well as for monitoring the synchronization from real-time demand data. With this model, statistical properties of the aggregate system can be analyzed, e.g. the likelihood of exceeding system limits.

5.2.3. Power Demand

Compared to industrial and commercial power demand, residential power demand can be assumed to contain the most variability and uncertainty. This is because human behavior has a major impact on residential power demand, while the load of industrial, commercial, or public buildings can usually be considered more static. Especially in crisis situations, the residential power demand is most prone to unexpected load shifts. Therefore, a focus on residential power demand modeling is essential for this study. Modeling demand at an individual level is indispensable to address the concept of ABM.

Power demand partially follows deterministic patterns, induced for example by the time of day, season, and weather variables. Therefore, the aggregated demand is often modeled by using these factors, e.g. by creating standard load profiles or regression models. However, at an individual demand level, e.g. buildings, the power demand appears to be much more stochastic, especially on shorter timescales, i.e. intra-hourly. This is because power demand patterns are often characterized by human behavior.

Stochastic models for the power demand have been developed to represent uncertainty. Residential demand models can be divided into top-down and bottom-up models [121]. In this context, bottom-up refers to the modeling at appliance level, however, other definitions exist.

Probability distributions are a simply way to represent the statistical nature of power demand and can be obtained with historical data of household power demand. Different parametric distributions, such as the Beta, Weibull, Log-normal, generalized extreme value distribution, as well as Gaussian mixture models have been proposed [122, 123, 124, 125], although none of them has emerged as a universal fit. The Log-normal distribution has proven to successfully model fat-tailed demand data at high-resolution [81]. For a more specific model, a distribution can be obtained for every hour of the day or month of a year, although this increases the number of models while reducing the data to fit them [124].

More detailed models utilize data of people's activities to model power demand at appliance level and have demonstrated their ability to generate realistic load profiles [126, 127, 111]. The demand is often modeled with the Markov chain Monte Carlo (MCMC) method. With this bottom-up approach, the implications of human behavior and decisions under varying conditions on power demands can be studied in detail, allowing predictions for unprecedented situations. While these models can be considered agent-based, existing implementations often neglect interactions between people. Moreover, this approach requires a large amount of calibration data about activities and electrical appliances and is computationally intensive [121].

5.2.4. Water Demand

In the context of DTs, simple water demand models, using either recorded or live streamed data, are the most common [28]. However, the modeling of water demand has a long history of research on its own, resulting in numerous models that describe functional relationships of explanatory variables of water demand.

Traditional econometric models of water demand use regression models to estimate water demand on variables, such as costs or socio-economic household parameters. Examples for such models have been reviewed by [128] and [129]. Due to the high fidelity required for DTs, the applicability of these models is limited, as they typically evaluate water demand over extended periods, such as monthly or annually. For short-time demand forecasting, data-driven models, e.g. artificial neural networks, are frequently used [130].

All the aforementioned methods are typically focused on aggregated water demand, i.e. the water demand of a whole city or neighborhood. However, as discussed in Section 5.1.5, DTs require spatially detailed models for water infrastructure. While a diverse set of spatially heterogeneous models for water demand exist, these models rely on spatially detailed data, highlighting the challenge of data scarcity for the model development [131]. These data requirements can in part be addressed by smart metering technologies, but further utilization of data and development of methods are needed [132]. Modeling approaches deemed promising for highly dynamic modeling and spatially distributed water demand are ABM and system dynamics models, with ABM providing additional capabilities to model agent interactions on a fine spatial scale, i.e. neighbor interactions [131]. ABM in this context can be used to estimate the impact of management strategies, but the predictive capabilities can be limited due to the high uncertainty regarding the definition and instantiation of ABMs [133].

A systematic literature review of agent-based models for residential water demand found a heterogeneous body of approaches, building on various of the aforementioned demand modeling strategies [98]. Agents' water demands can for example be generated through deterministic values or through stochastic demand pulses for demand profiles based on the frequency of appliance use, e.g. the models presented by [134], similar to the methods described for electricity demand in the previous subsection. The modeled water demand is then influenced by assumptions of the agent's decisions, e.g. decisions whether to conform with the behavior of neighbors or to reduce their demand according to public announcements. Despite the potential benefits of ABM for modeling socio-technical interactions, only a small sample was found to integrate extensive technical models of water distribution systems. As ABM shows the capability to simulate spatially distributed water demand at high temporal fidelity and can include reasoning about human behavior, ABM seems promising for modeling water demand in UDTs.

5.2.5. Mobility

As mentioned in Section 3.7.3, human travel behavior can exhibit limited rationality and is therefore difficult to model. There are multiple approaches to overcome this difficulty to capture human mobility behavior in urban areas. These approaches range from mathematical models, such as simple random waypoint models [135] or probabilistic models [136], to data-driven approaches, such as generative adversarial networks [137, 138].

Because simple mathematical models lack a foundation of behavioral patterns and data-driven models require massive amounts of data, both approaches face limitations for realistically modeling urban mobility. An alternative approach is to leverage time-use data to create time-activity profiles [108]. This is a popular method for generating the mobility demand of synthetic populations by incorporating ABM. Several works have used time-use diaries or large-scale time-use surveys to generate such time-activity profiles [139, 140, 141].

By incorporating socio-economic and spatio-demographic data, time-activity profiles can be matched with demographic profiles and activities can be located within an urban area. This involves identifying the relationship between time-use and demographic characteristics to generate time-activity patterns. By assessing the spatial distribution of demographic characteristics within the city, demographic profiles can be mapped to locations, representing the citizens' residence. In addition, activities can be assigned to their location in the city by using points of interest, such as schools or shopping centers. This results in detailed information about the exact whereabouts of the synthetic citizens over time. Moreover, this approach provides not only origin-destination pairs for each synthetic citizen, but also a context for each activity. An example of a model that follows this method is the agent-based demand model TAPAS ("Travel Activity PAttern Simulation") [109].

A limitation of time-activity models is their usual restriction to regular situations. Most of the existing time-activity models represent usual mobility patterns, indicating limited applicability for rare events, such as crises. While crisis applications are rarely incorporated in time-activity models, other models aim to model human mobility behavior during crises through the use of ABM. This approach involves the incorporation of decision models for the agents' responses to disruptions and constitutes a popular choice for modeling the complex dynamics of human mobility behavior during crises [113, 141].

5.3. Environment

The environment comprises all external factors that affect the UCIs of a city and its residents. This includes exogenous variables and external impact events.

Exogenous variables, such as time of day or weather conditions, can influence various CI systems and also impact human behavior. For example, the mobility behavior depends on the time of day or the season. Furthermore, outdoor temperatures affect the operation of power lines by reducing their operational limit.

While exogenous variables are relevant for normal operations, crises and disasters are frequently caused by *external events*, creating specific scenarios. The cause can further be divided into natural and man-made (accidental or intentional) disasters. Therefore, it is necessary to model the specific impact of a given scenario on the entire system.

A variety of scenarios for external events has been considered in the context of CI resilience. Literature has focused most commonly on floods, hurricanes, earthquakes, pandemics, and climate change [65]. These scenarios can affect urban areas at different timescales, creating a further challenge for their joint simulation with CI dynamics. Moreover, scenarios can be categorized by their area of impact as:

- **point events**, e.g. single component failure, explosions, fire incidents,
- **track-based events**, e.g. floods, tornadoes,
- or **city-wide events**, e.g. earthquakes, (snow-)storm, heat wave, power blackout.

Since different scenarios create different kinds of impacts, the exposures and failures need to be modeled for each scenario individually. This affects the area of impact, e.g., the impacted area of an explosion can be considered radial with decreasing impact from the center, while a storm would probably cover large parts of a city. In addition, different types of entities can be affected in different ways, e.g., underground power cables would not be affected from a hurricane, while overground infrastructure might be.

The modeling of impact events consists of two parts: exposure modeling and failure modeling. Exposure modeling first identifies all entities that are affected by a scenario and defines the quantitative impact of the exposure. The exposure can be based on geographic properties, e.g. in the event of a storm or explosion, or on logical features, e.g. systems affected by IT vulnerabilities. Second, the consequences to entities based on the impact need to be evaluated. The failure assessment can be deterministic, e.g. using a fixed threshold value, or stochastic by defining probabilities for a failure. On the one hand, stochastic failure modeling can represent a wider range of potential consequences, since exact thresholds might be unknown. On the other hand, introducing randomness in the model increases the computational effort to effectively cover the resulting outcomes by sampling. Furthermore, the failure can be continuous (partial failure) or binary (no effect or total failure). Fragility curves can be used to precisely characterize the impact of certain events to individual entities [114].

6. Resilience Assessment

Assessing UCI resilience effectively, holistically, and continuously is essential for future smart and secure urban infrastructure systems. To allow for grounded comparisons and decisions, resilience assessment usually needs to be conducted in a quantitative way. As elaborated in Section 3.6, DTs provide comprehensive simulation capabilities, which can be leveraged by applying the modeling framework presented in the previous section. From the integrated simulation, desired metrics can be computed to evaluate UCI resilience holistically. As DTs are coupled with the real system, they can provide real-time resilience monitoring and bridge the gap between empirical and simulation-based resilience assessment.

This section presents approaches on how to assess the resilience of interdependent UCIs as a system-of-systems and discusses central aspects that need to be considered in this regard. The definition of performance and summary metrics is introduced, along with general and domain-specific examples. We then focus on assessing resilience across CI domains in an integrated way and highlight important considerations for a holistic assessment regarding specific hazard events and uncertainty. Finally, we discuss the resilience assessment with DTs.

Quantitative resilience assessment for UCIs entails the definition of *resilience metrics*, which can be classified as graph-based or performance-based [142, 143]. *Graph-based metrics* can be used when the system can be represented as a mathematical graph and address topological features, e.g. connectivity or betweenness centrality. They are usually time-independent. In contrast, *performance-based metrics* represent the functional performance of a system over time. They can be determined through simulation studies or empirical investigation [12]. Since purely graph-based characteristics neglect the dynamic and emergent behavior of the system, we focus on performance-based measures in this work.

6.1. Performance and Summary Metrics

The resilience curve (exemplified in Figure 1) illustrates the evolution of a certain performance measure before, during, and after a disruption [12], representing a scenario. Scenarios can reflect various hazard types, different environmental conditions, and differences in the system configuration. Formally, a *performance metric* can be defined as a function $P(t)$,

$$P : [t_0, t_e] \rightarrow \mathbb{R}, \tag{4}$$

mapping a point in time $t \in [t_0, t_e]$ to a performance value that describes the corresponding state of the system. Here, t_0 and t_e denote the start and end time of the scenario, respectively.

In order to facilitate comparison of various curves, obtained from different scenarios, summary metrics can be defined to characterize the system's performance with a single value [12]. Let $\mathcal{P}$ denote the space of the performance metric $P(t)$. Then, a *summary metric* R maps the function of performance during the scenario to a scalar value

$$R : \mathcal{P} \rightarrow \mathbb{R} \tag{5}$$

and therefore represents a time-independent measure. This mapping is only meaningful if the performance metric is reasonably defined during the entire scenario, covering at least the absorption and recovery phases of the resilience cycle. Since information is lost during the transformation, summary metrics can not fully capture the system behavior and should be interpreted with care.

A variety of performance and summary metrics have been proposed, in the context of different objectives and applications. Metrics can be categorized into availability, productivity, and quality measures [12]. In the following, we highlight some general metrics of the literature and discuss examples for quantifying the resilience of UCIs, specifically power, water, and transportation systems.

A commonly used indicator for the satisfactory operation of a CI system is to compare the demand with the available supply at a given time t [144]:

$$P(t) = \frac{Supply(t)}{Demand(t)} \in [0, 1]. \tag{6}$$

This normalized metric is equal to 1 if the current supply matches the requested demand and lower than 1 if the demand cannot be fully served. As supply and demand are general aspects of CIs, the metric can be applied to any CI. For example, empirical analysis showed that the number of customers with power supplied over time follows the typical shape of the resilience curve (see Figure 1) in the case of Hurricane Sandy [145, 72].

Another general performance metric [146] relates the *recovery* at time t to the *loss* suffered by the system at a previous point in time t_d, i.e.,

$$P(t) = \frac{Recovery(t)}{Loss(t_d)} = \frac{\phi(t) - \phi(t_d)}{\phi(t_0) - \phi(t_d)} \tag{7}$$

where t_d can be chosen as the point of minimum performance ϕ, quantifying the normalized progress of the recovery process.

A summary metric from these or other performance metrics can be obtained, for example as the residual performance, disruption duration, integral of performance, recovery rate, or an ensemble of measures [12]. For example, the integral proposed by Bruneau [147]

$$R = \int_{t_0}^{t_e} (P_{max} - P(t))\, \mathrm{d}t \tag{8}$$

addresses the cumulative loss of performance, under the assumption that the performance can be related to a constant maximum value.

Often, it is practical to normalize R for easier comparison, for example as

$$R^* = \frac{1}{P_{max}} \frac{\int_{t_0}^{t_e} P(t)\mathrm{d}t}{t_e - t_0} . \tag{9}$$

Defining the end time t_e reasonably often represents an issue, as it directly influences R and R^*, impeding comparability for different courses of $P(t)$.

6.2. Domain-specific Examples

Several resilience metrics have been developed and tailored to the context of certain CI domains. In power systems, the "Energy not supplied (ENS)" metric, which can be formulated as an integral of (6), is commonly used for risk management and reliability assessment [148]. The "Value of Lost Load (VoLL)" is a similar summary metric, describing the economic costs of an interruption of electricity supply [149]. Besides, the traditionally used "N-k" criterion, considering the failure of any k electrical devices in the system, can be categorized as reliability measure, but not as a resilience metric. While this deterministic measure can assess system reliability for random, independent events, it is not suitable in the context of rare disaster events, e.g. the failure of many components within a certain area.

Assessing the resilience of water distribution systems has been increasingly discussed in recent years. A systematic literature review of the body of knowledge on the topic can be found in [143]. It was found that performance-based metrics were used more frequently than graph-based metrics. One example is the metric (6) which, in the context of water distribution systems, is known as the "Water Service Availability". Other performance-based metrics, such as the "Todini Index" [150], calculate the system's excess energy as an indicator for the system's robustness against crises. However, the review highlights that most metrics appear to focus on a single function or property of the system, e.g. the ability of a system to perform in a crisis.

In order to quantify resilience in transportation services, a number of metrics have been developed. One approach is to measure the travel time of trips and the extent of deviation in times of disruption [151]. An increase in travel time results in a reduction in throughput, which can be utilized to evaluate the resilience of the transportation system from a performance-based perspective [151, 152]. A comparable approach outlined in [153] assesses performance based on a congestion index. A comprehensive review of other resilience and vulnerability metrics for transportation systems can be found in [154]. The authors of this study found that most resilience metrics are based on travel costs, accessibility, and travel time delays. While such metrics may serve to analyze a situation retrospectively, they may be unsuitable for quantifying the transportation system's response to unprecedented disasters.

6.3. Cross-domain Resilience Assessment

Although a large number of resilience metrics has been proposed by several works in the literature, resilience is typically evaluated within CI sectors individually [11, 7]. Due to the interconnected nature of UCIs and the potential for cascading effects across multiple domains, we claim that the resilience of UCIs is an overarching system property which cannot be assessed for UCIs in isolation; rather, a system-of-systems approach is required. However, the integrated resilience assessment of coupled CIs is an open research question.

There is no general answer to this question, since the optimal approach depends on the underlying goal of the assessment, which differs among specific applications and contexts. A crucial aspect for holistic simulation-based assessment is that the simulation data, from which metrics are calculated, stem from an integrated simulation, where the sub-systems are coupled. Using separated domain simulations without considering interdependencies and cascading effects is inadequate for a holistic assessment. From the simulation results, various metrics of choice can be extracted, describing the performance either for certain sub-systems or the entire system generally. Depending on the application, multiple metrics can be provided to stakeholders for further decisions.

Nonetheless, if a direct comparison between two simulation runs is required, e.g. for deciding which system is "more resilient", an overarching scalar metric must be defined. While defining resilience within certain CI domains is quite challenging alone, defining a metric that captures resilience of UCIs as a whole is even more difficult. There are two principal options: Either defining summary metrics for each sub-system and combining them into a single value, or defining an overarching performance metric, which can then be mapped to a summary metric, e.g. using (8).

For the first option, existing metrics for CI domains in the literature can be adopted. The metrics should reflect stakeholder interests and goals and should be selected with care because different metrics may lead to different outcomes and potentially diverging implications. Then, the summary metrics for each sub-system

R_k have to be consolidated in a sensible way. Commonly, the weighted average has been used [155, 60, 156], i.e.,

$$\bar{R} = \sum_{k=1}^{K} w_k R_k \; . \tag{10}$$

How to choose the weighting factors is a non-trivial question and depends on several application-specific factors. In essence, the weights quantify the importance of the functionality of each sub-system, which can vary for different stakeholders. Moreover, summing up metrics for different systems implies relating them to a common basis. For example, if the individual metrics can capture the economic losses, the global metric could represent the total economic loss. If the R_k represent a physical quantity, the units have to be matched by the weights w_k.

An alternative is to calculate the product of summary metrics, given that they are normalized to the interval [0, 1] (with 1 meaning fully functional operation):

$$\bar{R} = \prod_{k=1}^{K} R_k \; . \tag{11}$$

This approach has the advantage that a complete failure of one sub-system is represented more significantly in the resulting metric.

If the main focus of an investigation remains on one particular domain, although interdependencies are modeled, it can still be reasonable to use a domain-specific metric only. For example, the resilience of a transportation network coupled with a power network can be assessed with a transportation-related metric, when the power network is regarded as a mere backbone system, whose performance is not directly relevant for the objective [73].

The second option refers to creating an integrated performance metric for the whole system, from which a summary metric can be obtained. This approach may be in favor if a time-dependent evaluation of the interdependent systems is desired. For example in [157], individual performance metrics for CIs were combined as a weighted sum and from the resulting performance curve various resilience measures were derived. New overarching performance metrics could be defined from a user perspective, overcoming the domain-separated perspective. By understanding UCIs as STSs, as depicted in the modeling framework in Figure 6, a measure that shall be optimized should actually be formulated from a human centered view. Such metrics could aim to represent the overall well-being of citizens more precisely, especially during crisis situations. For instance, the impact of unavailable water supply is contingent upon the time of day and the specific location of individuals. As another example, the individual perception of the consequences of a power outage likely exhibits a non-linear pattern, in contrast to economic measures.

6.4. General Resilience Assessment

The assessment of resilience can be further generalized to consider the inherent uncertainty of crisis events. The above presented methodology can be used to calculate a summary value R for *one* specific scenario. However, this is not enough to assess the *general resilience* of a system. Different kinds of scenarios as well as uncertainty within a scenario need to be considered in the assessment.

In the literature, many studies often limit the focus of resilience assessment and enhancement to one certain type of hazard. In this case, the *specified resilience* [6] to this particular disruptive event can be evaluated. Nonetheless, it is hard to generalize the specified resilience of UCIs for one hazard type to other types of hazards because the impact on CIs can strongly depend on the type of event. For example, an earthquake would create another kind of impact on CIs than a flood or a blackout caused by a cyber attack.

In order to gain a more accurate understanding of the system's general resilience, a holistic resilience assessment is required that considers a diverse range of scenarios. Resilience also includes to consider unexpected events; however, unknown disruptions cannot be simulated in advance. Therefore, the most effective approach might be to simulate a wide range of known scenarios with as many variations as possible to adequately capture the potential consequences on UCIs. As the impact modeling needs to be done for each event type individually, it can be a huge effort to include many event types. In addition, it might be challenging to find metrics that are general for all scenarios, as many suggested metrics were designed specifically for certain events [143].

Also, the uncertainty within a specific hazard type should be reflected in the analysis. While past events can be used as a reference, future occurrences of the same hazard need to be expected in different settings. Scenarios can be parameterized to simulate variations, including different intensities, areas of impact, and varying environmental conditions. Probabilistic impact modeling, as described in Section 5.3, may be advantageous to comprehensively cover the space of potential consequences to the system. For this task, Monte Carlo simulations may be utilized as a method of addressing the issue of probabilistic modeling.

Furthermore, sensitivity analysis and the concept of model selection (see Section 4.5) can assist in capturing the impact of uncertainties in models.

To effectively assess the simulation results among many scenarios, the metrics obtained for each scenario need to be combined. When considering performance metrics, the mean, median, and percentiles of the resilience curve could be plotted, resulting in an "expected trajectory" [12]. Nevertheless, meaningful summary statistics from a set of summary metrics are required for quick comparisons. From all resulting metrics for each scenario, a histogram could be obtained, representing a probability distribution for the metric, e.g. the ENS [148]. The statistical nature of this distribution can be analyzed and characteristic statistics can be derived. The expected value $E(R)$ of a resilience metric R has been called "expected resilience" [158].

While the mean can serve as an indicator for the average impact, concerns have been raised that optimizing only the mean value is subject to a risk-neutral approach, which neglects extreme values, i.e. significant impacts on the system [148]. To better account for high impact low probability (HILP) events as a risk-averse approach, which is fundamental in the resilience concept, rather a quantile of the distribution $F_R^{-1}(1-\alpha)$, i.e. the value at risk (VaR) or the conditional value at risk (CVaR) need to be considered. The CVaR quantifies the expectation of the occurrences above the VaR, i.e. representing the worst-case scenarios, as

$$\mathrm{CVaR}_{1-\alpha}(R) = \mathrm{E}\left(R \middle| R > F_R^{-1}(1-\alpha)\right) . \tag{12}$$

6.5. *Resilience Assessment in DTs*

Resilience assessment plays an important role for DTs in the context of crisis management, particularly in a real-time context. In a DT, where the virtual replica contains information about the current state of the real system, a "resilience monitoring" could provide an online evaluation of the current performance and resilience capabilities of UCIs. DTs can leverage resilience assessment and monitoring of UCIs and can connect simulation-based with empirical assessment.

Various relevant performance metrics, either domain-specific or overarching, could be provided to stakeholders, experts, and decision-makers in real-time. This could offer a comprehensive overview of the current state of UCIs, without the need of choosing a certain metric. The online monitoring of performance metrics is only possible for metrics that are defined on the basis of the current or past states of the system. In particular, for calculating a metric all required data based on the definition of the metric needs to be available. This is only possible with an ideal virtual replica. Practically, there will always be time delays due to data transmission and processing. The fact that measurement values can be obtained with different sampling resolutions and the delays can vary needs to be considered in the implementation. Also, not all information about every component might be available, in contrast to a simulation. Thus, the missing data might need to be estimated or the metric must be able to deal with missing data, introducing uncertainty. Especially during a crisis, when UCIs and the real-time data infrastructure might be damaged, this could be an issue. The resulting uncertainty in the performance metric should be communicated to the user.

Also time-independent resilience metrics such as summary metrics can be determined in a DT. The results from what-if and scenario simulations (see Section 3.4) can be used to compute desired metrics, summarizing the impact of a scenario quantitatively. Considering the previously discussed aspects for general resilience assessment, a more comprehensive assessment could be done with several simulations under different conditions and events. By summarizing the results, the resilience on the basis of the current state of the system could be determined. Moreover, comparisons with altered system states could be conducted.

While many models for CI assessment focus on certain resilience phases, often neglecting the prepare and adapt phase [65], a DT could provide resilience assessment for every moment in time and during all resilience phases. For example, during the normal operation, the impact of temporal maintenance works and resulting unavailability of redundant components on the reduction in resilience capabilities against potential impact events during this situation could be assessed. Moreover, during an ongoing crisis, the resilience of the damaged system to additional disturbances could be evaluated, addressing the paradigm of *multi-crises*.

Nevertheless, to comprehensively evaluate general resilience, especially when including probabilistic modeling, a large number of simulations is needed, making Monte Carlo simulation computationally challenging. For this reason, often a compromise between depth of assessment and computation time has to be made. Especially during critical situations, a timely result is of relevance. As individual simulation runs do not dependent on each other, they could be parallelized. Given sufficient computing resources and a scalable software platform architecture for the DT, Monte Carlo simulations for such assessments could be feasible.

Empirical resilience assessment is usually done retrospectively, since it considers the complete evolution of a scenario until the system has recovered, as described above. If a DT stores all data from the virtual replica in a database, recordings from previous events can be analyzed. Moreover, the same event can be simulated with enhanced CI systems to evaluate the level of adaptation. However, the empirical assessment during a crisis event in real-time is limited since only information up to the current time would be available. Therefore, the simulation-based resilience assessment on the basis of the system's current state as described above could provide highly valuable information, presenting a significant advancement for disaster management.

7. Conclusion & Outlook

In this work, we explored the application of the DT concept to improve the resilience of UCIs. After identifying various challenges associated with the application of UDTs, we defined overarching concepts that facilitate the creation of a UDT. We then presented a modeling framework, which enables a holistic view on UCIs as system-of-systems, designed for what-if analyses and comprehensive resilience assessment.

Key challenges for the development and application of UDTs have been discussed. Beside domain-specific challenges, there are several general challenges that impede the application of DTs in the context of CIs. These challenges are of technical nature (e.g. providing IT infrastructure), conceptual nature (e.g. defining models and developing simulation platforms), and of practical nature (e.g. overcoming political and administrative barriers). While some of those challenges can be overcome with sufficient financial resources, societal efforts, or future research, other challenges appear to be of fundamental nature, such as validation, data scarcity for rare events, and the impossibility of experimentation.

Major concepts regarding the modeling and analysis of UCIs were defined to address the challenges involved. In particular, modeling concepts for UCIs have been presented to deal with the complexity of urban areas. The application of ABM as a bottom-up approach emerged as a suitable approach for modeling cities as STSs and has been discussed in the context of CIs. The novel STDT concept addresses the socio-technical interdependencies of UCIs, providing a basis for future DT applications related to urban areas. Furthermore, we identified concepts to facilitate the modeling process for UDTs. The introduced concept of model selection can help reducing model uncertainties, which in turn reduces computational efforts for probabilistic resilience assessment. The discussed transfer of models can overcome the issues of data scarcity among CIs.

A modeling framework for UCIs considering the three dimensions of technical system, social system, and environment has been proposed. This framework can serve as a cornerstone for the integration of socio-technical modeling in DTs and CI simulations. The integrated modeling of socio-technical facets and CI dependencies offers a holistic approach for measuring the resilience of cities. By combining ABM with network-based simulations, the approach can deal with the complexity of CIs, allowing for the analysis of emergent effects. Specific implementation approaches were presented for the modeling concepts interdependencies, ABM, and synchronization, as well as technical and social models for the domains of power, water, and transportation systems. Finally, the environmental part provided an overview for the modeling of external impact events considering diverse threat scenarios.

Our study significantly contributes to the discourse on urban resilience by offering insights into the challenges, identifying conceptual methodologies, and presenting concrete modeling approaches. By framing UCIs as STSs and incorporating the human influence throughout the modeling process, our approach offers a more comprehensive understanding of the intrinsic complexities of urban systems. We provided a comprehensive overview for mastering the quantitative resilience assessment of UCIs, including a discussion of resilience and performance metrics, as well as general considerations for the integrated assessment of interdependent UCIs. As cities continue to evolve and face unprecedented challenges, the application of DTs emerges as a promising path for strengthening urban resilience, ultimately ensuring the well-being and stability of urban populations in the face of unforeseen crises.

7.1. Practical Implications

The proposed framework for UDTs gives rise to a number of practical implications, which will be discussed in the following. As the framework was defined in a general approach for UCIs, a large spectrum of applications can be created. The proposed framework has a range of practical implications spanning from urban crisis management, AI-driven decision support systems, over assessing infrastructure resilience to optimization and planning.

UDTs can significantly improve crisis management strategies by providing real-time insights and leveraging what-if simulations for safe, rapid, and interactive experimentation. This allows decision-makers to assess potential outcomes and implement optimized response strategies quickly, which mitigates damages. Municipal authorities and emergency services can better anticipate and prepare for a wide range of crisis scenarios, such as natural disasters, power outages, or transportation disruptions by simulating their consequences, thereby enhancing overall urban resilience. For example, in the event of a power grid failure, the UDT can simulate cascading effects on water and transportation systems, enabling more informed and coordinated responses. The UDT could serve as a control center and provide decision support systems that assist decision-makers of crisis management in making data-informed decisions and propose mitigation strategies to prevent or minimize cascading failures. In this context, the human-in-the-loop concept plays a major role [13]. Smart decision support tools can be implemented for example by offering multiple alternatives, with a summary of their consequences obtained through simulations. AI-driven tools can be leveraged for example by using historical data of human decisions and computational intelligence methods for finding optimal solutions.

UDTs can be enriched with spatial information such as 3D models of the urban area for making the human-computer interface (HCI) with the virtual replica more visual for the user [13]. By adding the time dimension, this could provide a temporal-spatial 4D model, which can be combined with VR/AR techniques for immersive monitoring and what-if analyses. These capabilities can support authorities in visualizing complex systems and preparing more effectively for real-world crises. Moreover, UDTs can be employed for training emergency response teams by virtually replaying various recorded or hypothetical crisis scenarios. This capability allows authorities to prepare for complex crises, training personnel on potential real-life situations, and optimizing response strategies.

Additionally, the presented methodology paves the way for continuous monitoring and assessment of UCI performance and resilience in UDTs. By accounting for interdependencies between UCIs and cascading effects, the multi-layered approach allows for a holistic evaluation of urban resilience across various hazards. With the quantitative evaluation of UCI resilience, different system configurations and extensions can be compared comprehensively and objectively. This enables the cost-efficient optimization of the system as a whole, maximizing resilience with limited resources for infrastructure investment.

The framework and resilience assessment methodology can further be used to identify vulnerabilities within urban systems in a proactive way. For example, critical nodes for the restoration of the system including the associated costs can be analyzed and optimized [159]. Whether in normal operations or crisis scenarios, the UDT can highlight critical elements within these systems, providing stakeholders with the opportunity to address weak points early before they cause widespread disruption. Moreover, the influence of individual nodes and links on the overall resilience can be quantified, providing an indicator for their importance and vulnerability within the interconnected networks.

In the context of real-time monitoring, UDTs provide an ideal platform for anomaly detection applications, even across CI domains. With the extensive amount of continuously collected data, anomaly detection methods can be developed, possibly in combination with AI-based technologies, for example by comparing the system state with past data. This way, UDTs enhance situation awareness and promote the early detection of failures and emerging issues, which ultimately improves overall urban resilience.

Moreover, UDTs enable city planners and infrastructure operators to optimize maintenance schedules and resource allocation. This predictive maintenance capability can minimize service disruptions of UCIs and reduce costs by accurate predictions of infrastructure component failures, reducing service disruptions. By anticipating maintenance needs, cities can prevent system breakdowns and ensure the continuous operation of essential services.

The proposed UDT framework fosters collaboration across different CI sectors, such as power, water, and transportation, by providing a unified platform for data exchange and scenario modeling. In the face of the apparent CI dependencies, operators from different domains can work together in a more coordinated manner by enhancing communication and data exchange for improved crisis responses. Urban data platforms and knowledge bases can play an essential role in this context. This cross-domain integration strengthens the city's overall resilience by reducing silos and enhancing cooperation among stakeholders.

The socio-technical modeling approach, which includes human behaviors and interactions with urban systems, allows urban planners and policymakers to create more resilient cities by understanding how societal factors influence the functioning of UCIs. For example, the UDT can simulate the impact of population behavior during a crisis, such as evacuation patterns, or assess the social impacts of infrastructure failures on different demographic groups. This ensures that resilience strategies are not only technically sound but also socially equitable, leading to more inclusive urban resilience planning.

7.2. Future Work

Although the conceptual challenges are partially addressed by our proposed concepts and modeling framework, several aspects necessary for leveraging UDTs remain open for future research. While some of them concern the development of novel methods for sub-functionalities in the UDT, others require focus on the advancement of interdisciplinary tools and standards. Beside research-related challenges, several practical challenges need to be solved by practitioners and policymakers until UDTs are established in future smart cities.

Our interdisciplinary modeling framework pointed out the need for comprehensive simulation tools for UCIs with new interfaces for their use in DT simulations. In addition, appropriate IT platforms for future UDTs need to be designed to leverage the extensive simulation tools using cloud computing or edge computing. Future conceptual efforts could also be devoted to developing standards for interdisciplinary data exchange and urban data platforms.

The potential of machine learning and AI-based techniques within the DT concept needs to be investigated in more detail. The applications are manifold, spanning across several functionalities within the DT, but may also be limited in some aspects. In an industrial context, AI-based methods in DTs are mainly focused on model creation, big data analytics, and optimization of production processes [43]. In the context of UCIs and crisis management, the application of data-driven methods is manifold, though differs from applications in industrial contexts. Modular UDT designs allow for a flexible modeling approach where individual models can be supplemented or replaced with data-driven models. This could help to improve accuracy compared to physical modeling, especially if the system behavior is non-linear or is hard to model analytically. However, as black-box approaches are often bad in generalizing system behavior to unseen situations, e.g. critical events, it should be considered with care, especially if the data does not cover extreme operating points. Employing gray-box modeling could be interesting in this regard to combine the advantages of physical and data-driven modeling.

An important aspect of a UDT is the human-computer interface (HCI). How to quickly and comprehensively grasp and monitor the extensive amount of temporal-spatial data contained in the virtual replica is subject to open research questions. Furthermore, the integration of human and artificial intelligence in the human-in-the-loop concept is a major challenge for which more research is needed.

As has emerged, assessing the resilience of multiple CI in an integrated way is still open for research. Based on the presented principal approaches, applying resilience assessment in case studies and evaluating their practical feasibility could yield useful insights. Standardized methods for resilience management and assessment can aid the broad implementation of resilience-enhancing measures in practice.

As a UDT is meant to operate continuously, like UCIs, system changes need to be considered in a long-term context. This concerns for example the monitoring of system properties that are actually considered static, for example, changing system parameters due to aging, or drifts in demand patterns.

In this study, we focused particularly on the city scale. However, CIs are intertwined also at larger scales. Thus, large-scale DTs, such as nation-wide DTs, or federations of DTs are the next step.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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