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ÚSTAV ELEKTROENERGETIKY

ADVANCED TOOLS FOR CRITICAL INFRASTRUCTURE ANALYSIS

POKROČILÉ NÁSTROJE PRO ANALÝZY KRITICKÝCH INFRASTRUKTUR

DOCTORAL THESIS
DIZERTAČNÍ PRÁCE

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ABSTRACT

This doctoral thesis focuses on advanced methods and tools for simulating and analyzing interdependent critical infrastructures, with a primary emphasis on the energy and data communication sectors. The motivation arises from the growing complexity and interconnectivity of urban infrastructures, which introduce new challenges related to reliability, unavailability, cascading failures, and maintenance planning. The proposed platform enables combined simulation of multiple infrastructure layers through a modular and scalable architecture, allowing future integration of additional systems such as water supply, transportation, or gas networks. A key contribution is the implementation of a structured simulation engine based on state matrix management, which enables detailed tracking and visualization of failure propagation and mutual dependencies across domains. Reliability analysis is supported by stochastic modeling techniques, including time-dependent unavailability evaluation using Weibull distributions and the simulation of corrective and preventive maintenance strategies. The platform includes a graphical user interface with map-based visualization, supporting intuitive scenario design and resilience assessment. A dedicated module for maintenance optimization was implemented, leveraging reliability metrics to identify cost-effective maintenance schedules. A novel synthetic test network combining power and data infrastructures was developed to evaluate the simulator's capabilities and support reproducible research. The platform was validated using both anonymized real-world data and synthetic scenarios, and its performance and accuracy were benchmarked against existing open-source reliability tools. The presented research delivers a robust simulation and analysis framework for interdependent infrastructure systems and supports informed decision-making in the domains of energy and communication. It establishes a foundation for future developments in predictive maintenance, interdependency modeling, and resilience assessment in smart city environments.

KEYWORDS

Critical infrastructure, interdependency, simulation platform, smart grid, reliability analysis, unavailability modeling, maintenance optimization, cascading failures, communication network.

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ROZŠÍŘENÝ ABSTRAKT

Tato disertační práce se zabývá využitím pokročilých metod a nástrojů pro analýzy vzájemně propojených kritických infrastruktur, se zvláštním zaměřením na elektroenergetické sítě a datové komunikační systémy. Motivací k výzkumu je vzrůstající úroveň vzájemného propojení a digitalizace těchto infrastruktur, které přinášejí nové výzvy v oblasti spolehlivosti, dostupnosti a analýzy šíření kaskádních poruch. Práce je koncipována jako soubor komentářů k celkem devíti recenzovaným publikacím, které byly publikovány v časopisech, nebo autorem prezentovány na odborných konferencích. Ty pokrývají tři hlavní oblasti výzkumu: (i) návrh a vývoj simulačního nástroje, (ii) modelování nedostupnosti systému a optimalizaci údržby a (iii) ověření aplikovaných metod na reálných scénářích. Platforma umožňuje vícevrstvou simulaci vzájemně propojených infrastruktur s modulární a škálovatelnou architekturou a podporou budoucí integrace dalších subsystémů (například vodárenství, dopravy nebo plynárenských sítí). Klíčovým prvkem platformy je implementace simulačního jádra založeného na správě stavové matice, která umožňuje detailní sledování a vizualizaci šíření poruch a vzájemných závislostí. Pro hodnocení spolehlivosti byly do simulační platformy implementovány stochastické modely zahrnující časově závislé výpočty nedostupnosti na základě Weibullova rozdělení a simulace strategií korektivní i preventivní údržby. Součástí platformy je grafické uživatelské rozhraní s možností vizualizace na mapových podkladech a také modul pro analýzu optimalizace údržby, který využívá metriky spolehlivosti a odolnosti sítí k návrhu nákladově efektivních plánů údržby. Významnou částí výzkumu byla průběžná validace používaných metod na různých testovacích sítích. Kromě využití existujících modelů byl pro účely prezentace výsledků a funkcionality simulátoru navržen a implementován nový model propojující elektroenergetickou a datovou infrastrukturu. Dále byla v práci navržena metodika pro identifikaci klíčových parametrů a závislostí v rámci propojených infrastruktur. Platforma byla postupně optimalizována z hlediska výpočetního výkonu, kdy byly testovány alternativní datové formáty a možnosti škálovatelnosti výpočtů pro velké modely. Dále byla provedena srovnávací analýza platformy s dostupnými open-source nástroji, která potvrdila vyšší přesnost a výpočetní efektivitu vyvinutého řešení. Výsledky výzkumu poskytují praktické nástroje pro hodnocení rizik, předpověď poruch a optimalizaci spolehlivosti v propojených infrastrukturách. Simulační platforma je využitelná především pro provozovatele distribučních sítí a městské správce pro podporu plánování investic, návrhu strategií údržby a hodnocení odolnosti v projektech chytrých měst. Práce zároveň vytváří metodologický základ pro budoucí vývoj v oblastech prediktivní údržby, modelování vzájemných závislostí a hodnocení kyberfyzikálních interakcí v rámci digitalizovaných a decentralizovaných infrastruktur.

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Author's Declaration

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Academic year:	2024/25
Topic:	Advanced Tools for Critical Infrastructure Analysis

I declare that I have written this paper independently, under the guidance of the advisor and using exclusively the technical references and other sources of information cited in the paper and listed in the comprehensive bibliography at the end of the paper.

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author's signature*

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Contents

List of Authors Publications

This doctoral thesis consists of a summary and of the following publications, which are referred to in the text by their numerals. Further details of these publications, including a description of the author's involvement, are in Appendix A of this thesis.

I. Matej Vrtal, Jan Benedikt, Radek Fujdiak, David Topolanek, Petr Toman, and Jiri Misurec. Power grid and data network simulator. *2022 22nd International Scientific Conference on Electric Power Engineering (EPE)*, pages 1–4, Kouty nad Desnou, Czech Republic, 2022. doi:10.1109/EPE54603.2022.9814104.

II. Matej Vrtal, Jan Benedikt, Radek Fujdiak, David Topolanek, Petr Toman, and Jiri Misurec. Investigating the possibilities for simulation of the interconnected electric power and communication infrastructures. *Processes*, 10(12):2504, 2022. doi:10.3390/pr10122504.

III. Matej Vrtal, Vit Krcal, and Petr Toman. Application of graph theory in urban infrastructure analysis. *27th International Conference and Exhibition on Electricity Distribution (CIRED 2023)*, pages 3954–3957, Rome, Italy, 2023. doi:10.1049/icp.2023.0505.

IV. Matej Vrtal, Radek Fujdiak, Jan Benedikt, David Topolanek, Michal Ptacek, Petr Toman, and Jiri Misurec. Determination of critical parameters and interdependencies of infrastructure elements in smart grids. *2023 23rd International Scientific Conference on Electric Power Engineering (EPE)*, pages 1–6, Brno, Czech Republic, 2023. doi:10.1109/EPE58302.2023.10149250.

V. Matej Vrtal, Radek Fujdiak, Jan Benedikt, Pavel Praks, Radim Bris, Michal Ptacek, and Petr Toman. Time-dependent unavailability exploration of interconnected urban power grid and communication network. *Algorithms*, 16(12):561, 2023. doi:10.3390/a16120561.

VI. Matej Vrtal, Jan Benedikt, Radek Fujdiak, Pavel Praks, and Petr Toman. Computation time optimization strategies for critical infrastructure simulator. *Proceedings of the 12th International Scientific Symposium on Electrical Power Engineering (ELEKTROENERGETIKA 2024)*, pages 123–130, Stara Lesna, Slovak Republic, 2024.

VII. Matej Vrtal, Michal Beloch, Pavel Praks, Radek Fujdiak, Jan Benedikt, and Petr Toman. Comparative evaluation of open-source tools for infrastructure reliability analysis. *Proceedings of the 12th International Scientific Symposium on Electrical Power Engineering (ELEKTROENERGETIKA 2024)*, pages 131–138, Stara Lesna, Slovak Republic, 2024.

VIII. Matej Vrtal, Daniel Krpelik, Pavel Praks, Radim Bris, Radek Fujdiak, and Petr Toman. Improving smart grid resilience using unavailability analysis and maintenance optimization. *IET Conference Proceedings CP882*, 2024(27):212–216, 2024. doi:10.1049/icp.2024.2600.

IX. Matej Vrtal, Vit Krcal, Jan Koudelka, Daniel Krpelik, Radek Fujdiak, and Petr Toman. Resilience analysis in medium voltage distribution system: case study. *IET Conference Proceedings CP882*, 2024(27):217–221, 2024. doi:10.1049/icp.2024.2601.

List of Figures

List of Tables

Introduction

The proper functioning of critical infrastructures is essential for societal and economic stability worldwide. These infrastructures, encompassing sectors such as energy, transportation, water supply, telecommunications, and healthcare, represent essential support systems for the functioning of contemporary society and its economy. They enable the delivery of essential services that populations and economies depend on daily. However, as societies become increasingly interconnected and reliant on complex technological systems, these infrastructures are exposed to a growing range of threats, including natural disasters, technical failures, cyber-attacks, and malicious acts. The disruption of even a single component can lead to cascading effects, potentially paralyzing key societal functions and endangering public safety. As a result, governments and institutions have prioritized the development of strategies to enhance the resilience, security, and operational continuity of these vital systems.

From the perspective of the European Union (EU), specifically the European Commission (EC), critical infrastructure plays a pivotal role in enhancing quality of life, security, and the efficient functioning of markets across member states. Through the European Programme for Critical Infrastructure Protection (EPCIP) and Directive 2008/114/EC, the EU provides a methodological framework for identifying, assessing, and protecting critical infrastructure components. These regulations primarily focus on the energy and transportation sectors, but their implementation is delegated to individual member states, allowing adaptation into national legislation while adhering to a unified European methodology.

The directive outlines two fundamental approaches for identifying critical infrastructures. The cross-sectoral approach focuses on potential economic or societal impacts, including extreme scenarios where failures in emerging infrastructure could lead to loss of lives. Additionally, the sector-specific approach identifies distinct types of critical infrastructure within each domain. Regular review and reassessment of these infrastructures are required to ensure their resilience and adaptability to emerging challenges [1].

To support the analysis, design, and deployment of modern critical energy infrastructures, the EU introduced the smart grid architecture model (SGAM), illustrated in Figure 1. SGAM provides a standardized, technology-neutral framework for representing and evaluating smart grid use cases. It ensures interoperability across systems, stakeholders, and technologies while facilitating comparisons between various smart grid solutions. The model is structured around three primary axes: domains, zones, and interoperability layers. Domains represent stages in the electrical energy value chain, including bulk generation, transmission, distribution, distributed energy resources (DER), and customer premises. Zones capture the hierarchical control levels within the power system, ranging from physical processes to market-level operations. Interoperability layers address integration across business processes, functions, information flow, communication protocols, and physical components. SGAM aligns with the EU's overarching goal of enhancing critical infrastructure resilience. By promoting standardized methodologies it supports the integration of advanced technologies, strengthens cybersecurity, and improves the reliability and operational efficiency of modern energy networks. As smart grids evolve, SGAM serves as a foundational tool for ensuring adaptability and long-term sustainability.

In the legislative framework of the Czech Republic, critical infrastructure is defined by Act No. 240/2000 Coll., which describes it as an element or a set of critical infrastructure elements whose disruption would have a severe impact on national security, the provision of essential life needs for the population, public health, or the national economy. Czech legislation also defines the concept of European Critical Infrastructure (ECI), understood as infrastructure located in the territory of the Czech Republic, whose disruption would significantly affect another EU member state.

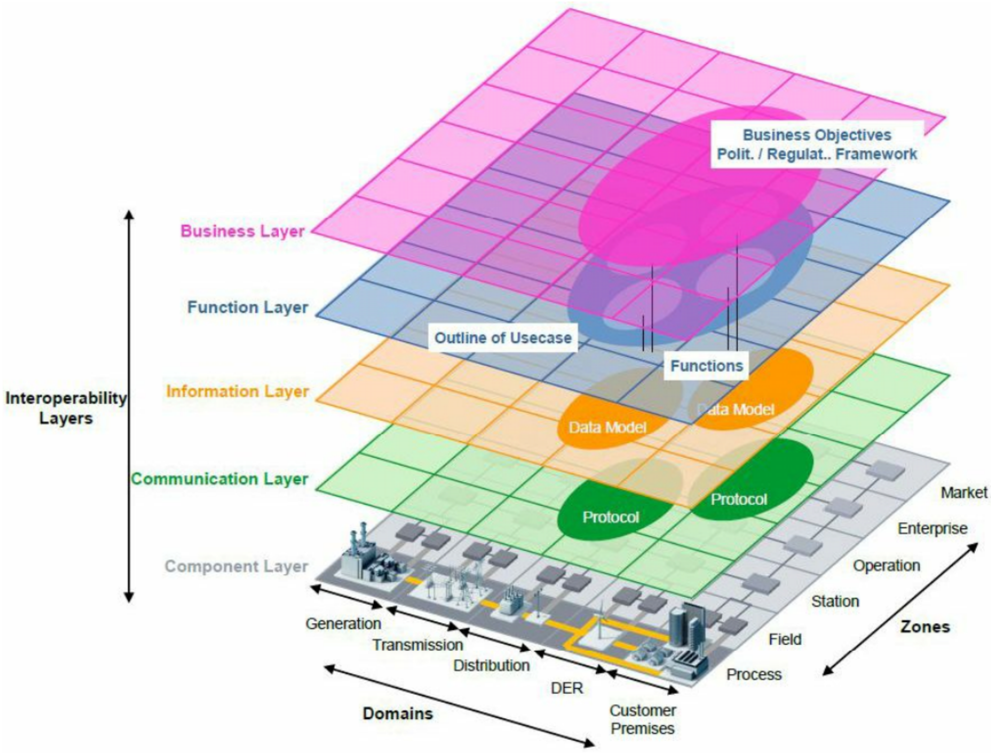


Figure 1: Smart grid architecture model introduced by the EU [2].

In determining a critical infrastructure element, the designation is categorized into two groups. Such an element generally encompasses buildings, facilities, resources, or public infrastructure. If it forms part of the ECI, it is classified accordingly. As specified in Section 2 of Government Decree No. 432/2010 Coll., critical infrastructure is organized into several sectors, including energy, water management, food and agriculture, healthcare, transportation, communication and information systems, financial markets and currency, emergency services and public administration.

Although energy and communication systems are considered two distinct sectors from a legal perspective, they are deeply interconnected and mutually dependent. One of the roles of the energy network is to supply power to communication and control data networks, while the control network is responsible for managing specific sections of the energy network. To prevent unexpected outages, it is essential to analyze and simulate the behavior of both infrastructures under modeled scenarios. The contribution to addressing this issue through the development of a simulation platform is precisely the focus of this thesis. The results of simulations can significantly contribute to improving the resilience and protection of both infrastructures and also improve reliability indicators. Such simulations can reveal cascading failures caused by domino effects, which are often difficult to detect without a comprehensive analysis. These findings underline the necessity of an integrated approach to the management and optimization of interconnected critical infrastructures [3].

Interdependence and Resilience of Critical Infrastructures

In recent years, the interdependence between critical urban infrastructures, particularly power grids and data networks, has become crucial for maintaining societal and economic stability. Rapid technological advancements and the growing reliance on digital systems have intensified these interconnections, introducing vulnerabilities that can compromise infrastructure resilience. A key concern is the risk of cascading failures, where a localized issue in one system propagates through interconnected networks, potentially causing widespread service disruptions and threats to public safety. Understanding and addressing these vulnerabilities is essential for enhancing the resilience of critical infrastructures.

The increasing integration of advanced technologies and intelligent devices into power grids has amplified the complexity of infrastructure management. Modern grids rely on vast volumes of data generated by DERs, smart meters and automation systems. These data streams are essential for real-time monitoring, control and optimization of grid operations but simultaneously introduce challenges related to data latency, cybersecurity and communication reliability. Information flows bidirectionally between generation, transmission, distribution and end-user systems, highlighting the significant role of data networks in supporting the operational stability of the power grid. As infrastructure complexity grows, the dependency on robust communication networks becomes more pronounced, requiring advanced data processing techniques, secure communication protocols and resilient architectures to maintain reliable power delivery. This relationship is illustrated in Figure 2, which depicts the flow of information and energy across the interconnected systems, emphasizing the critical role of data networks in supporting power grid stability and functionality.

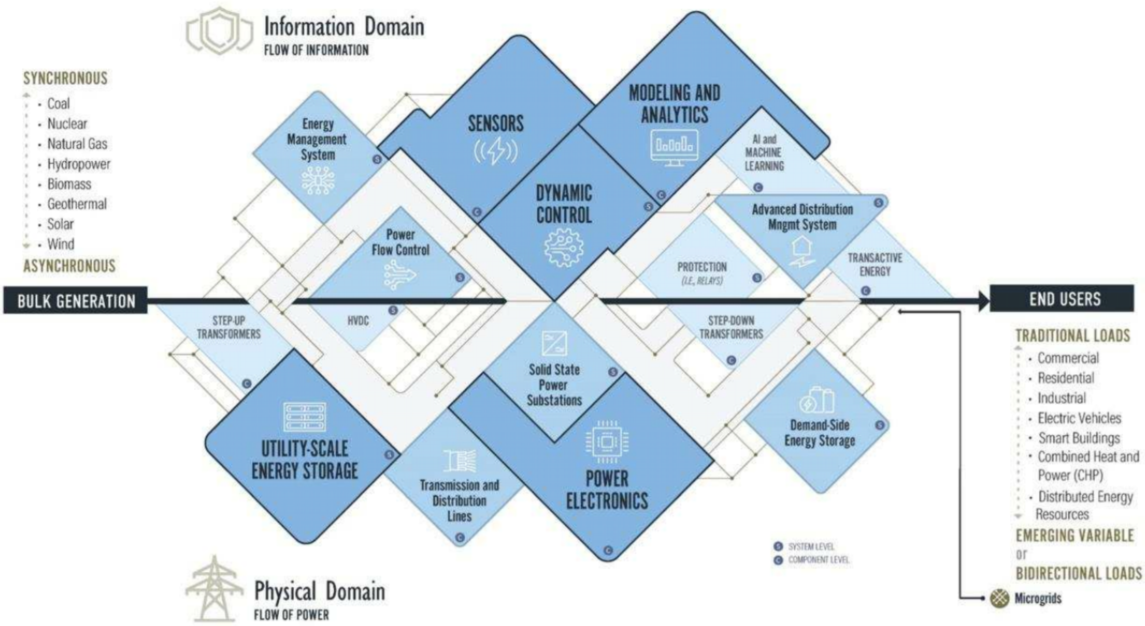


Figure 2: Increasing information loads on the evolving power grid [4].

The importance of understanding these dependencies is highlighted by real-world incidents that have demonstrated the cascading effects of infrastructure failures. A notable example is the 2003 Italy blackout, where failures in cross-border electricity transmission lines led to widespread power outages affecting over 56 million people and causing significant disruptions in telecommunications, transportation and healthcare services [5]. Similarly, the 2006 Germany blackout exposed vulnerabilities in rail transport and industrial operations, as mismanagement of grid maintenance triggered cascading failures across multiple European countries, leading to railway disruptions in France, Spain and Italy [6]. Beyond blackouts, cyber threats have also illustrated the interconnected nature of infrastructure, as seen in the 2015 Ukraine power grid cyberattack, where a coordinated attack on supervisory control and data acquisition (SCADA) systems resulted in power outages and affected financial and communication systems [7]. Additionally, supply chain disruptions, such as the Colonial Pipeline ransomware attack in 2021, though primarily affecting the United States, demonstrated the global impact of cyber vulnerabilities, influencing fuel prices and aviation logistics in Europe [8]. These incidents underscore the necessity for integrated simulation and risk assessment models that account for interdependencies between energy, communication and transportation systems to improve infrastructure resilience. The growing interest in this topic is also evidenced by the steadily increasing number of publications in the field. Figure 3 illustrates the total number of publications focused on "smart grid", "critical infrastructure", "infrastructure resilience" and "reliability modeling" since the year 2000, based on data retrieved from the database [9].

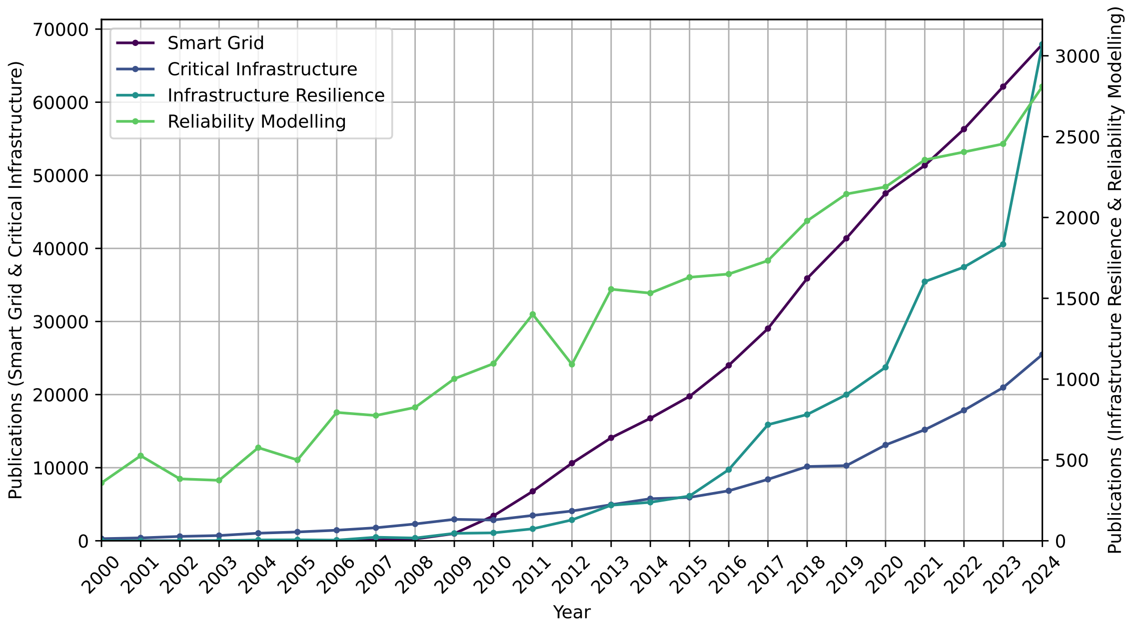


Figure 3: Number of publications published annually on the given topic based on selected keywords of this doctoral thesis.

Today, energy and communication infrastructures are increasingly adopting decentralized architectures enabled by intelligent technologies for control, monitoring and management. While this evolution improves operational flexibility, it also introduces cyber threats and systemic vulnerabilities that may propagate across interconnected systems. Addressing these risks requires integrated simulation and analytical tools capable of capturing dynamic interdependencies between energy and data networks. Such tools support the identification of critical weak points and the assessment of cascading impacts, enabling the development of targeted strategies to enhance infrastructure resilience. Scenario-based analyses further allow the systematic identification of hidden dependencies, facilitating the design of robust infrastructures and adaptive operational strategies.

Economic and Non-Economic Impacts of Power Supply Interruptions

Interruptions in power supply, whether planned or unplanned, have significant consequences across technical, economic and social domains. While economic losses are often the primary focus when evaluating the impact of outages, a comprehensive assessment must also consider non-economic effects. Therefore, one of the objectives of this thesis is to propose a platform that integrates both economic and non-economic losses to provide a more holistic evaluation framework.

Power supply interruptions can be broadly categorized into planned and unplanned outages [10]. In the context of this thesis, the term power supply interruption specifically refers to unplanned outages, which are inherently more disruptive. Technical analysis alone cannot fully justify decisions regarding network optimization and an economic return on investment is a decisive factor for approving or rejecting infrastructure improvements. The relationship between the costs of investments in grid reliability and the financial impact of outages is illustrated in Figure 4. Distribution system operators (DSOs) aim to approach the optimal cost-efficiency point, denoted as point A in the optimization framework. From a mathematical perspective, this optimization problem corresponds to finding the minimum of a defined cost function [11].

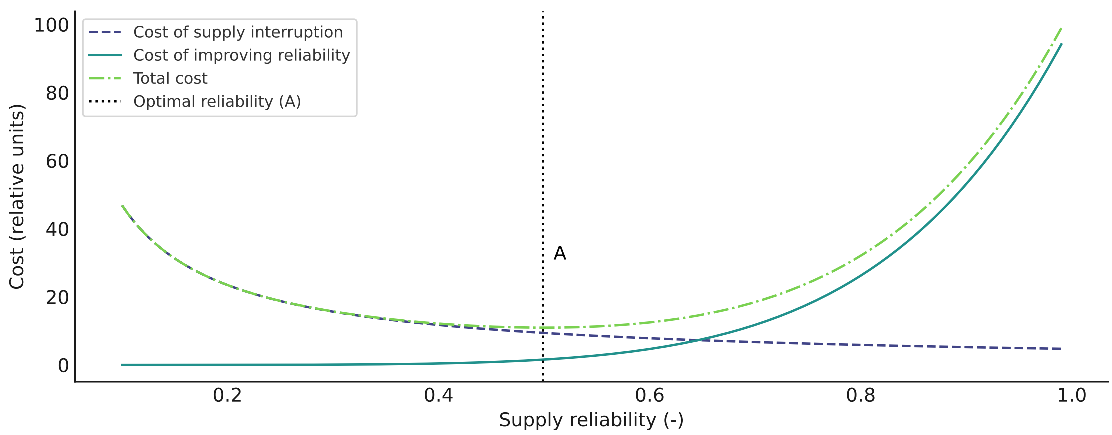


Figure 4: Graphical representation of the relationship between costs associated with investment in grid reliability and costs of power outages, constructed according to the equations presented in [12].

The increasing economic consequences of power outages amplify the demand for reliable grid operation. Optimization tasks in distribution networks focus on balancing operational costs with investments in grid modernization and development.

Subsequent sections of this thesis are therefore focused on exploring optimization methods to enhance grid reliability.

Determining the costs associated with power outages remains a complex challenge. Numerous studies attempt to establish a standardized function for estimating average outage costs based on the type of consumer site. These studies typically classify consumers into four primary groups: industrial, commercial and service, residential and agricultural sectors [13]. Each group exhibits distinct consumption patterns and varying levels of vulnerability to outages.

Power outages result in both direct and indirect economic losses. Direct losses are typically easier to quantify, as they are closely tied to the duration of the outage. Examples of direct losses include production halts, service disruptions (e.g., transportation, telecommunications), revenue losses, equipment damage, data loss, accidents and injuries. In contrast, indirect losses are more challenging to measure because their effects often emerge over time. Examples of indirect losses include increased crime rates (e.g., vandalism, looting), overtime compensation for employees, cancellation of social events, property damage and rising insurance premiums [14]. Research indicates that indirect costs can, in some cases, surpass direct costs [15, 16]. The economic cost of customer interruptions (CIC) is commonly expressed using the following relationship [10]:

$$CIC = \frac{\text{total cost of 1h outage}}{\text{average electricity consumption per 1h}} \quad \text{[EUR/kWh]}. \qquad (1)$$

Over the past few decades, CIC evaluation has become a prominent research area. There are three main methodologies for determining CIC - indirect analytical methods, customer surveys and case studies [17], which were used for this thesis purposes. Indirect analytical methods rely on publicly available data, such as electricity prices, annual energy consumption, or gross domestic product (GDP). While this approach can provide general estimates, it lacks precision [18]. Customer surveys, on the other hand, offer a more targeted method by directly collecting data from affected stakeholders, often yielding more accurate results [14].

In summary, evaluating the impacts of power outages requires a multidisciplinary approach that integrates technical, economic and social considerations. A deeper understanding of these impacts, supported by advanced simulation models and optimization methodologies, is essential for developing strategies that minimize the consequences of outages and enhance grid resilience. For this reason, one of the key objectives of this thesis is the development of a platform that provides a comprehensive perspective on the issue and supports the assessment of interdependencies within interconnected critical infrastructures.

Interconnected System Unavailability and Maintenance Optimisation

Ensuring the reliability and availability of interconnected critical infrastructures requires effective maintenance strategies that balance corrective and preventive maintenance. As these systems grow increasingly complex, incorporating stochastic modeling techniques has become essential for optimizing maintenance schedules and minimizing unavailability.

Mathematical modeling of stochastic processes for infrastructure reliability has been widely explored, with foundational work on Markov regenerative processes and renewal theory providing key methodologies [19, 20]. These models allow for the representation of component failures and renewals, enabling accurate predictions of system behavior over time. While Markov chains offer a well-established framework for modeling multi-state system dynamics [21], they are often constrained by the assumption of constant transition rates. Semi-Markov models extend this approach by incorporating generalized sojourn times, making them more suitable for real-world maintenance processes [22]. Additionally, stochastic Petri nets allow for modeling complex operations with non-exponential failure and repair distributions, though their computational complexity remains a challenge [23, 24].

One of the primary challenges in system unavailability analysis is the state-space explosion caused by the complexity of real-world infrastructure systems. Approximate numerical methods, such as proxels [25] and non-Markov Petri nets [26], have been developed to address this issue and improve computational feasibility. A recurrent integral formula for unavailability has been proposed to provide an analytical framework for assessing corrective maintenance strategies, where system failures are restored immediately upon detection [27]. Additionally, methods for modeling components with latent failures, where failures are only identified during scheduled inspections, have been explored [28]. This thesis includes a comparison of different approaches to unavailability assessment, focusing on evaluating their suitability for application in complex interconnected systems. The unavailability calculations are further utilized for reliability assessment and the analysis of maintenance optimization possibilities.

While corrective maintenance plays a key role in addressing immediate system failures, long-term reliability improvement also requires proactive strategies. In this context, preventive maintenance is crucial in reducing the frequency of sudden failures, particularly for aging components with an increasing failure rate [29]. Compared to corrective restoration, preventive actions provide cost advantages by allowing planned system shutdowns, reducing emergency repair costs and mitigating downtime impacts. However, traditional methods for preventive maintenance scheduling often face computational limitations, particularly in systems where the mean time to failure (MTTF) is significantly larger than the mean time to repair (MTTR).

To address these challenges, modern approaches integrate optimized maintenance scheduling with reliability assessment models, ensuring a balance between operational cost and infrastructure resilience. Analytic simplifications of time-dependent unavailability calculations have been introduced to offer computationally efficient alternatives while maintaining numerical stability for long-term system evaluations [30, 31, 32]. By integrating these methodologies into maintenance planning, this thesis aims to explore possibilities to improve system reliability, minimize economic losses and enhance the resilience of interconnected critical infrastructures.

Reliability and Risk Modelling of Critical Infrastructures

Ensuring the reliability and resilience of interconnected critical infrastructures requires robust risk assessment and predictive modeling. Proactive maintenance strategies and fault analysis techniques play a key role in mitigating failures and minimizing operational disruptions.

Traditional fault tree analysis (FTA) provides a structured approach to identifying failure points and estimating system reliability [33]. Extensions such as event trees and attack trees enhance this methodology by incorporating cybersecurity risks and failure propagation in interconnected systems [34]. Dynamic fault trees further enhance traditional reliability models by incorporating time-dependent behaviors, making them particularly applicable to cyber-physical systems [35, 36].

A systematic review of reliability, availability, maintainability and security methodologies highlights the strengths and limitations of various infrastructure protection techniques, emphasizing the need for holistic and scalable models [37]. Advanced approaches, such as repairable multi-state fault trees, enable more precise reliability predictions based on real-time system data [38]. Despite these advancements, existing simulation tools often lack interoperability and scalability, limiting their application to complex, interdependent infrastructures. Many models focus on specific domains (e.g., power grids or communication networks) without fully capturing cascading failures across multiple sectors. Additionally, computational constraints hinder real-time analysis of large-scale networks [35].

To address these challenges, this thesis aims also to propose a dedicated reliability and risk assessment module as a part of the simulation tool. This module should integrate advanced modeling techniques, enable seamless data exchange between simulation layers and support infrastructure analysis. By filling these gaps, related research can enhance the resilience of interconnected critical systems, optimize failure response strategies and improve risk mitigation in dynamically evolving infrastructures.

Research Objectives and Structure of the Thesis

As already mentioned, this thesis focuses on the development of a software platform designed to simulate the impacts of power grid failures on critical and data infrastructures and vice versa. Insights from previous chapters highlight the necessity of early detection of vulnerabilities within energy infrastructure to enhance its reliability. The proposed simulator primarily targets analyses within energy, communication and data infrastructures. However, it is intentionally designed to allow future integration of additional infrastructures without significant modifications to the software architecture.

A substantial portion of this thesis is dedicated to the reliability of interconnected critical infrastructures and the analysis of strategies for improving reliability metrics. Furthermore, the thesis explores methods for optimizing maintenance processes and enhancing network resilience. Another important goal of this thesis is to evaluate the usability of existing test networks for critical infrastructure analysis and introduce an innovative test network tailored for this purpose.

The primary objectives of this thesis can be therefore summarized as follows.

- Review of existing simulation and analysis methodologies for interconnected critical infrastructures.
- Identification of key functional requirements (FRs) for the proposed simulation platform.
- Description of both high-level and low-level designs of the developed platform, including algorithm specifications and data exchange formats.
- Exploration of simulation scenarios and time synchronization challenges in multi-infrastructure environments.
- Optimization of computational time, with preparation for execution on supercomputing infrastructure.
- Presentation of the test networks used during simulator development, including chronological descriptions and modifications.
- Introduction of a novel interconnected critical infrastructure test network.
- Interpretation and quantification of dependencies and unpredictable events within interconnected critical infrastructures.
- Determination of the key performance parameters in unavailability calculations.
- Introduction of a dedicated module for system unavailability analysis within the simulator.

- Analysis of maintenance optimization strategies aimed at improving reliability indicators.

Given the thesis's structure, which adopts a commentary style based on published papers, its structure is as follows. The overall concept of the developed simulator is introduced in Section 1. This is followed by an overview of the test networks used across various research papers for different purposes, along with the introduction of a newly developed interconnected test network in Section 2. A separate section is dedicated to analyzing critical infrastructure reliability and exploring maintenance optimization strategies in Section 3. Section 4 summarizes practical outcomes, analyses and case studies presented throughout the research. Finally, Section 5 is dedicated to a discussion of the findings, potential applications, limitations and directions for future research.

1 Critical Infrastructure Simulator

The increasing interconnection of power grids and communication networks has led to a growing demand for simulation tools capable of analyzing the dependencies and vulnerabilities of these infrastructures. Modern power distribution systems are transitioning from centralized architectures to decentralized and intelligent networks, integrating advanced automation and control mechanisms [39, 40]. However, these advancements also introduce new challenges, such as increased complexity, cyber-security risks and unforeseen system interdependencies, which require sophisticated simulation and modeling tools. A comparative study presented in **Publication II** evaluates currently available simulation solutions for power grids and communication networks. These tools were assessed based on key requirements discussed with municipal representatives and grid operators, specifically active development, power and data network co-simulation, open-source solution, other infrastructure simulation capabilities, interactive graphical interface, type of synchronization and simulated network scale (maximum number of nodes). The study concludes that none of the existing solutions meet more than half of these requirements, highlighting the need for the development of a new simulation platform.

Recent studies emphasize the necessity of a comprehensive simulation environment capable of evaluating resilience, reliability and failure propagation in interconnected urban infrastructures. Existing tools lack the capability to simultaneously simulate both power and communication networks with high accuracy, limiting their effectiveness in assessing real-world scenarios. Furthermore, traditional methods fail to address time-dependent unavailability and reliability metrics, which are crucial for critical infrastructure resilience assessment, which was analyzed in **Publication V**.

To address these limitations, this thesis aims to develop a novel critical infrastructure simulator. This simulator must integrate advanced graph-theoretical models, probabilistic failure analysis and interactive visualization to analyze and optimize interconnected infrastructures. Unlike existing solutions, it should enable real-time interaction via graphical user interface (GUI), scenario-based resilience testing and infrastructure optimization strategies. This approach will provide system operators a powerful tool for evaluating potential risks, improving infrastructure robustness and planning effective preventive maintenance measures. The following subsections describe the core functionalities of the developed simulator, including its mathematical modeling framework, software architecture and data flows in analyzing urban power grids and communication networks. After the whole development process description, a dedicated subsection focuses on computational time optimization strategies, which are crucial for ensuring efficient simulations. These optimizations are detailed in **Publication VI**.

1.1 Motivation and System Architecture

The motivation for developing a new tool for analyzing interconnected infrastructures arises from the growing interest of DSOs and municipalities in a simulator that, unlike existing solutions, enables not only control and analysis of the electrical system but also integration of data and other critical infrastructures, such as water and gas networks or traffic systems. The simulator should offer an interactive GUI with emphasis on cybersecurity. A thorough analysis and comparison of existing tools based on key parameters, including virtualization and multi-infrastructure integration capabilities, was conducted in **Publication I**. The results confirmed the need for a new platform, as none of the current solutions fully met the operational and analytical requirements of DSOs and municipal authorities.

Platform development involved close cooperation with experts in telecommunications, data networks and cybersecurity, ensuring a holistic system design. Therefore, it is essential to define the scope of this dissertation within the broader platform context, as shown in Figure 1.1. The core of this work is the development of the simulation module for the power grid, including algorithms for data handling and simulation control, described in Section 1. Another key contribution is the analytical module (Section 3), which uses system unavailability analysis for maintenance optimization and strategic planning. The thesis also reflects the author's contributions to other platform components, especially the GUI and data flow design, though these are not the main focus.

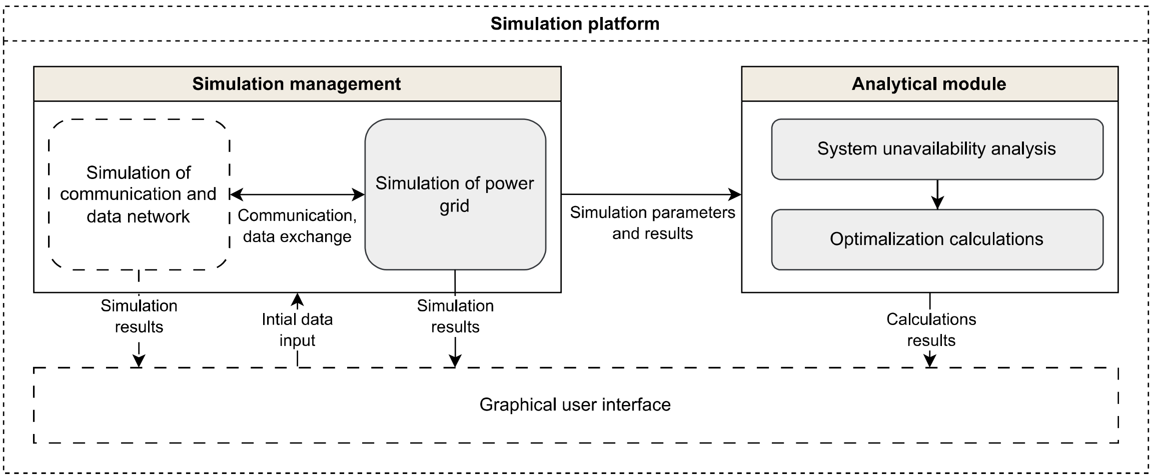


Figure 1.1: Structure of the main results of this thesis in the context of the developed simulation platform.

Based on discussions with DSOs and municipal representatives, the fundamental FRs were defined at the beginning of the development as follows:

- **FR1** – GUI for interactive simulation setup and analysis,
- **FR2** – simultaneous simulation of interconnected infrastructures (power grid and communication network),
- **FR3** – support for various input and output data formats,
- **FR4** – modular architecture allowing easy extension to additional infrastructure types (e.g., transportation, healthcare),
- **FR5** – backward detection of cascading failures between interconnected infrastructures,
- **FR6** – visualization of results on map backgrounds with support for multiple layers,
- **FR7** – high scalability and data security requirements.

1.1.1 High-Level Architecture

The simulator consists of interconnected software components, each handling specific functions. Key modules include project management, data processing and simulation execution. The project management module organizes projects, links datasets and manages settings, while the data processing module standardizes input data for consistency and interoperability. At the core, the simulation engine executes simulations, schedules tasks and manages virtualization. It interfaces with the GUI, enabling users to upload network topologies, configure parameters and visualize results efficiently - **FR1**.

The software processes input data formatted in JavaScript object notation (JSON), which encapsulates a virtual representation of the simulated network. The unified JSON file contains network elements, their interconnections and supplementary metadata used for simulation purposes. The adoption of virtualization within the simulation framework enhances scalability, simplifies system management and enables rapid deployment. This will be the subject of the following sections of the thesis.

The virtualization environment acts as the execution layer where simulations take place. It integrates supporting subsystems, including geolocation data system for spatial representation of infrastructures, database for storing simulation results, caching system to optimize performance, additional analytical and visualization tools for advanced evaluation. The interaction between these components, along with the protocols and file formats used, is illustrated in Figure 1.2. As shown in the figure, the system is designed to facilitate bidirectional data exchange within the interconnected infrastructure simulator, specifically between the power grid and communication network, thereby fulfilling **FR2**. The detailed description of the high-level system architecture is provided in the **Publication II**.

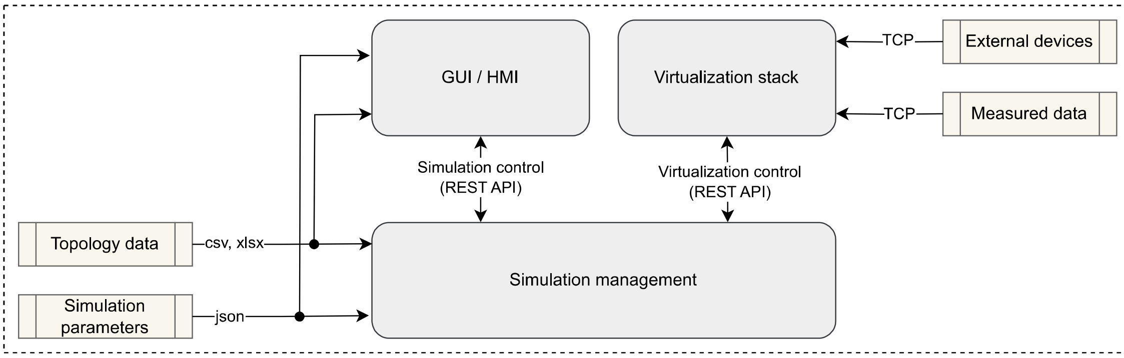


Figure 1.2: High-level system architecture and supported input files overview.

The primary communication mechanism within the platform is the representational state transfer (REST) application programming interface (API), which operates on the request-response model using the hypertext transfer protocol (HTTP). The REST API facilitates communication between the graphical interface and the simulation engine, as well as between the simulation engine and the virtualization environment.

In addition to the REST API, the platform supports multiple file formats for data exchange. The JSON format serves as the principal standardized format used across the platform for transmitting data. Additionally, the platform allows integration with other formats, including Matlab (.mat) for compatibility with numerical computing environments, Microsoft Excel (.xlsx) for structured tabular data and extensible markup language (.xml) for hierarchical data representation - **FR3**.

The modular architecture ensures scalability, interoperability and adaptability, making the simulation platform a versatile and effective tool for analyzing complex interdependent infrastructures. By enabling real-time user interaction via GUI, scenario-based resilience testing and optimization strategies, the platform provides DSOs with a robust environment for evaluating risks, enhancing infrastructure resilience and optimizing preventive maintenance planning.

1.1.2 Low-Level Design and Algorithm Description

Following the presentation of the main concepts and requirements of the overall simulator architecture in **Publication I**, a more detailed low-level design and algorithmic structure of the simulator were introduced in **Publication II**. The objective was to enhance the previously proposed simulation platform by enabling concurrent simulations of energy and data networks, facilitating the analysis of vulnerabilities and reducing potential risks to critical infrastructures.

Currently, JSON is used as the unified data format. Input data from various sources are processed by submodules corresponding to specific input formats, converting them into a common JSON structure. The resulting dataset is then linked to a newly created simulation project. During this data transformation process, geolocation services can be utilized to accurately position individual simulated nodes on a map-based interface. The simulation management module processes project data to generate simulation scenarios, which are subsequently executed in the virtualization stack. Based on the defined input parameters, a structured simulation workflow is created, ensuring systematic execution within the virtualized environment.

The simulation workflow utilizes a structured system of simulation windows, where each simulation window represents a discrete computational cycle for individual infrastructure layers. Each layer corresponds to a specific simulation process, as illustrated in Figure 1.3. This architecture allows for the seamless extension of the simulation by incorporating additional independent layers, thereby fulfilling **FR4**.

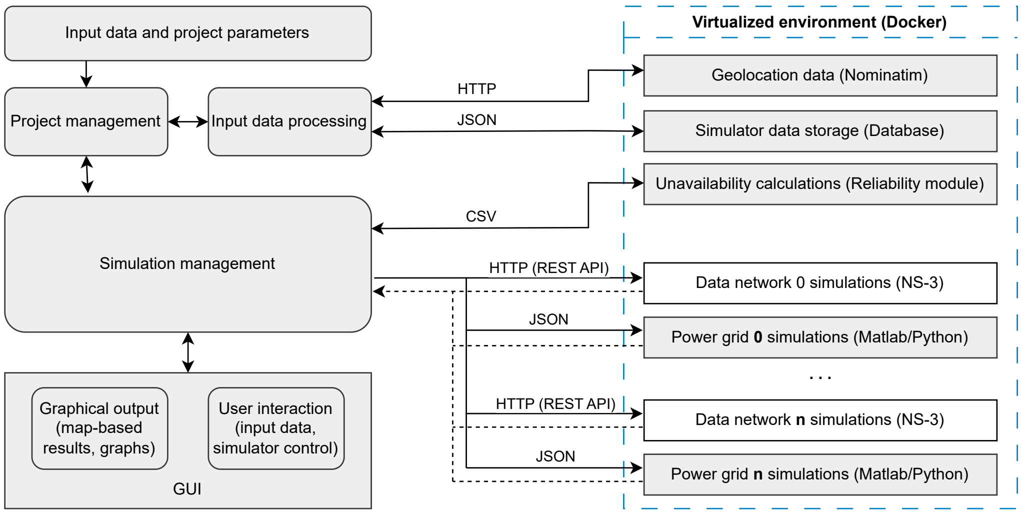


Figure 1.3: Low-level system design and data flows within the simulation platform.

The currently implemented framework supports simulations of power grids and communication networks, enabling the integration of reliability calculations and availability analysis of individual components (detailed in Section 3.2). At the same time, the platform is fully prepared for the integration of additional layers.

When creating a new project, user is asked to upload one or more files defining the structure of the simulated critical infrastructure. These files are parsed and converted into a unified data structure that remains consistent throughout the software tool. Once the conversion process is complete, the simulation execution is automatically initiated. The simulation consists of multiple steps. The first step involves generating a simulation scenario composed of simulation windows. The system iterates through these windows until all simulation cycles have been completed. Each simulation window contains two core sub-algorithms, as depicted in Figure 1.4.

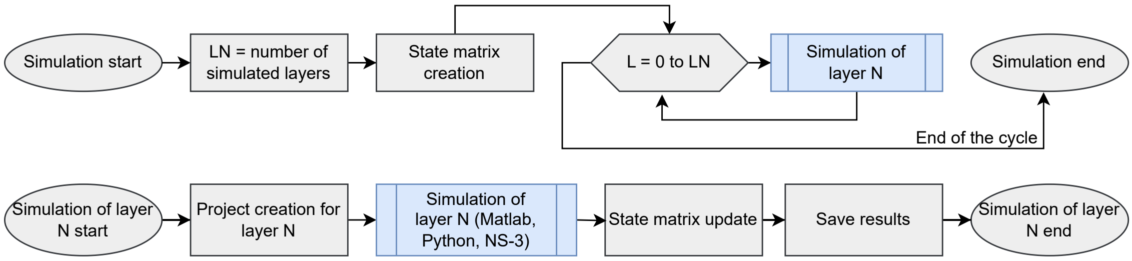


Figure 1.4: Algorithmic design for layered simulations across the entire simulation platform.

The primary sub-algorithm initializes a state matrix (further described in the next subsection), which represents the initial state of the entire simulated infrastructure. Based on the number of infrastructure layers involved in the simulation, a loop is created to execute the secondary sub-algorithm, which simulates each layer sequentially. The layer simulation sub-algorithm utilizes the input dataset describing the specific infrastructure layer, along with the state matrix, to generate a project for the corresponding simulation engine. Once the simulation is completed, the results are stored in a database and the state matrix is updated accordingly. This iterative process continues until all infrastructure layers have been simulated. After all simulation windows are processed, the software advances to the next simulation cycle, repeating the execution workflow.

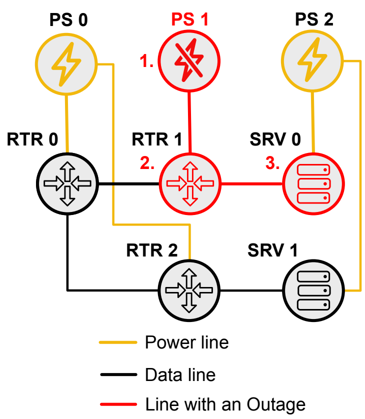
Upon completion of all simulation cycles, the results are displayed to the user through the graphical interface. A timeline control within the GUI allows users to navigate through different simulation windows and examine results at specific points in time. This approach enables a detailed analysis of the evolution of critical infrastructure conditions, providing valuable insights for resilience assessment and optimization.

1.2 Power Grid Module Within the Simulator

The fundamental structure of data exchange within the simulation platform is based on a hierarchical JSON format, which was initially introduced in **Publication I**. This structured data representation captures essential information about network nodes and their interconnections, ensuring a comprehensive view of the infrastructure topology. Each node and network connection is categorized based on whether it belongs to the power or data network, a distinction explicitly defined within the dataset attributes. From the perspective of power systems, network connections can represent transmission lines, transformers, coupling elements, or switching devices.

Beyond topological information, the JSON dataset also includes parameter definitions relevant to the simulations. For the power grid, these parameters includes line parameters, transformer parameters and switch states. The whole power grid simulation part is described in detail in **Publication III.** In case of data infrastructure, critical parameters include transmission capacities and details regarding backup power sources such as uninterruptible power supplies. This standardized dataset ensures consistency across simulations and enables interoperability between various infrastructure models.

Upon the initialization of the primary simulation process, which is structured using simulation windows, this thesis proposed a state matrix which is generated to track the status of all nodes across the simulated infrastructure layers. As shown in Figure 1.5, the state matrix records binary values representing the operational state of network elements. The matrix is dynamically updated throughout the simulation process to reflect changes in infrastructure availability.



	PS 0	PS 1	PS 2	···	PN n
RTR 0	1	0	0	···	0
RTR 1	0	0	0	···	0
RTR 2	1	0	0	···	0
SRV 0	0	0	1	···	0
SRV 1	0	0	1	···	0
···	···	···	···	···	0
DN n	0	0	0	0	0

Figure 1.5: Visualization of outages simulation using the state matrix.

Should additional infrastructure layers be introduced, the state matrix automatically extends to incorporate these new elements, thereby facilitating cross-layer interactions and dependencies. This entire process enables retrospective analysis of the causes of individual failures by providing a clearly traceable history of interdependent events, thereby fulfilling **FR5**.

Throughout the simulation, the state matrix is continuously modified after each sub-simulation to account for infrastructure failures and operational changes. The updated state matrix serves as an input for subsequent simulation cycles, ensuring that each layer's behavior is influenced by preceding simulation results. This iterative approach enables the detection of cascading failures, where disruptions in one infrastructure layer propagate to another. The state matrix updates occur both between simulation windows and within a single simulation window, as illustrated in Figure 1.5.

An essential function of the simulation platform is to analyze interdependencies between infrastructures and identify cascading failures. This process is exemplified in Figure 1.5, which illustrates a cascading failure scenario initiated by a power outage at a critical power supply node (PS 1). Initially, the outage affects only the power layer, as indicated by the state matrix update in step 1. However, in the subsequent simulation cycle, the inoperability of the power node leads to the failure of a data routing node (RTR 1) in step 2. This failure, in turn, disrupts connectivity to a dependent server (SRV 0) in step 3, rendering it inoperative due to the loss of network connectivity.

This cascading failure analysis highlights the interdependencies between power grids and data networks. A single disruption in one layer can trigger failures in seemingly unrelated components, demonstrating the need for comprehensive simulation models capable of capturing these complex interactions. Additionally, the model accounts for time-dependent failures, where an outage in one layer may indirectly affect control mechanisms that subsequently disrupt additional infrastructure components, as further described in **Publication II**.

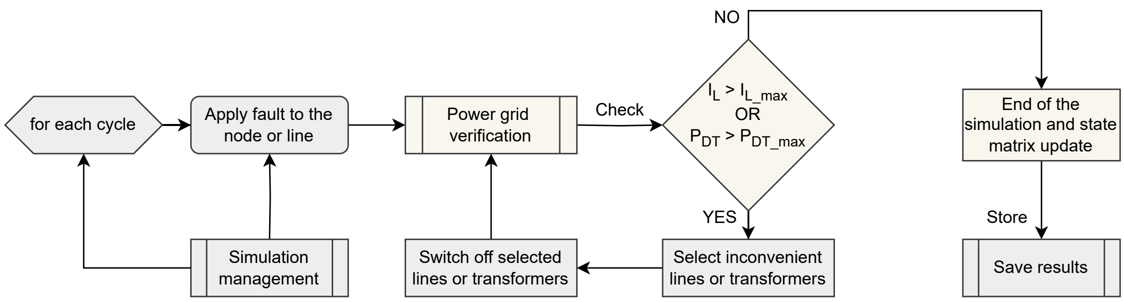


Figure 1.6: Flowchart of simulations within the power grid simulator part.

The simulation workflow employs structured data transmission between the simulation management system and individual layer-specific simulation environments. As depicted in Figure 1.7, the simulation management system generates sub-projects for each infrastructure layer, integrating the relevant state matrix data. Depending on the simulation environment, output data are obtained either through API calls, such as in the NS-3 network simulator, or via JSON-formatted result files, such as in power grid simulations. This flexible data exchange mechanism ensures compatibility with various simulation tools while maintaining a unified data structure across the entire platform, thereby contributing to the fulfillment of **FR6**. To enhance security, the system supports secure REST API communication, ensuring encrypted data transmission between components. Additionally, for internal data storage and processing, the simulator employs isolated Docker/Kubernetes containers, which provide process separation and minimize security risks associated with multi-instance execution. Further details on this implementation are provided in [41].

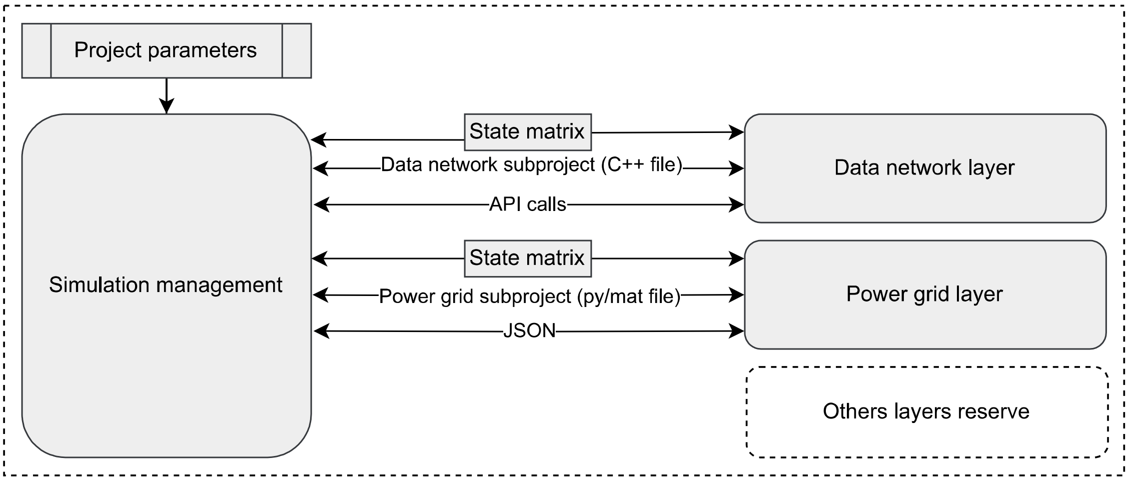


Figure 1.7: Data flows in the simulation platform [41].

The simulation platform utilizes the state matrix and structured data exchange to accurately model infrastructure dependencies and predict cascading failures, which offers deeper insights into system resilience and supports the development of strategies to mitigate critical infrastructure disruptions.

1.3 Visualization of Results and GUI

A significant aspect of the simulation platform's development involved the design and implementation of a GUI that facilitates the interpretation of simulation results. The initial concepts for this interface were presented in [42], with further enhancements and refinements discussed in **Publication VI**. The primary objective of the graphical interface was to ensure user-friendliness and intuitive operation, making the simulator accessible to both technical and non-technical users - **FR7**. A clear and structured visualization was therefore crucial for enabling users to effectively analyze simulation outputs and understand infrastructure dependencies.

Figure 1.8 illustrates the visualization of interconnections between the power and data infrastructure within the interactive environment and is derived from a case study conducted for a specific urban infrastructure, as in **Publication I**. In this representation, orange connections denote power infrastructure links, while blue connections indicate telecommunications dependencies. To simplify interpretation for non-expert users, specific symbols were introduced. For the power grid part, a house icon represents a power supply point (such as a substation) and a lightning bolt icon symbolizes individual distribution lines.

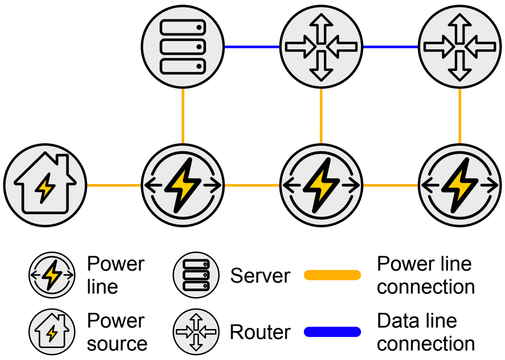


Figure 1.8: Example of interactive visualization showing the relationship between power and data infrastructure [42].

The simulation results can be displayed within a selected map layer, allowing for enhanced analysis. This feature is particularly beneficial for probabilistic simulations, where outputs such as heat maps provide an intuitive representation of infrastructure load distribution. These visualizations offer insights into the operational stress on individual infrastructure elements and help identify critical weak points within the interconnected networks.

Included within the data network simulation is an analysis of network traffic, visualized through a heat map, as shown in Figure 1.9. This figure presents an anonymized geographic overlay used solely for demonstrative purposes because of the sensitivity of the data used in the case study. The heat map illustrates the density of data flow within different sections of the simulated network. Such a visualization is essential for analyzing network congestion, as it highlights areas experiencing high utilization. In cases where a node becomes overloaded, the absence of redundant pathways may lead to critical failures affecting large portions of the simulated infrastructure.

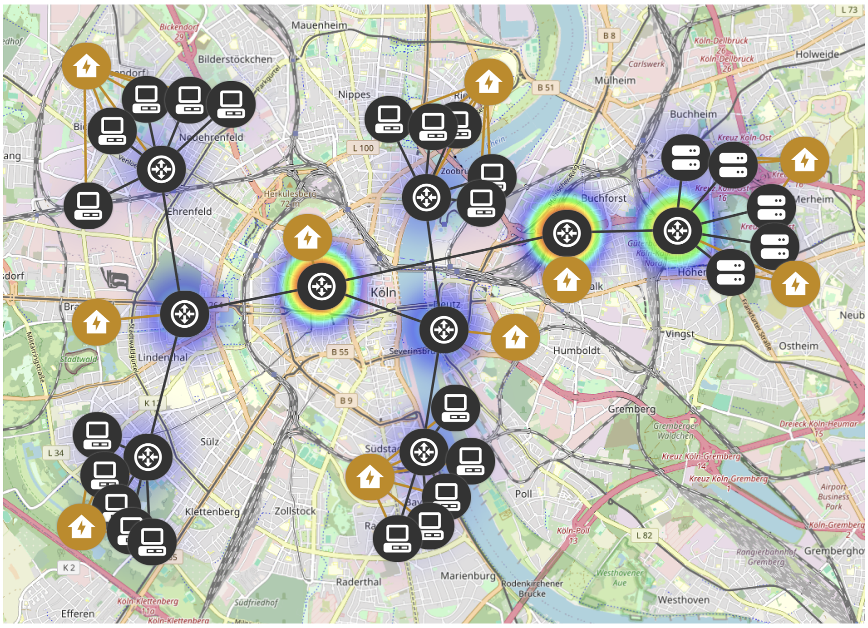


Figure 1.9: Heat map visualization representing data flow in the network [41].

The updated version of the graphical interface, as described in **Publication VI**, introduces enhanced customization options, including the ability to select from multiple geographic overlays. The supported map styles are depicted in Figure 1.10. These variations provide flexibility for different analysis requirements, allowing user to choose the most suitable representation for their simulation data.

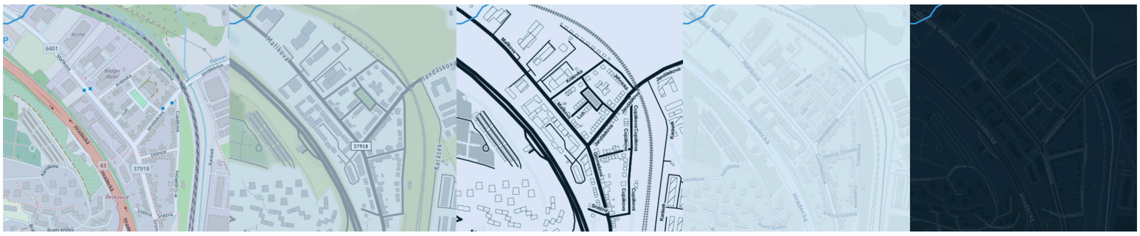


Figure 1.10: Examples of currently supported map styles.

The integration of an intuitive and adaptable graphical interface significantly enhances the usability of the simulation platform. By providing clear visual representations of infrastructure dependencies, network performance and failure propagation, the interface serves as a critical tool for decision-making and resilience analysis. Future developments will focus on further improving the interactivity of the system, including real-time scenario adjustments and enhanced analytical overlays for infrastructure optimization.

1.4 Optimization of Computational Time

The computational efficiency of the simulator is a crucial aspect that directly impacts its usability for large-scale infrastructure simulations. The complexity of interconnected infrastructure models, combined with the need for high temporal and spatial resolution, imposes significant computational demands. To address these challenges, several optimization strategies have been implemented, focusing on input data processing, data format selection and the integration of supercomputing infrastructure. The optimization methodologies outlined in this section are based on the findings presented in **Publication VI**.

1.4.1 Input Data Processing

The initial computational bottleneck in the simulation workflow was the processing of input data, which required substantial memory and execution time. The original implementation utilized the Pandas library for data handling, with JSON as the primary data exchange format between power and communication network simulations. However, JSON's text-based nature introduced inefficiencies in parsing and memory management. To address performance limitations related to inter-simulator communication, several alternative data formats were systematically evaluated. The benchmarking focused on input/output time, file size and memory consumption. While JSON ensures interoperability, its inefficiency for high-volume data processing led to the testing of six alternative formats: CSV, Feather, HDF, Msgpack, Parquet and Pickle, as shown in Figure 1.11.

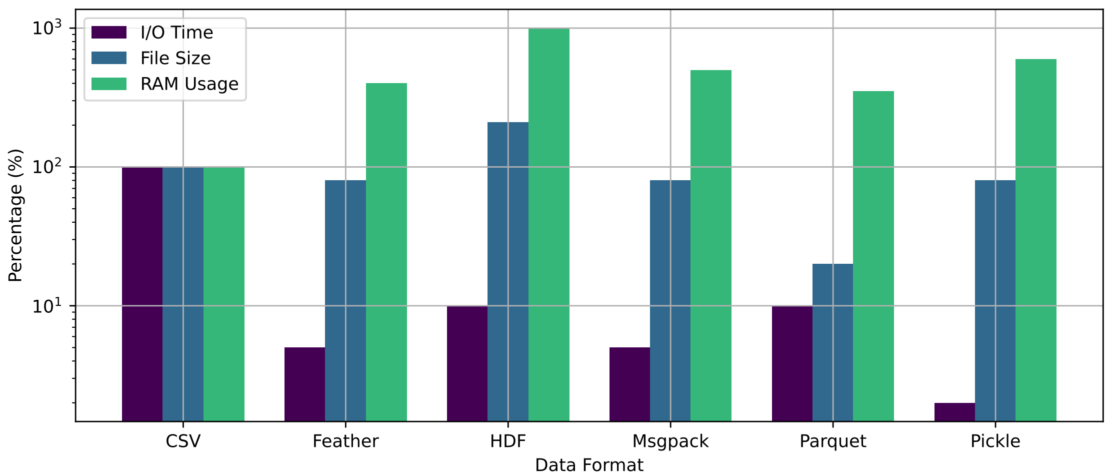


Figure 1.11: Comparative evaluation of data formats tested for simulator operations.

The results demonstrated that Feather and Pickle offered the fastest processing speeds reducing data handling time to just 2–3 % of that required by CSV, though at the cost of higher RAM usage. Among the tested formats, Parquet proved to be the most balanced solution, achieving a file size reduction of up to 85 % compared to the original JSON format while maintaining reasonable computational efficiency.

As a result of these evaluations, the simulator was extended to support multiple data formats, enabling dynamic format selection based on the specific requirements of each simulation scenario. This flexible approach enhances scalability and allows users to prioritize speed, memory usage, or compatibility as needed. A graphical summary of these results is also provided in **Publication VI**, including a comparison of the achieved computational speed-up.

1.4.2 Supercomputing Infrastructure and Kubernetes Orchestration

To further enhance computational efficiency, the simulator has been adapted for deployment within a high-performance computing (HPC) environment by integrating Kubernetes-based orchestration. This approach enables dynamic allocation of computational resources, ensuring that compute-intensive simulation tasks are offloaded to the supercomputing infrastructure while administrative and control operations remain on the user's local machine.

Figure 1.12 illustrates the modified system architecture supporting Kubernetes deployment. The simulation management layer operates locally, handling user interactions, project configurations and job scheduling. Simulation tasks are dispatched to Kubernetes-managed compute nodes, where they are executed in parallel across distributed computing resources. The use of containerized environments ensures seamless scaling and resource isolation, preventing interference between concurrent simulations. By leveraging the Kubernetes orchestration framework, simulations can be executed across multiple computing nodes, significantly reducing execution time. Initial benchmarks demonstrated a notable improvement in computational efficiency, with reductions in simulation runtime proportional to the number of allocated processing units. Additionally, the security of simulation data is ensured through encrypted communication channels between the user's local machine and the HPC infrastructure.

The computational time optimization strategies implemented in the simulator have resulted in substantial improvements in simulation performance. Modifications to input data processing reduced inefficiencies in data retrieval, while the adoption of optimized data formats minimized processing overhead. The integration of Kubernetes-based orchestration within an HPC environment further accelerated

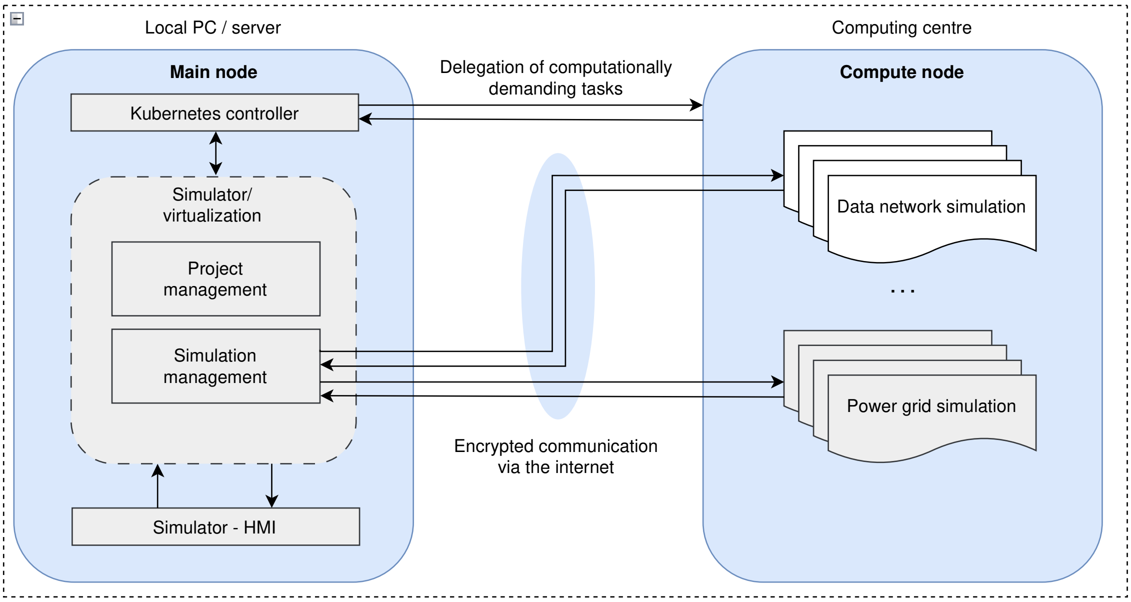


Figure 1.12: Modified architecture integrating Kubernetes for optimized computational performance.

execution, enabling large-scale infrastructure simulations within practical time constraints.

2 Test Networks Description, Dependency Definition and Contingency Quantification

The increasing interdependence of critical infrastructures in modern urban areas, particularly between energy, communication and data systems, has created new challenges in ensuring their stability and resilience against disruptions. Unlike traditional energy grids, smart grids rely significantly on data transfer and communication infrastructure for effective management and monitoring. This shift toward interconnected infrastructures requires not only sophisticated simulation tools but also appropriate test networks that capture complex interdependencies and support contingency scenarios. The types of interdependencies between individual infrastructures in smart cities are clearly illustrated in Figure 2.1.

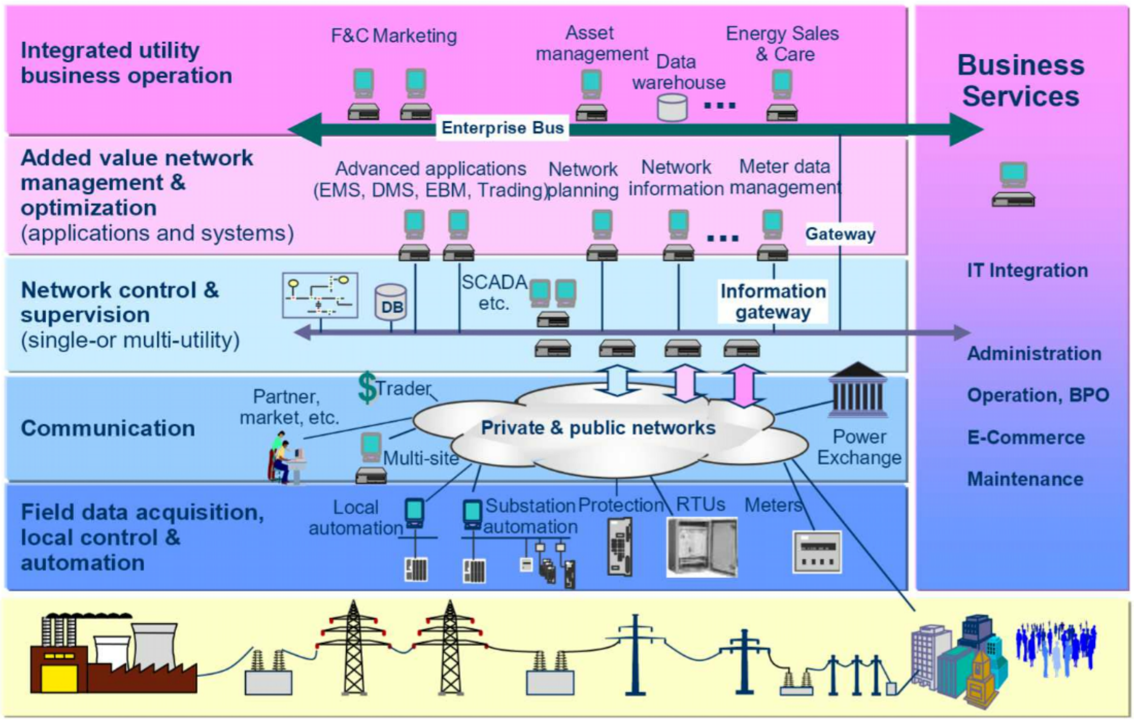


Figure 2.1: Dependencies between the individual infrastructures in smart cities [43].

To facilitate the development of the new simulation platform, it requires an access to a test network capable of simulating interactions between multiple infrastructure layers, with the flexibility to expand in the future to include other layers such as transportation and gas networks. However, existing test networks primarily focus on individual infrastructures, particularly on the distribution and transmission of electrical power and do not address integration with communication or data layers. One of the most commonly used models in this field includes IEEE standardized networks, such as the IEEE 13-Bus, IEEE 30-Bus and IEEE 118-Bus models. These models are designed for power flow analysis, voltage control and fault simulation in distribution and transmission systems, focusing exclusively on the electrical domain [44, 45, 46].

For instance, the IEEE 13-Bus model is commonly used for low voltage (LV) distribution network analysis, while the IEEE 30-Bus (shown in Figure 2.2) and 118-Bus models are more complex, covering larger transmission networks. However, their lack of integrated data and communication layers limits their applicability to interconnected infrastructures, where it is essential to simulate the impacts of failures within one network on the functionality of other connected systems. This limitation underscores the need for test networks that account for interdependencies between different critical infrastructures.

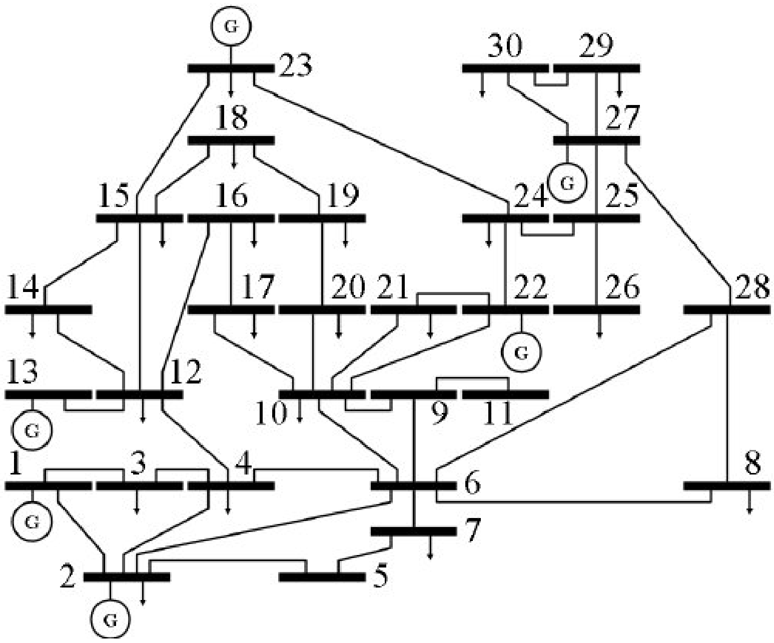


Figure 2.2: Graphical representation of the IEEE 30-Bus test system topology [47].

Beyond IEEE models, another prominent set of test networks for power systems has been developed by CIGRE, offering, for instance, CIGRE Benchmark Networks for MV and HV grids. For illustration, the graphical representation of the CIGRE MV network model topology is shown in Figure 2.3. These models are designed for advanced simulations of transmission systems, focusing on system stability and load balancing optimization [48, 49]. While these networks are effective for analyzing purely electrical phenomena such as system stability and efficient load management, they are not designed to model interconnected infrastructures. The lack of support for communication with data systems or the integration of additional infrastructure layers significantly limits their practical applicability in urban critical infrastructures, where mutual dependencies play a crucial role.

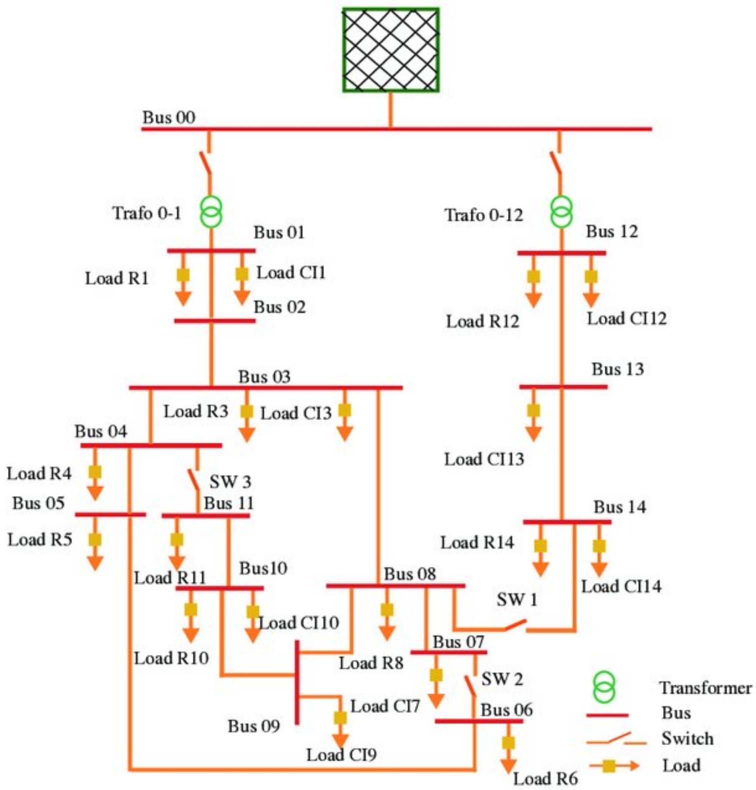


Figure 2.3: Graphical representation of the CIGRE MV network model topology [50].

To address interoperability and critical infrastructure protection, the National Institute of Standards and Technology (NIST) has developed standards and guidelines for cyber-physical systems that include the security of energy networks [51, 52]. Although NIST standards emphasize security and interoperability, they do not provide independent test networks capable of connecting multiple infrastructure layers. Instead, they serve as a reference framework for cybersecurity. Therefore, these standards alone are unsuitable for detailed simulations of the interactions between different types of infrastructures, as required for interconnected urban systems.

Some scientific studies have attempted to simulate interconnected infrastructures, primarily by combining electrical and communication systems. For example, [53] explores infrastructure designs that simulate not only energy but also communication networks, allowing for the analysis of failures and outages in one system's impact on others. A modular approach is proposed to connect individual subsystems, providing partial support for the simulation of interconnected infrastructures. However, these models are not publicly available as test networks and have limited scalability for expansion to additional infrastructure layers, making them challenging to apply in scenarios requiring extensibility, such as the integration of transportation or gas networks.

Another example is [54], which focuses on the co-simulation of energy and communication networks using adaptive models that simulate the effects of communication network failures on the operational stability of energy networks. This approach highlights the critical role of communication networks in controlling distribution and transmission networks and demonstrates the use of co-simulation for contingency scenarios. While it provides advanced analytical tools, this model was not designed as a test network with an extensible structure for additional layers. Limitations in expandability and modularity hinder the application of these models to complex urban infrastructures, where the capability to integrate additional networks, such as transportation or water systems, is essential.

Within the European distribution network model (DiNeMo) research project, a model was proposed for interconnected infrastructure simulation, focusing on the distribution of energy and communication systems. While this model provides basic capabilities for the analysis of interconnected critical systems, its development was subsequently suspended and it lacks robust support for integrating further infrastructure layers, such as transportation networks or natural gas infrastructure [55]. Although DiNeMo allows for basic simulations of interdependencies between energy and communication systems, its structure is insufficiently flexible for scaling to additional infrastructure layers. This limitation restricts its application in broader contexts that require extensible, modular test networks.

Given these limitations, an essential part of this thesis was focused on the development and clarification of test networks that allow for a more comprehensive simulation of interconnected infrastructures. The following sections will chronologically present the test networks used throughout the dissertation, describing their evolution as the simulator was developed and optimized. Each of these test networks was carefully selected or designed based on the ability to model dependencies between infrastructure layers and facilitate contingency scenario analysis. The developed models were further validated through simulations, ensuring their suitability for assessing the resilience of interconnected infrastructures.

2.1 Test Networks and Infrastructures Used

The first test network, which was used for initial simulations and introduced in **Publication I**, utilized data provided by the DSO. This dataset included key operational parameters of the power distribution infrastructure, providing valuable insights into the simulator's performance under realistic conditions. In parallel, the data network segment was supported by measurements conducted in collaboration with a mobile network operator, capturing critical characteristics of an actual control network within the Czech Republic. To maintain data confidentiality, all datasets were anonymized for publication purposes. The paper presents simulation capabilities focusing on outage scenarios within interconnected energy and communication infrastructures, where the communication network component includes the city's entire traffic signaling system. A representative model of the interconnected infrastructure was developed, incorporating both the electrical characteristics of the power grid and the communication network, including its control and monitoring systems. Despite the inability to publicly share detailed simulation results, the developed software was provided to city representatives, who are the end users of the solution. Their feedback and expert consultations significantly contributed to the further refinement and optimization of the simulator.

An example of a graphical output from the simulation is shown in Figure 2.4. Symbols within the visualization environment denote various infrastructure elements - for instance, substations and distribution lines, and transportation nodes are each mapped using distinct iconography. The entire simulation output can be displayed on a selected mapping background using the virtualization component of the software.

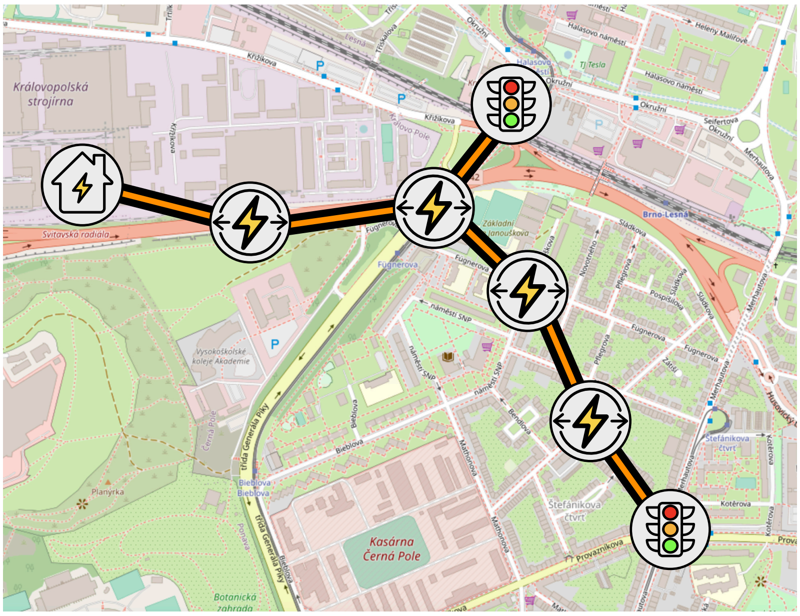


Figure 2.4: An example of a graphical representation of the power supply route in the interactive mapping environment of the simulator.

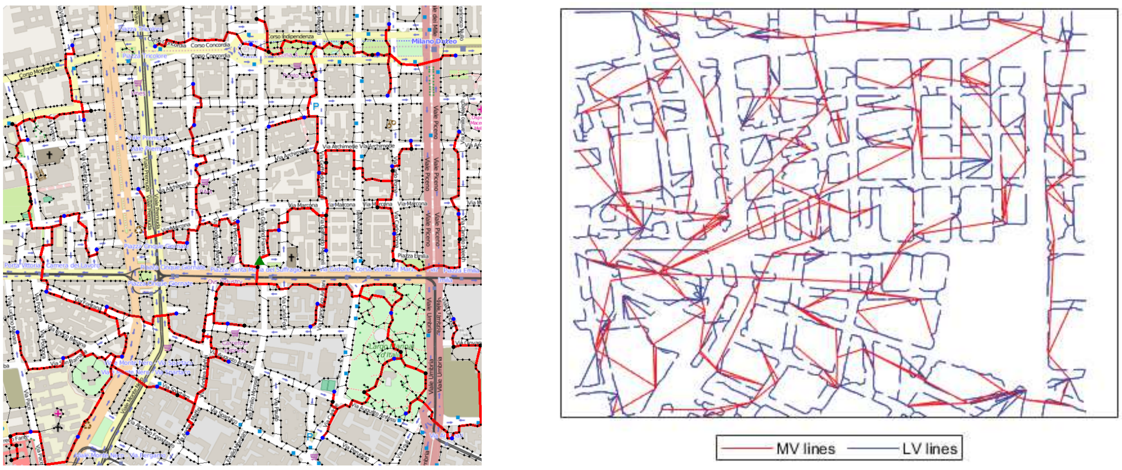
Given the sensitivity of the data used in the initial tests, the need to ensure reproducibility in publications and within this dissertation necessitated the exploration of alternative test networks that could be used for result dissemination while maintaining data confidentiality.

2.1.1 The Distribution Network Model - DiNeMo Platform

To facilitate critical infrastructure simulations while maintaining reproducibility, the research initially adopted reference distribution network models developed by the Joint Research Centre (JRC) [56]. These reference models include comprehensive datasets representing fictional networks across three different scenarios: urban, suburban, and rural. Additionally, the dataset comprises information on ten detailed network topologies commonly found in real-world distribution networks.

As this thesis focuses primarily on the development of models for urban critical infrastructure, the urban distribution network model was selected for the initial testing phase. The anonymized data were imported into the simulator and a visualization module was developed for graphical representation of the network, as shown in Figure 2.5. The model currently consists of:

- 3,239 nodes,
- 3,116 power lines spanning LV and MV networks,
- 317 distribution transformers.



(a) Initial version of the JRC urban network [56].

(b) Anonymized version of the network visualized within the simulator platform [57].

Figure 2.5: Graphical representation of the urban distribution network reference model.

In Figure 2.5, LV power lines are depicted in blue, while MV lines are shown in red. Even without a geographic base layer, it is evident that, unlike LV lines, MV lines are mapped without precise coordinate adherence (b). The simulator also allows the integration of generator parameters at balancing nodes and the definition of loads at individual connection points, enabling advanced network analysis. This model was initially used for demonstrating the simulator's functionality in **Publication I**.

To further enhance the simulator's capabilities, efforts were made to develop an independent module for seamless integration with DiNeMo. This module aimed to facilitate the creation of an anonymized network model while maintaining the required level of complexity for resilience analysis. Unfortunately, during the course of this research, the DiNeMo module was discontinued, necessitating the exploration of alternative approaches for achieving similar objectives. Given this development, subsequent research focused on identifying alternative test networks that could effectively replace DiNeMo while ensuring that the simulator remained adaptable to evolving infrastructure modeling needs.

2.1.2 Urban Distribution Infrastructure

For the development of the power network simulation component, a test network of an urban distribution infrastructure was used. The model of this extensive meshed network, initially introduced in [58], was originally utilized for the development of a method for configuration optimization to minimize short-circuit currents. During the simulator's development, this network was primarily used to verify its operability and analyze the extent of outages under various failure scenarios, as previously described in Figure 1.6. As part of this verification, an algorithm was developed in Python, whose flowchart is shown in Figure 2.6.

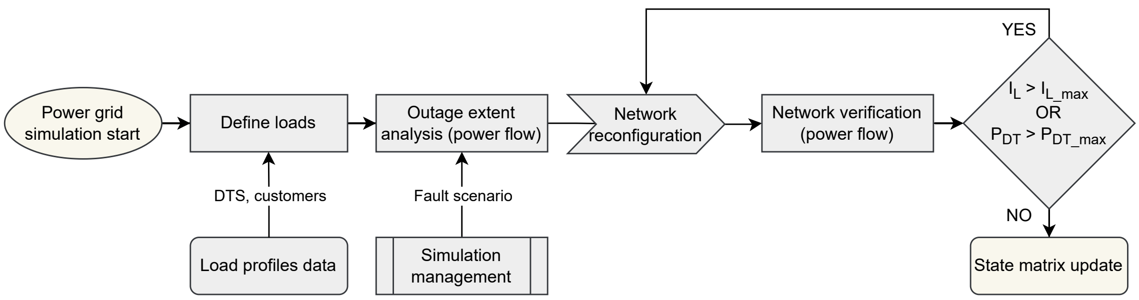


Figure 2.6: Flowchart of the process of network verification in the power grid simulator.

The simulation process begins with defining the loads at individual consumption points, followed by verifying the operability of the distribution network. If a fault is detected, its location is identified and the extent of the outage is analyzed. The network is then reconfigured using switching elements and its operational status is re-verified. If the network remains non-functional, the reconfiguration continues. Otherwise, the current network topology data is transferred to the communication network simulator. The communication infrastructure is then analyzed and the resulting data is sent back to the power network simulation. The process either continues from the step of outage localization or, if no further analysis is required, the simulation concludes.

The entire simulation process, particularly in relation to the data infrastructure analysis module, is presented in **Publication III**. A similar process is conducted for the communication network, with the resulting data being fed back into the power network analysis. The simulation then resumes from step 3 (outage extent analysis), ensuring the evaluation of interdependent failures in both infrastructures.

The full-scale network that was used for this purpose consists of:

- 1,268 nodes,
- 1,498 power lines,
- 79 MV/LV distribution transformers situated in 55 MV/LV underground distribution transformer stations,
- 55 manually controlled bus couplers, located either at medium voltage (MV)/LV transformer stations or within larger switchgear installations.

Due to the large-scale dimensions of the original network, only a specific segment (highlighted in blue in Figure 2.7) was extracted for the most of simulation purposes. The selected area is supplied by five independent MV/LV transformers and comprises 77 nodes, 5 transformers, 6 couplers and 75 power lines.

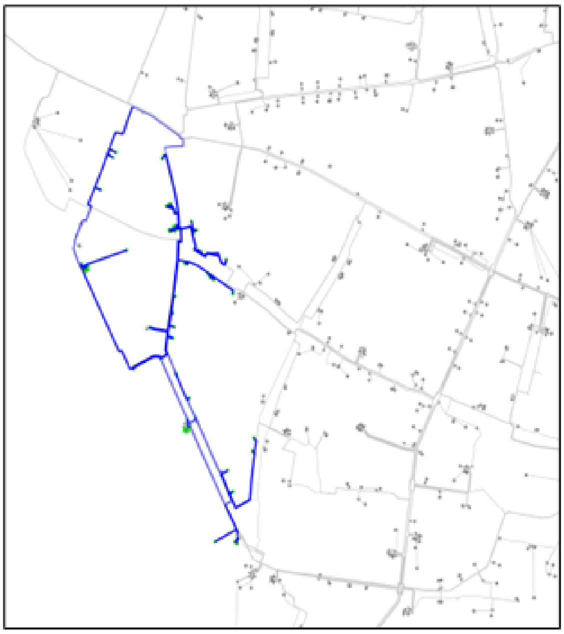


Figure 2.7: A section of the urban distribution network, with the analyzed part highlighted in blue.

Further details on the network configuration and its application in simulations can be found in **Publication III**.

2.1.3 Medium Voltage Overhead Network

For the case study presented in **Publication IX**, an anonymized MV network was utilized, as illustrated in Figure 2.8. This network represents a real-world 22 kV overhead distribution system, which is supplied by a 110/22 kV transformer, denoted by the blue square in the diagram.

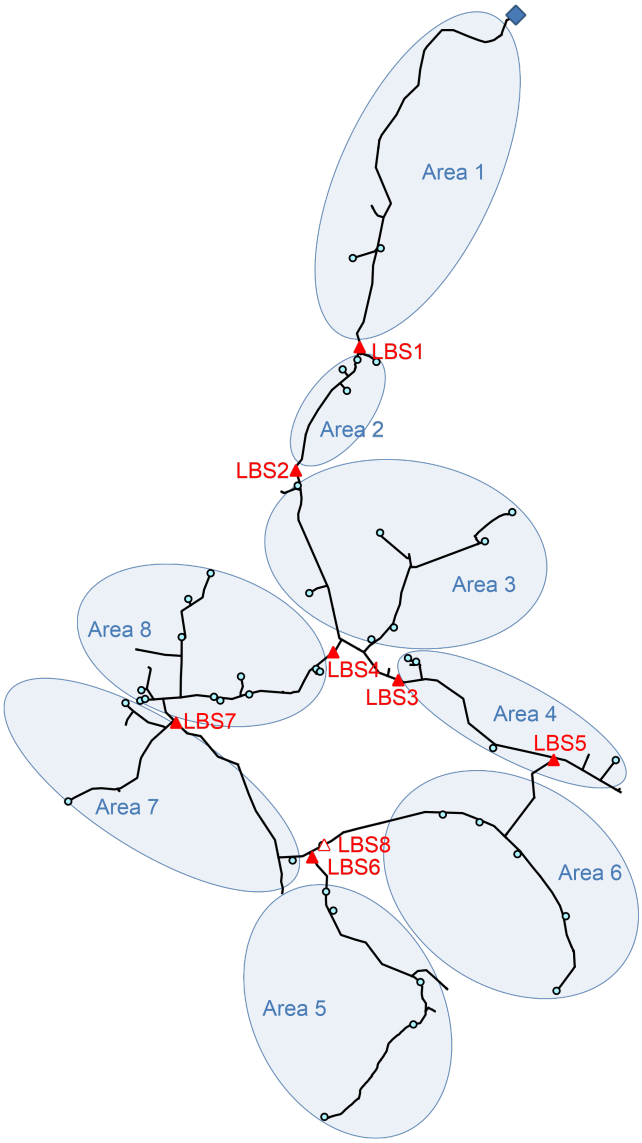


Figure 2.8: Considered part of the distribution network.

The network contains eight remotely controlled load break switches (LBS), which are marked as red triangles. The filled triangles indicate closed LBS, while the unfilled triangles represent open LBS. The network operates in a radial configuration, meaning that one LBS remains open under normal conditions. Additionally, blue circles in the figure denote MV/LV distribution transformers, which play a crucial role in the network's operation.

The network model was created and employed due to its interconnection with the communication infrastructure via LBS. The proper interpretation of these dependencies is crucial, as failures in communication can impact the operation of LBS, potentially leading to extended outages or incorrect switching operations. These interdependencies will be analyzed in further detail in the subsequent chapters.

Based on the possible configurations of the LBS, the network was divided into eight operational zones. The key technical parameters of the MV network include a total of 326 nodes, 59 distribution transformers, 95 disconnectors, 75 power line segments and 8 LBS, with a total nominal power of 11.57 MVA distributed across the distribution transformers.

2.1.4 Smart Grid Test Network Development

In **Publication IV**, a novel smart grid test network was developed to serve as a representative model for interconnected infrastructure analysis. This test network was designed with two primary objectives: to facilitate comprehensive analysis of power outages and system reliability within interconnected infrastructures and to support optimization strategies for aging infrastructure maintenance through discrete maintenance approaches. The network includes detailed modeling of each infrastructure component, with a particular focus on points of interaction to ensure realistic simulation results. The development of this interconnected infrastructure followed a structured iterative design approach, with each iteration refined through discussions involving the research team and key stakeholders. The first iteration, depicted in Figure 2.9, established the fundamental structure of the interconnected infrastructure.

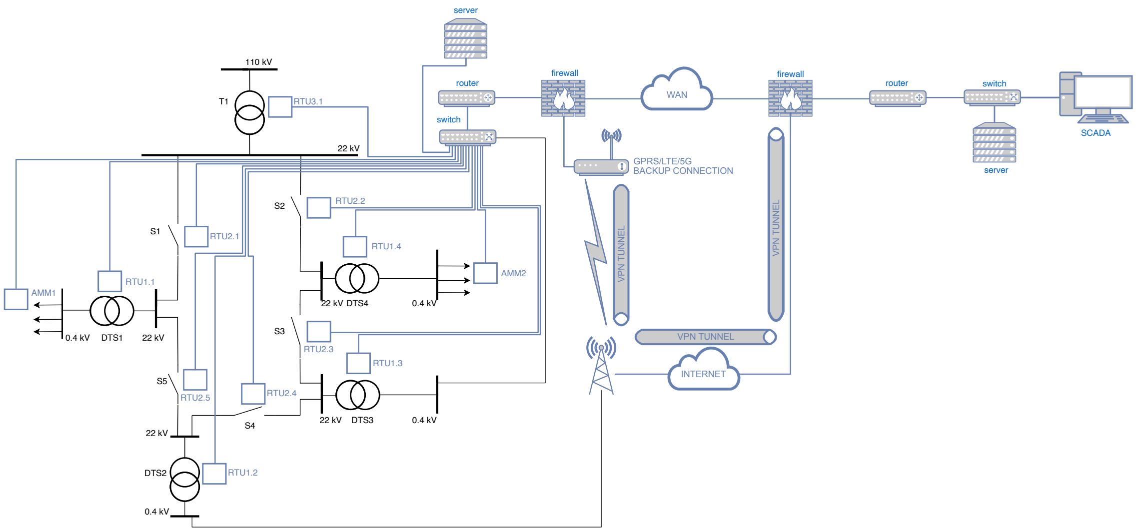


Figure 2.9: Initial topology of the smart grid test network.

It featured a comprehensive data network comprising a SCADA data center as the central control hub, a monitoring and control network enabling real-time measurement and control of the power system, an optical fiber backbone with a redundant mobile network backup for improved resilience and security mechanisms based on virtual private network (VPN) tunnels to ensure data integrity and cybersecurity. Additionally, the model included remote terminal units (RTUs) and automated metering management (AMM) systems responsible for monitoring voltage and current levels, as well as managing energy network operations. The power network in this iteration was structured with a 110 kV transmission input, stepped down to 22 kV via a HV transformer. The voltage was further reduced to 0.4 kV, supplying end-user devices through distribution transformers. However, this version did not yet include a dedicated power supply for the control, monitoring and communication components.

In the second iteration, illustrated in Figure 2.10, key refinements were implemented based on discussions, particularly with the DSO. The RTU and AMM connectivity was transitioned from an optical fiber backbone to a mobile wireless network, utilizing LTE or 5G for enhanced flexibility and scalability. The SCADA data center connectivity was simplified by removing redundant backup connections. Additionally, the power supply for data infrastructure components was integrated into the energy network, ensuring that control and monitoring elements remain operational even during planned power outages.

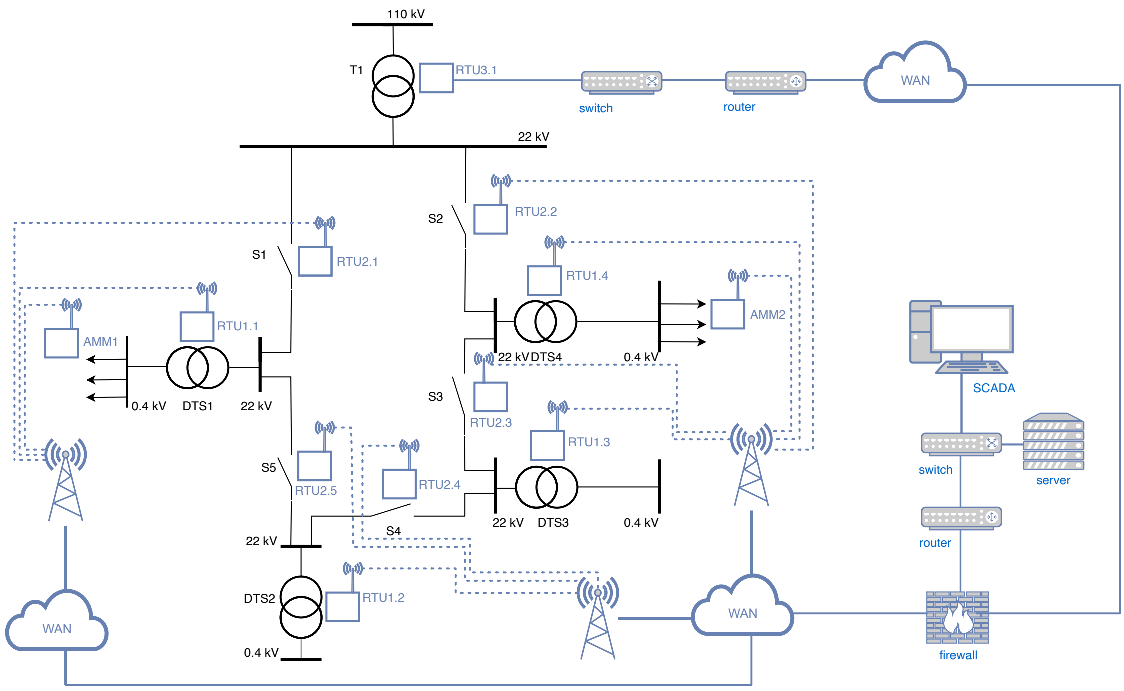


Figure 2.10: Refined smart grid topology with integration of communication layer.

Following two additional refinements, the final test network topology, shown in Figure 2.11, was adopted. The primary enhancement in this final version included the integration of power supply branches for mobile network transmitters. These transmitters are powered directly from supply points of the power grid, introducing a cascading failure effect (if one power branch fails, it may trigger a domino effect leading to a data network outage). Furthermore, the SCADA data center infrastructure was further simplified, optimizing its architecture and operability.

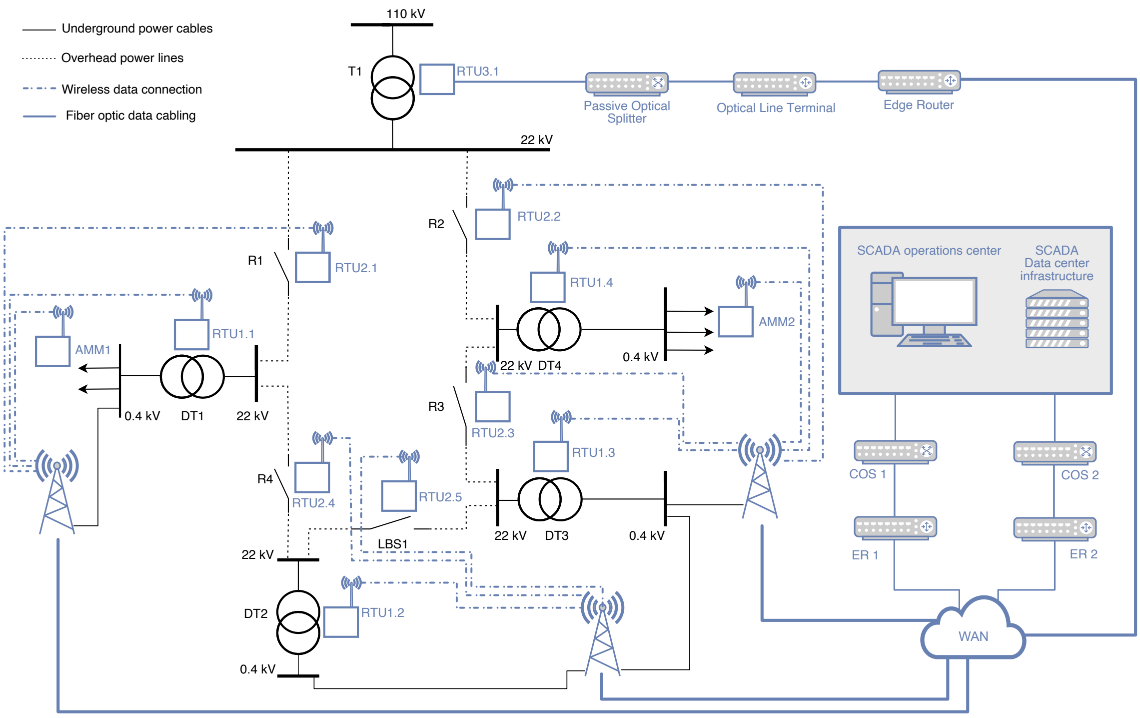


Figure 2.11: Final interconnected smart grid test network integrating power and communication infrastructures.

This interconnected test network models real-world dependencies within smart grids, where control and monitoring systems directly impact grid stability and reliability. The test network was subsequently utilized in several research papers, including **Publication II**, which analyzed interconnected system reliability, **Publication V**, which focused on performance evaluation of interdependent power and communication networks and **Publication VIII**, which examined maintenance optimization strategies for interconnected infrastructures. The model serves as a foundational structure for quantifying the impacts of power and data network interactions, providing a reproducible and scalable platform for further investigations into critical infrastructure resilience.

Within the referenced publications, a detailed analysis was conducted to identify key network components in terms of reciprocal dependencies between interconnected infrastructures. The analysis RTUs as critical components, given their role in facilitating remote monitoring and control of essential power distribution elements. The RTU architecture consists of input/output modules, a central processor with onboard memory and specialized communication interfaces that ensure integration with sensors, reclosers and LBS. Equipped with fault-tolerant features such as backup power and redundant communication channels, RTUs enhance network resilience but remain vulnerable to external environmental factors, hardware and software malfunctions and communication failures that may impact network control.

To address these vulnerabilities, the test network incorporates four distinct RTU configurations, each fulfilling a specialized function. The first type consists of RTUs installed at distribution transformer stations, labeled as RTU1.1-4 in Figure 2.11. These units monitor digital states such as switch positions, provide remote control over feeder switches, detect distribution network faults, assess power quality and aggregate data from other infrastructure components. The second category includes RTUs for MV line reclosers, labeled RTU2.1-4, which manage reclosers on MV lines by providing status updates on recloser operations, as well as controlling reclosers remotely and locally. These RTUs measure three-phase voltage and current levels, detect line faults and operate protective relays. The third type of RTU is installed in HV/MV substations, designated RTU3.1. These units facilitate communication with the SCADA system via Ethernet or optical fiber connections, with cellular modem backup for enhanced reliability. They collect data from protective relays and power quality meters, ensuring robust system monitoring. The final category includes RTUs for sectional LBS, labeled RTU2.5. These RTUs enable remote and local control over sectional switches, provide three-phase voltage and current measurements, detect power line faults and execute automatic fault disconnection, particularly during voltage-free pauses.

Each RTU configuration plays a critical role in power system stability by supporting real-time network monitoring, predictive maintenance and failure mitigation strategies. The impact of RTUs on network resilience and failure mitigation was analyzed in detail in **Publications VIII and VII**, which will be further discussed in Sections 3 and 4.

2.2 Network Contingency Quantification

In complex interconnected infrastructures, understanding and quantifying the contingency of each network component is crucial for ensuring resilience and operational reliability. Previous studies have examined various aspects of contingency analysis and dependency mapping in critical infrastructures, focusing largely on isolated networks or theoretical models. For instance, some works have detailed approaches to power system contingency analysis using probabilistic methods and fault tree analysis [59, 60], while others have explored communication network resilience, emphasizing fault tolerance in standalone systems [61, 62]. Additionally, models like those discussed in [63, 64] provide insights into cascading failures and interdependencies, although they often lack practical test networks for interconnected system validation.

In contrast, this dissertation addresses the practical quantification of network contingencies within the smart grid test network introduced in Section 2.1.4. Unlike previous models, the approach taken here focuses on an applied test network that directly integrates both power and communication systems, with dependency pathways and failure impacts reflected across both infrastructures. Given the complexity of dependencies across both individual and interconnected systems, it is essential to use a clear and interpretable representation. While the detailed topology of the test network (see Figure 2.11) provides a comprehensive overview, a more structured dependency representation is needed to analyze contingency impacts. For this reason, an oriented acyclic graph (AG) was chosen as a mathematical representation to map system dependencies. The AG provides a straightforward depiction of how each component's functionality influences the overall system's operability, enabling the identification of critical elements within the network. Each node within the graph represents either a subsystem or an individual component, while edges indicate functional dependencies.

The highest node in the AG, labeled as system state (SS), signifies the operational status of the entire network (i.e., functioning vs. failure), while terminal nodes represent specific subsystems or components. Unlike conventional schematics, the AG's edges denote dependencies between elements, following these principles:

- the graph is acyclic, meaning each pair of directly connected nodes has a single directed edge,
- single SS node at the top indicates the operability of the entire system,
- directed edges between nodes show hierarchical dependencies, where subordinate nodes contribute to the state of superior nodes,
- internal nodes (non-terminal) represent subsystems with stochastic behavior. These nodes function correctly when at least m of their subordinate nodes are operational, where $m \in [1, \text{number of input edges}]$. If $m = 1$, the node follows an OR logic; if m equals the number of inputs, it follows an AND logic,
- terminal nodes represent the functionality of individual components that make up the system. Events that affect these components, whether stochastic (failure distributions) or deterministic (planned maintenance), impact the system's overall operability.

2.2.1 Power Grid

The process of creating an AG begins with examining the power grid segment of the test network, as outlined in **Publication IV**. Figure 2.12 presents a simplified topology of the distribution network, highlighting key components. For demonstration purposes, the system's operability condition is defined as ensuring the power supply to a critical component located at a supply point, which is powered through cable C3.

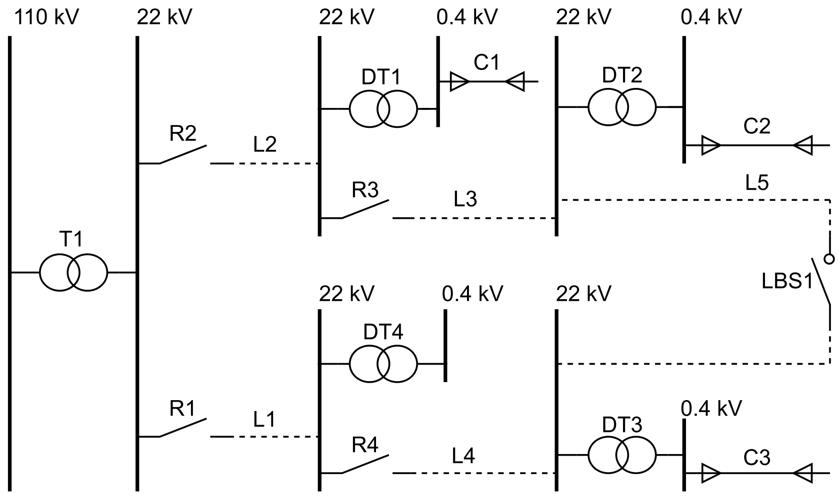


Figure 2.12: Representative topology of the distribution network, including essential components.

Thus, node SS in the AG denotes the state where this OM is energized. From this condition, it follows that cable C3 and transformer T1 must be consistently operational. Additionally, the power supply depends on a route of feeders and remotely controlled LBS, collectively represented as subsystem $u1$. This route is divided into two branches, identified as $u2$ and $u3$, forming the resulting AG shown in Figure 2.13.

In this example, potential backup power sources from MV or HV levels are simplified and excluded. Reclosers are also omitted from the AG since their failure would be considered a complete power interruption (defined here as the inability to interrupt a fault). However, the LBS is included as it typically remains open under normal operating conditions and plays a critical role in backup power restoration.

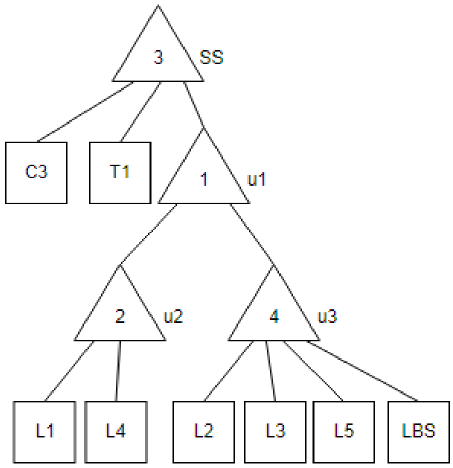


Figure 2.13: Acyclic graph of the power grid segment.

2.2.2 Communication Network

A similar AG creation process applies to the data network portion of the test network as described in **Publication IV**. For the communication system, the operational condition is defined as the ability of the control center to operate the LBS in the power distribution network. In Figure 2.14, the relevant section of the communication network required for controlling the LBS is shown, while other components are excluded from the AG model for simplicity.

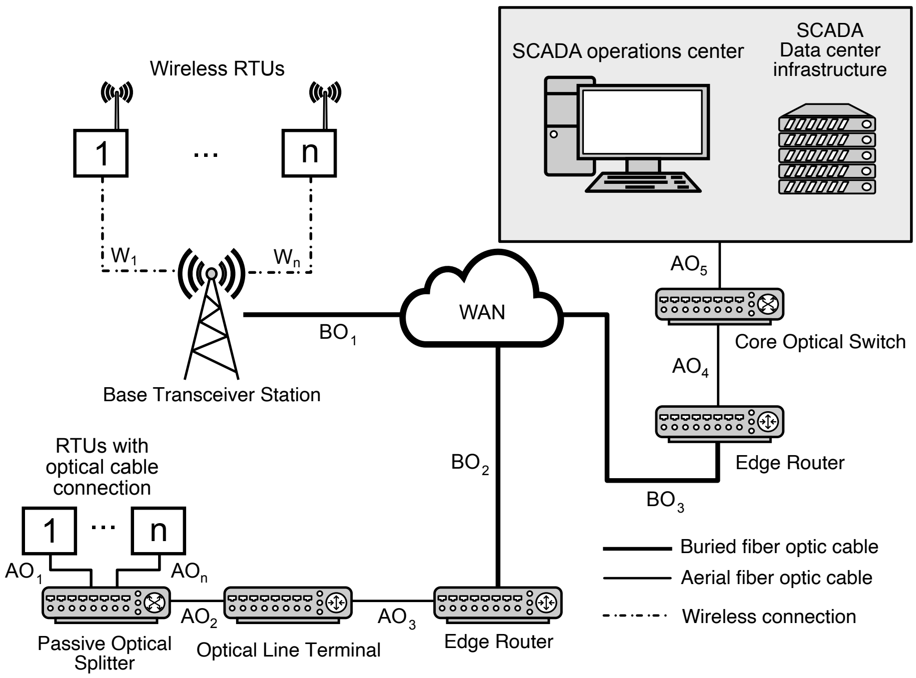


Figure 2.14: Representative topology of the control and communication network, including essential components.

The dependencies within the data network are mapped in the AG shown in Figure 2.15, capturing the interdependencies among its components without incorporating power supply dependencies, which are addressed in the next section.

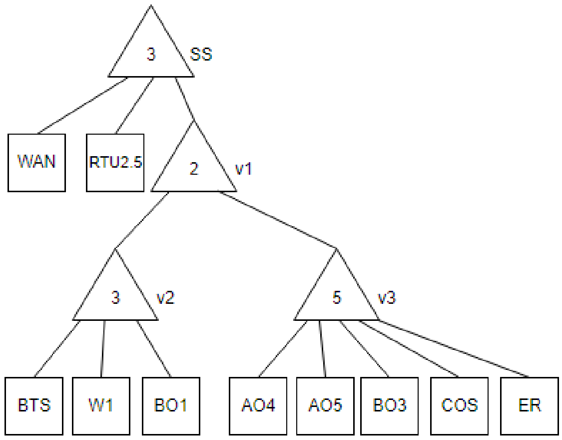


Figure 2.15: Acyclic graph of the data network segment.

2.2.3 Interconnected Networks

Finally, the dependencies between the power distribution and communication networks are incorporated into a comprehensive AG for the entire test network, as shown in Figure 2.16. This representation highlights the critical points of interconnection and dependency between the two infrastructures, allowing for a more thorough contingency analysis.

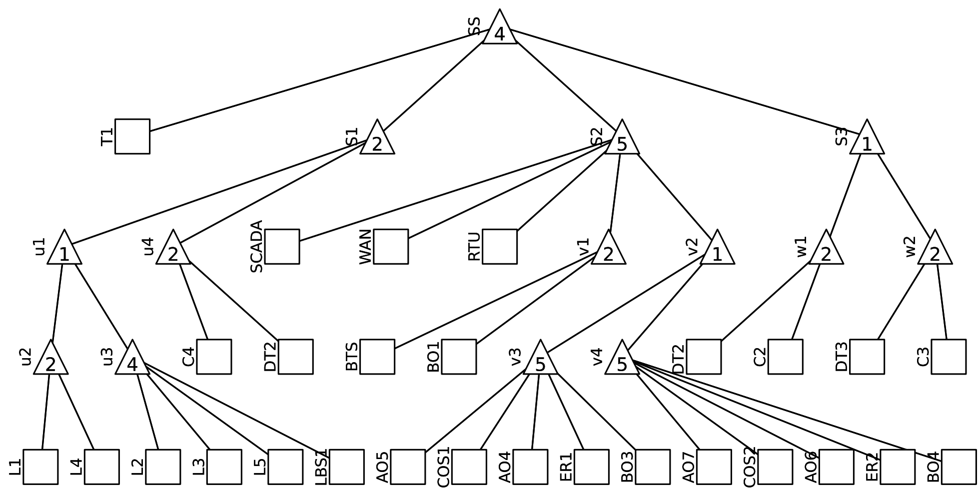


Figure 2.16: Acyclic graph of the interconnected test network [65].

By constructing AGs for each network and integrating them, a structured and interpretable model is developed to support contingency planning and dependency analysis across interconnected systems. The smart grid test network serves as a comprehensive and scalable platform for analyzing interdependencies within critical infrastructures. Through iterative refinement, it has evolved into a detailed model that effectively integrates power and communication networks. As outlined in this section, the test network provides the foundation for the simulations and analyses presented in this thesis. Furthermore, its creation and validation represent a significant scientific contribution, offering a reproducible and adaptable model for future research on critical infrastructure reliability and maintenance optimization.

3 System Unavailability Exploration and Maintenance Optimization Strategies

Based on the findings of this thesis, the increasing complexity and interdependence of power and communication networks in smart grids present substantial challenges to maintaining system resilience and reliability. Unintended power outages not only result in financial losses but also pose broader social, cybersecurity, and operational risks. The reliance of telecommunications infrastructure on stable power supply further exacerbates these risks, as prolonged power failures can lead to cascading effects, including communication disruptions and increased vulnerability to cyber threats. These interdependencies highlight the necessity of identifying and managing critical parameters within interconnected infrastructures to enhance operational efficiency and reliability.

This section addresses three objectives of the dissertation thesis: the determination of key performance indicators (KPIs) for assessing system reliability, the integration of a dedicated module for system unavailability analysis, and the exploration of maintenance optimization strategies aimed at improving reliability metrics. The ability to quantify system unavailability and assess maintenance strategies is crucial for mitigating risks associated with power outages and optimizing the allocation of maintenance resources.

Several publications contribute to the content of this section by providing theoretical foundations and methodological advancements. **Publication IV** presents an in-depth analysis of smart grid infrastructure, focusing on the identification of critical parameters and interdependencies essential for subsequent modeling and optimization. This work serves as the basis for defining the KPIs that are integral to reliability assessments. Building upon these findings, **Publication V** explores the concept of system unavailability, comparing methodologies used in traditional power systems with those required for interconnected infrastructures. The publication emphasizes the necessity of incorporating both power and communication network dependencies into unavailability calculations to accurately reflect real-world conditions. **Publication VIII** examines the role of maintenance optimization in enhancing system resilience. This work employs multi-objective optimization techniques to balance operational costs and reliability improvements, demonstrating the methodology on a real-world critical infrastructure model introduced in Section 2.

3.1 Key Performance Indicators Determination

Publication IV addresses the identification and definition of critical parameters and interdependencies within interconnected power and communication infrastructures. The main goal was to facilitate the efficient and reliable operation of smart grids. In such integrated infrastructures, specific dependencies arise, such as the reliance of wireless communication devices on LV power grid and the dependence of RTUs and AMM devices on the functional status of the distribution network. According to the findings of this publication, RTUs were identified as critical components in interconnected infrastructures, as they play a key role in controlling and monitoring switches within the distribution network, measuring voltage and current, detecting faults, and performing automated operations. A failure in RTUs could prolong power restoration times, directly impacting reliability indices such as system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI).

The publication also introduces a methodology for measuring the reliability and availability of various network components, utilizing indicators such as mean time to failure (MTTF), mean time between failures (MTBF), and Mean Time to Restore service (MTTRes). These parameters are essential in assessing system resilience and planning maintenance strategies. To ensure consistency and clarity in analysis, fundamental parameters like failure rate (λ_p) and repair rate (λ_r) are established as standard metrics across analyses. The investigation also highlights that many publications addressing similar issues often use only a subset of reliability parameters, leading to potential ambiguities for readers regarding terminology. For example MTTF and MTBF are frequently confused or misinterpreted. To address this, an entire section of **Publication IV** is dedicated to clarifying the definitions and applications of these parameters, thus setting a standardized basis for further analysis. Figure 3.1 visually demonstrates the relationship between MTTRes and related time intervals in incident management, including Mean Time To Incident (MTTI), Mean Time To Known issue (MTTK), MTTRep, and Mean Time To Validate (MTTV).

This figure clarifies how these intervals interrelate and contribute to the overall MTTRes metric, helping standardize incident management timing and terminology. The relationship between MTBF, MTTRes, and MTTF is depicted in Figure 3.2. This figure highlights how MTBF encapsulates both MTTF and MTTRes, providing a comprehensive measure of reliability that reflects both time-to-failure and restoration times. Such visualization aids in distinguishing between these metrics, reinforcing that MTBF accounts for both the lifespan until a failure and the subsequent recovery period.

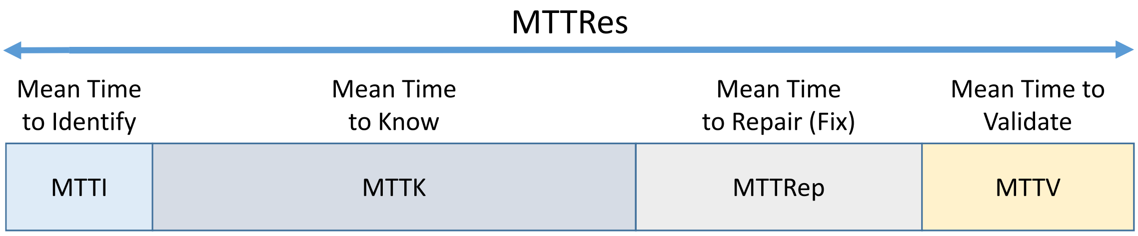


Figure 3.1: Graphic display of relationship between parameters MTTRes, MTTI, MTTK, MTTRep, and MTTV.

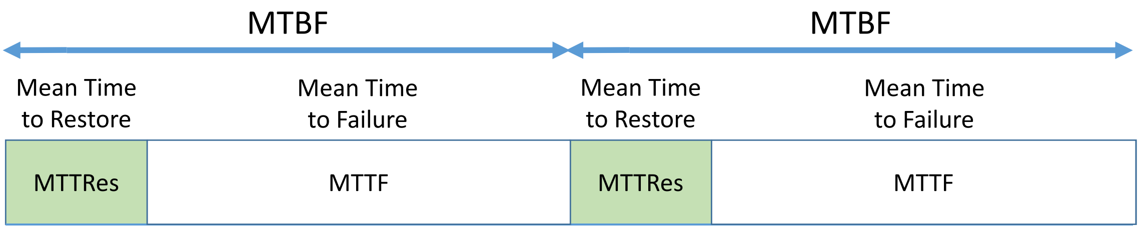


Figure 3.2: Graphic display of relationship between parameters MTBF, MTTRes, and MTTF.

To ensure clear comprehension, two fundamental parameters are emphasized: failure rate (λ_p) and repair rate (λ_r). The failure rate (λ_p) is defined as:

$$\lambda_p = \frac{\Sigma n_f}{\Sigma T}, \tag{3.1}$$

where ΣT represents the cumulative operating time across devices, and Σn_f is the total number of failures within that timeframe. The repair rate (λ_r) is similarly defined by:

$$\lambda_r = \frac{\Sigma n_r}{\Sigma T_{res}}, \tag{3.2}$$

where ΣT_{res} represents the total time required to return a device to its operational state after a failure, encompassing identification, repair, and validation times.

Differentiating between availability and reliability is critical - availability measures the component's readiness for immediate use, while reliability assesses its ability to perform without failure over a specified period. In reliability analysis, MTBF and MTTF are fundamental metrics that provide insights into expected performance intervals. MTTF is often used for non-repairable components and is calculated as:

$$\text{MTTF} = \frac{\Sigma T}{\Sigma n_f} = \frac{1}{\lambda_p}. \tag{3.3}$$

For components that can be repaired, MTBF, which considers both the failure and restoration cycles, is defined as:

$$\text{MTBF} = \text{MTTF} + \text{MTTRes} = \frac{1}{\lambda_p} + \frac{1}{\lambda_r}. \tag{3.4}$$

Availability (A) and unavailability ($\bar{A}$) are further derived from these parameters:

$$A = \frac{\text{MTTF}}{\text{MTTF} + \text{MTTRes}} = \frac{\lambda_p + \lambda_r}{\lambda_p}, \tag{3.5}$$

$$\bar{A} = 1 - A. \tag{3.6}$$

Utilizing standardized KPIs and relationships enhances the analysis and optimization of reliability and availability in interconnected systems. The methodology outlined in **Publication IV** not only clarifies these KPIs but also provides a solid foundation for further research, ensuring precision and consistency in high-impact incident management within critical infrastructure. It further examines critical parameters specific to each component, presenting a structured approach for determining key parameters and their interdependencies. A reference table facilitates a comprehensive view of each component's role in system reliability and enables effective cross-referencing in network reliability assessments.

The determination of KPIs was also crucial for setting parameters based on real data from the DSO, as detailed in **Publication II**. These KPIs, derived from operational data, were applied in further analyses of critical infrastructures, enabling validation and refinement under real-world conditions to support more accurate resilience assessments.

3.2 Module for System Unavailability Calculation

Publication V delves into the analysis of time-dependent unavailability in critical infrastructure, specifically for the smart grid presented in Section 2.1.4. This study combines expertise from the fields of energy and communication, integrating renewal theory for multi-component systems. A major outcome of this research is the identification of critical components within the interconnected network and their interdependencies, illustrated using an AGs.

In calculating system unavailability, the components of the interconnected energy infrastructure are divided into repairable and non-repairable categories, mapping out the topology and reliability characteristics of both the power grid and the communication network. In **Publication V**, unavailability calculations were performed for each infrastructure separately, revealing that the communication network exhibited nearly double the unavailability of the power grid over a 5-year period.

The methodology presented in this study employs the Weibull distribution to evaluate time-dependent reliability in interconnected systems. By modeling component failures over specific time horizons, this approach facilitates both system unavailability estimation and contingency forecasting, supporting efficient infrastructure planning and maintenance scheduling.

3.2.1 Weibull Distribution for Unavailability Calculations

For reliability analysis, the Weibull distribution is particularly suitable, as it effectively captures component lifespan and failure behavior, enabling optimized maintenance strategies. Its flexibility allows for modeling diverse failure rate behaviors, crucial for accurately predicting component degradation over time.

The Weibull distribution, widely used in reliability engineering, was selected for system unavailability calculations (more details in **Publication IV**). It accommodates various failure patterns through two key parameters:

- scale parameter (λ), representing the typical lifetime of a component or system,
- shape parameter (β), defining the distribution's shape and indicating failure behavior.

If $\beta < 1$, the distribution exhibits a decreasing failure rate, ideal for components with high initial failure rates that stabilize over time. When $\beta = 1$, the failure rate remains constant, typically representing random failures. For $\beta > 1$, the distribution models wear-out failures, characterized by an increasing failure rate. This flexibility enables the model to represent time-dependent unavailability accurately for each component in the infrastructure.

The Weibull probability density function (PDF) is defined as follows [66]:

$$f(x; \lambda, \beta) = \begin{cases} \frac{\beta}{\lambda} \left(\frac{x}{\lambda}\right)^{\beta-1} e^{-(x/\lambda)^\beta} & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{3.7}$$

and the cumulative distribution function (CDF) is:

$$F(x; \lambda, \beta) = 1 - e^{-(x/\lambda)^\beta}. \tag{3.8}$$

For repairable systems, MTTR can also be represented by an exponential distribution (a special case of the Weibull distribution where $\beta = 1$).

3.2.2 Model for Unavailability of a Terminal Node with Corrective Maintenance

To calculate the unavailability function $U(t)$ of a terminal node, a model incorporating corrective maintenance is required. In corrective maintenance analysis, two key random variables must be considered: the lifetime X of a component, defined by a distribution function $F(t)$ or PDF $f(t)$, and the repair time Y, with distribution $G(t)$ or PDF $g(t)$. Using renewal theory and alternating renewal processes, the unavailability function $U(t)$ is given by [67]:

$$U(t) = 1 - A(t) = F(t) - \int_0^t h(x)[1 - F(t-x)]dx, \tag{3.9}$$

where $U(t)$ is the time-dependent unavailability function, $A(t)$ is the availability function, and $h(x)$ represents the renewal density for the alternating renewal process.

For practical computation, an alternative form of this equation is used, known as the recurrent linear integral equation [67]:

$$U(t) = \int_0^t f(x)[1 - G(t-x)]dx + \int_0^t (f * g)(x)(t-x)dx, \tag{3.10}$$

where $*$ denotes convolution. This approach has been validated as an effective methodology for calculating unavailability in complex, high-reliability systems [67]. Once all necessary parameters are obtained, this model provides a foundation for analyzing the reliability of individual components within the network.

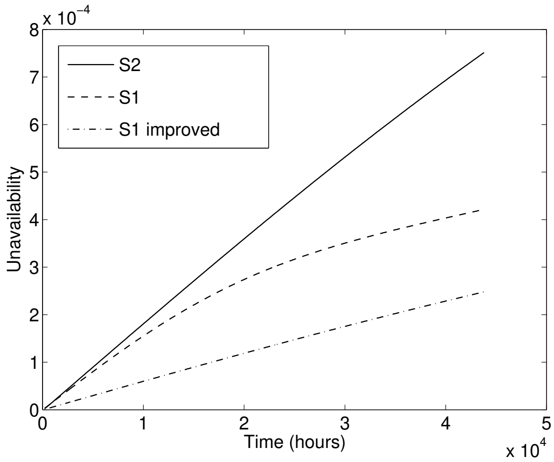
This module, supported by Weibull-based modeling and precise parameterization, enables robust unavailability calculations. The flexibility to adjust for different component lifetimes and repair cycles enhances maintenance scheduling and improves infrastructure resilience.

3.2.3 Time-Dependent Unavailability Analysis

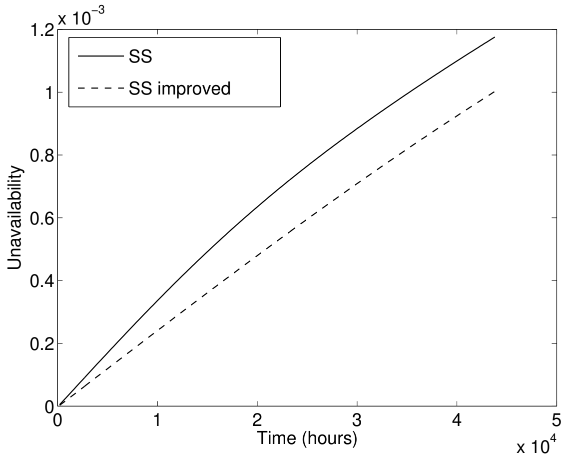
The unavailability calculation simulator module described above was applied to the test network presented in Section 2.1.4. The results achieved in **Publication V** show, that the initial design of the interconnected infrastructure exhibited a relatively high level of unavailability, prompting model optimizations through targeted component adjustments. These optimizations, achieved with minimal cost increases, effectively reduced overall unavailability and enhanced system resilience, particularly within the power network. The analysis confirms that the modified design improves reliability, demonstrating lower unavailability compared to the original setup.

In Figure 3.3, a comparison of unavailability evolution over a 5-year mission time is shown for both the original and improved parameters of system S1, as well as for system SS in both configurations. The calculations reveal that the improved design significantly reduces system unavailability.

A detailed calculation of the S2 system's unavailability was also extended to a 10-year horizon, as shown in Figure 3.4. After 10 years, the S2 system unavailability reaches 1.27×10^{-3}, which is comparable to the SS system unavailability after 5 years,



(a) Original and improved parameters of system S1.



(b) Original and improved parameters of system SS.

Figure 3.3: Comparison of the unavailability evolution within a mission time of 5 years for original and improved parameters of systems S1 and S2 (a) and system SS (b).

indicating a gradual increase in unavailability over time. These findings suggest a proportional increase in SS system contingency, estimated at approximately 5×10^{-4} over the next 10 years, projecting a total unavailability of 1.7×10^{-3} for SS after a decade.

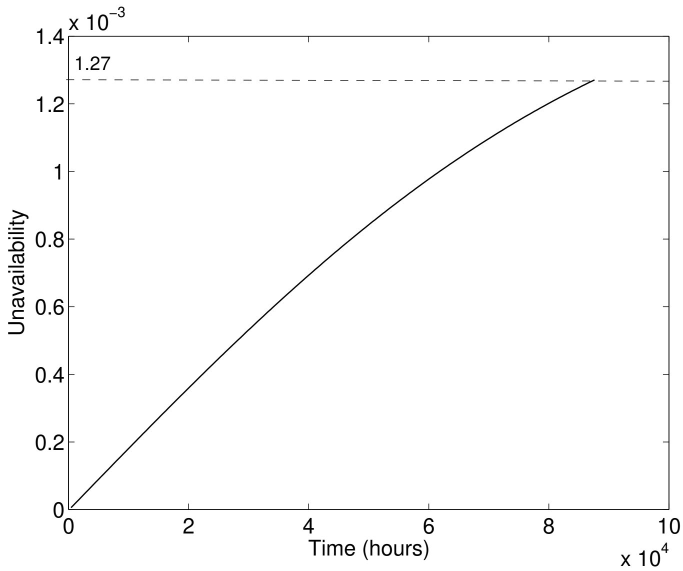


Figure 3.4: The unavailability evolution within the mission time of 10 years for system S2.

3.3 Improving Smart Grid Resilience and Reliability Using Unavailability Analysis and Maintenance Optimization

Unlike previous publications that focused on analyzing the evolution of unavailability in interconnected infrastructures, further research (e.g. **Publication VIII**) has been directed towards leveraging unavailability for optimizing maintenance strategies. In this thesis, predictive maintenance in smart grids is perceived as a method for ensuring the reliability and efficiency of electricity supply. Traditional maintenance approaches, such as reactive or scheduled preventive maintenance, often lead to inefficient resource utilization or unplanned outages. Modern approaches, based on data analysis and advanced models, enable optimization of maintenance actions and reduction of overall costs. These approaches can be broadly categorized into the following four groups:

- condition-based maintenance, which involves continuous monitoring of key operational parameters of equipment and analyzing these for anomaly detection. This approach is widely used due to its relatively easy implementation and ability to identify faults at an early stage. Thermal imaging detects elevated temperatures in electrical branches and transformers, which may indicate overloads or deteriorated connections [68]. Examples of such methods include oil-based diagnostic techniques that analyze transformer oil to detect dissolved gases signaling insulation degradation [69], or vibration monitoring in rotating machinery to identify mechanical faults such as imbalance and bearing wear [70].
- Data-driven predictive maintenance, which approaches leverage machine learning and big data analytics to model equipment degradation and predict failures. Machine learning models trained on historical data can forecast transformer and line failures [71]. Bayesian models and probabilistic prediction methods determine the probability of failure based on operational data analysis [72]. Anomaly detection techniques identify deviations from normal operational behavior using deep learning techniques [73].
- Physics-based approaches, which involve simulating equipment degradation and assessing the impact of different operating conditions on component lifespan. Digital twin technology creates virtual replicas of smart grids, allowing predictive analysis and optimization of operations [74]. For example, electromagnetic and thermomechanical modeling techniques simulate temperature effects and load impacts on component degradation [75].
- A separate category can be considered reliability-centered maintenance (RCM).

This approach incorporates probability-based life modeling, where Weibull distributions and Markov processes are used to estimate failure probabilities [76]. Risk-based maintenance prioritization methods focus on identifying the most critical components in the network [77]. Additionally, machine learning models can be applied to further optimize maintenance actions by predicting the optimal timing for interventions [71].

RCM has been selected as the primary approach in this research and has been implemented in the development of a dedicated module within the smart grid simulation framework, benefiting from extensive prior research experience in this field. RCM optimizes maintenance by prioritizing critical components, reducing downtime and costs while improving fault prediction through probabilistic models. It is particularly beneficial in smart grids, where complexity requires a structured approach. Additionally, it supports renewable energy integration by enhancing grid reliability. However, RCM demands extensive system modeling, expert knowledge, and historical failure data, making implementation complex and costly. Despite these challenges, its structured planning balances cost efficiency and reliability.

Publication VIII focuses on enhancing the resilience of smart grids through component unavailability analysis and maintenance optimization. The paper addresses the question of "how to minimize operational costs while improving system resilience", employing multi-objective optimization to combine cost and reliability metrics. The methodology is demonstrated on a simplified model of real-world critical infrastructure, as detailed in Section 2. Specific research results and practical implementation are presented in Section 4, while the following subsections provide the theoretical background for the development of this simulator module.

3.3.1 System Reliability Modeling

RCM serves as a foundation for optimizing maintenance strategies in smart grids. To effectively implement RCM, a robust understanding of system reliability is required. This chapter introduces a mathematical framework for modeling system reliability, enabling structured risk assessment and optimized maintenance planning. The ability to model system reliability is crucial for identifying critical components, optimizing maintenance schedules, and improving grid resilience.

Smart grid systems are composed of multiple interdependent components, and their overall performance is determined by the states of these components and their interrelations. The binary structure function $\varphi : 0, 1^N \rightarrow 0, 1$ relates component states to the SS, where N represents the number of components. Common methods for constructing φ include FTA and reliability block diagrams (RBD). For systems with groups of homogeneous components, survival signatures provide an efficient representation [77].

Direct computation of smart grid reliability is challenging due to the exponential growth of the state space with the number of components (N). Reliability functions map the probability vector of individual component functionality ($\vec{p}$) to the overall system reliability, enabling more efficient evaluations.

System reliability models can be categorized based on their configurations as:

- series systems, where failure of a single component leads to system failure,
- parallel systems, where the system operates as long as at least one component remains functional,
- k-out-of-n Systems: the system functions if at least k out of n components are operational and
- networked systems - more complex systems where connectivity plays a role in determining reliability.

As discussed in Section 3.2, the developed simulator module evaluates resilience and reliability metrics based on the calculation of overall system unavailability. This approach has been further extended to incorporate the effects of preventive maintenance as a means to enhance these metrics. The unavailability function $U(t)$ evolves over time as a consequence of component failures and subsequent repairs. According to renewal theory, it can be expressed using a recursive integral formulation:

$$U(t) = \int_0^t f(x) \cdot [1 - G(t-x)]\, dx + \int_0^t (f * g)(x) \cdot U(t-x)\, dx, \tag{3.11}$$

where f is the PDF of the time to failure (TTF), and g, G are the PDF and CDF of the time to corrective repair.

For preventive maintenance, the failure density $f(x)$ is replaced with f_P:

$$f_P := f_c + P(\mathrm{TTF} > T_P)\delta_{T_P}, \tag{3.12}$$

where $f_c(x) := f(x)I_{\{x<T_P\}}(x)$ models failures before the preventive maintenance time T_P, and δ_{T_P} is the Dirac delta function. Substituting f_P into Equation (3.11) leads to:

$$\begin{aligned} U(t) = &\int_0^{\min(t,T_P)} f(x)[1 - G(t-x)]\, dx \\ &+ \int_0^t (f_c * g)(x) \cdot U(t-x)\, dx \\ &+ I_{\{t>T_P\}} P(\mathrm{TTF} > T_P)[1 - H(t-T_P)] \\ &+ I_{\{t>T_P\}} P(\mathrm{TTF} > T_P) \int_0^{t-T_P} h(x) U(t - T_P - x)\, dx, \end{aligned} \tag{3.13}$$

where h and H are the PDF and CDF of the time to preventive repair. The accuracy of this extended model has been confirmed through Monte Carlo simulations and comparison with known asymptotic values, validating its suitability for further use in optimization of maintenance strategies.

To enable proper formulation of the optimization problem, where the objective is to determine the optimal preventive maintenance interval in terms of both cost and timing, it is essential to accurately quantify the costs associated with both corrective and preventive maintenance actions. The total system maintenance cost is computed as the sum of individual component costs. For components subject to preventive maintenance, the expected cost over the mission time T_m can be expressed as:

$$\begin{aligned} \text{cost}_{\text{prev}} = {} & n_{\text{prev}} P(\text{TTF} < T_P) \cdot C_c \\ & + n_{\text{prev}} P(\text{TTF} > T_P) \cdot C_p, \end{aligned} \tag{3.14}$$

where n_{prev} is the expected number of renewals during the mission time T_m:

$$n_{\text{prev}} = \frac{T_m}{\text{MTTF}_{\text{prev}} + \text{MTTR}_{\text{prev}}}. \tag{3.15}$$

Here, MTTFprev and MTTRprev correspond to the mean time to failure and mean time to repair under the applied preventive maintenance strategy. For the purposes of this thesis, anonymized maintenance cost values were used, as provided by the DSO. In performed studies, all optimization procedures are carried out using normalized or relative cost values to preserve confidentiality while maintaining the validity of the optimization approach.

3.3.2 Applications in Smart Grid Reliability

In large-scale systems such as smart grids, analytical evaluation of reliability often becomes computationally intractable. To overcome this limitation, various computational methods have been developed and are widely used in the literature. Monte Carlo simulations are frequently employed to estimate system reliability through repeated random sampling, making them particularly effective for modeling the stochastic behavior of complex networked infrastructures [78]. Bayesian reliability modeling offers a dynamic approach by updating reliability estimates based on real-time operational data and historical failure records, thereby improving the accuracy of predictive assessments [79]. Continuous-time Markov chains are also extensively applied to model component degradation over time, especially for evaluating the long-term reliability of aging grid infrastructure [80].

These modeling approaches support a wide range of applications aimed at enhancing the resilience of smart grids. Reliability analysis of key power distribution assets (such as substations, transformers, power lines, and switchgear) is commonly performed using FTA and RBD [75]. Furthermore, as the penetration of renewable energy sources increases, stochastic models are essential for evaluating their impact on overall grid reliability by accounting for the inherent variability in both generation and demand [81]. Modern smart grid reliability frameworks also address cyber-physical resilience by incorporating the effects of cybersecurity threats, communication failures, and the interaction between physical and digital infrastructure layers [82].

Building on the foundation of time-dependent unavailability modeling and cost assessment, the proposed methodology used in **Publication VIII** directly supports the evaluation and optimization of reliability in smart grid infrastructures. By capturing the dynamic behavior of component failures and restorations, the time-dependent unavailability model enables a much more accurate and granular analysis of system reliability than traditional steady-state metrics. This is particularly critical in smart grids, where heterogeneous components exhibit varying degradation profiles and where preventive actions can significantly alter system behavior over time.

To optimize maintenance strategies with respect to both reliability and cost, a multi-objective optimization framework was adopted and is described mainly in [83]. The primary goal is to determine optimal preventive maintenance intervals for individual components, balancing reduced system unavailability against the incurred maintenance expenses. The methodology is built upon a renewal process formalism, where preventive and corrective maintenance actions are both incorporated into the unavailability model through recurrent integral equations. These equations account for different repair time distributions and failure characteristics and have been analytically simplified for components with uniformly distributed repair times, enabling efficient evaluation even in large-scale systems.

For solving the multi-objective optimization problem, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was selected due to its robustness and effectiveness in exploring Pareto fronts in complex, non-linear optimization landscapes. NSGA-II is particularly suited for problems with conflicting objectives (such as minimizing unavailability while minimizing cost) without requiring explicit weighting of the criteria in advance. The algorithm was implemented using the open-source Python framework Pymoo, which provides flexibility and scalability for high-dimensional optimization tasks.

Numerical evaluation of component unavailability, which is needed repeatedly during optimization, is performed using a hybrid approach. For general distributions where analytical convolution is not feasible, numerical integration using rectangular quadrature rules is applied. However, in cases where the MTTR is significantly smaller than the MTTF (a common situation in power systems) the proposed analytical simplifications yield substantial improvements in both accuracy and computational efficiency. These simplifications are especially beneficial when evaluating large numbers of candidate maintenance schedules, as required by evolutionary algorithms. The results obtained through the described methodology, including the evaluation of time-dependent unavailability, cost modeling, and optimization using NSGA-II, are presented and discussed in the following section.

4 Practical Implementation and Discussion

As part of the developed simulator, several practical implementations have been conducted to contribute to the research objectives outlined at the beginning of this thesis. These implementations serve to validate the functionality of the proposed solution, optimize its performance, and explore its applicability to real-world scenarios. The practical results have been presented at multiple international conferences, with corresponding publications attached to this thesis (Appendix A). This section provides a detailed discussion of these publications, analyzing the achieved results and their implications for the investigated problem domain.

The results are primarily based on a series of validation tests aimed at verifying the functionality of the proposed simulation framework. These tests were performed using various test networks introduced in Section 2, ensuring an evaluation of the simulator under different conditions. Furthermore, the presented findings include analyses of interconnected infrastructures, specifically in terms of reliability and resilience metrics. Subsequent research was focused on maintenance optimization, with the objective of minimizing system unavailability while enhancing reliability and resilience indicators. A dedicated study also compared the final simulation framework with commercially available tools, evaluating its strengths, limitations, and potential for broader adoption.

The following sections provide an in-depth discussion of these key aspects, including the validation of simulation results, reliability assessments, maintenance optimization strategies, and comparative studies with existing solutions.

4.1 Application of Graph Theory in Critical Infrastructure Analysis

The first part of **Publication III** focuses on the application of graph theory for analyzing interconnected energy and communication infrastructures. It introduces fundamental graph theory concepts, where networks are modeled as nodes and edges, facilitating the analysis, visualization, and optimization of distribution and communication systems. The proposed approach is subsequently utilized for topology verification during the initialization of the power grid model, as detailed in the paper.

Additionally, the study investigates how graph-based analysis facilitates the identification of interdependencies between power and communication infrastructures, highlighting key vulnerabilities that may compromise system resilience. Two main simulation methodologies are discussed in this context:

- probabilistic simulations, which model the likelihood of failures in network components,
- failure impact simulations, which assess the consequences of specific outages on system performance.

By establishing a solid theoretical foundation, this section highlights the importance of graph theory in the analysis and optimization of urban distribution networks. The practical section of **Publication III** focuses on validating the functionality of the developed simulator by applying verification algorithms to a real-world urban distribution network, as it was earlier depicted in Figure 2.6. The test network, described in Section 2.1.2, was used to evaluate the simulator's ability to model, analyze, and optimize the reliability of interconnected infrastructures. Due to the size of the network, only a selected portion was utilized for simulation purposes. This subset was converted into a graph representation (shown in Figure 4.1), where transformers, switching elements, and lines were modeled as graph edges, allowing for critical component identification within the network.

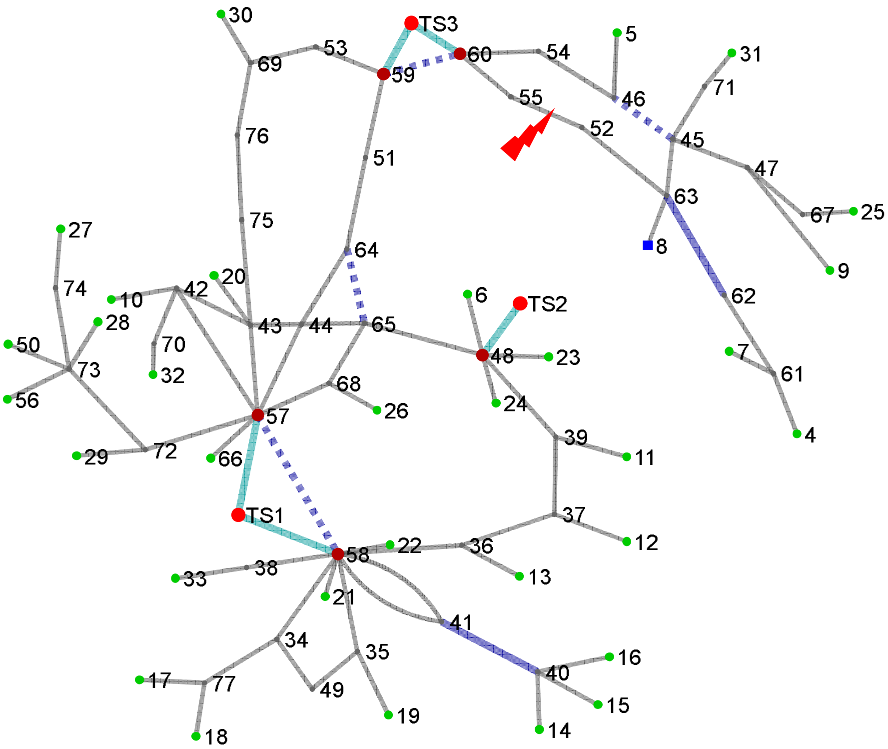


Figure 4.1: Topology of the selected test network part converted into a graph.

The simulation aimed to assess the network's operational stability, ensuring that voltages remained within the permissible range and that transformer and line loads did not exceed defined limits. The network topology was initially converted into a graph, enabling easy detection of weak points, such as nodes without redundant power supply. The simulation followed these steps:

- defining load conditions at individual nodes,
- verifying network operational stability under normal conditions,
- identifying critical failures based on calculated reliability metrics,
- analyzing the impact of a failure on the overall network,
- reconfiguring the network using available switching elements,
- verifying the post-fault network state to ensure full system restoration.

The practical validation focused on a simulated failure of the most critical line, identified based on the load analysis results from the simulator. Tables 4.2 and 4.2 provide an overview of the top five most heavily loaded transformers and lines before the fault occurrence.

From bus	To bus	Sn (kVA)	I (A)	Load (%)
1	58	630	239.36	26.48
3	60	630	215.74	23.86
2	48	630	150.11	16.78
1	57	630	144.45	16.04
3	59	630	103.22	11.46

Table 4.1: Load results before the reconfiguration for the five most loaded transformers.

From bus	To bus	Imax (A)	I (A)	Load (%)
63	52	320	195.54	61.11
55	52	367	195.54	53.28
60	55	371	195.54	52.71
61	7	252	132.14	52.44
72	57	320	127.59	39.87

Table 4.2: Load results before the reconfiguration for the five most loaded lines.

Based on this evaluation, a fault was simulated on the line between buses 52 and 56, representing the worst-case scenario. The fault location is illustrated in Figure 4.1. Following this failure event, the simulator performed an automated network reconfiguration to restore power to the affected areas. The results of this reconfiguration process are summarized in Table 4.3, which presents the adjusted load distribution after the corrective switching operations. The post-reconfiguration analysis confirmed that all affected nodes were successfully restored, ensuring the network's full operational status. Moreover, voltage deviations across the network remained within acceptable limits, not exceeding 2 %. Extended results, including transformer load analysis and a detailed description of the voltage evaluation methodology at individual nodes, are provided in **Publication III**.

From bus	To bus	Imax (A)	$I_1(A)$	$Load_1(\%)$	$I_2(A)$	$Load_2(\%)$
63	52	320	195.54	61.11	-	-
55	52	367	195.54	53.28	-	-
60	55	371	195.54	52.71	-	-
61	7	252	132.14	52.44	132.14	52.44
72	57	320	127.59	39.87	127.59	39.87
46	54	320	-	-	215.75	67.42
60	54	367	-	-	215.75	58.79

Table 4.3: Comparison of line load results before and after reconfiguration.

As previously outlined in Figure 2.6, upon successful network verification, the algorithm proceeds with updating the state matrix and transferring the data to the simulation's data processing module.

4.2 Reliability and Resilience Analysis in Medium Voltage Distribution System

Beyond the core functionalities of the simulator, a module for evaluating resilience and reliability metrics was also implemented in the power grid simulator component. The verification of its functionality has been presented in two publications.

The study presented in **Publication IX** focuses on evaluating the resilience of a real MV distribution network in the Czech Republic (as described in Section 2). The analyzed system operates in either a radial or ring configuration, enabling effective fault isolation while maintaining supply continuity for unaffected customers. The study examines the impact of LBS failures on the resilience of the MV distribution network. However, potential failures (whether caused by mechanical issues or communication disruptions) can lead to prolonged outages, affecting both resilience metrics and reliability indices such as SAIDI and SAIFI. To assess these impacts, the case study defines three distinct outage scenarios.

- **Scenario 0:** LBS operates correctly and isolates the fault.
- **Scenario 1:** The nearest LBS fails to operate.
- **Scenario 2:** The nearest LBS cannot be remotely controlled but can be manually switched.

Although the study was conducted on a real network, for the purposes of this publication, the network load distribution was modeled based on the nominal power of the DTS. The average transformer load factor was determined to be 30 % of the nominal transformer rating, which was applied within the simulation framework to approximate realistic operating conditions. Therefore, the results should be considered demonstrative, serving to validate the functionality of the resilience assessment module, rather than reflecting the actual network load conditions.

Each scenario is evaluated using resilience metrics [84], including expected maximum load loss ($\mathcal{L}_l$), load interruption rate ($\mathcal{S}l$), automatic restoration time ($\mathcal{T}rs$), and energy not supplied (ENS). The study employs a simulation-based approach to identify the weakest LBS in the network, determined based on the highest disconnection impact. By simulating various failure cases, the study quantifies the effect of LBS malfunctions on system resilience. Figure 4.2 presents one of the graphical outputs of the module's computations (the resilience trapezoid associated with events).

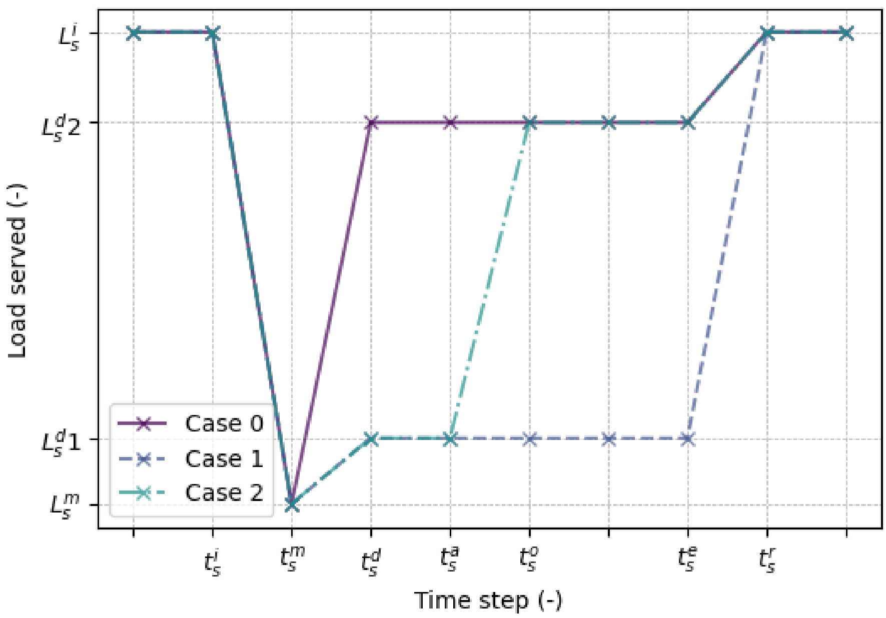


Figure 4.2: Conceptual resilience trapezoid associated with events.

Results presented in Table 4.4 indicate that scenarios 1 and 2 significantly increase ENS, which directly translates into higher economic losses. The automatic restoration load ratio ($\mathcal{L}_{rs}$) decreases when LBS fails to operate, highlighting the critical role of remote controllability. The comparison of unavailability evolution over a 25-year mission time demonstrates that optimizing preventive maintenance intervals significantly reduces long-term system unavailability.

Metric (-)	Case 0	Case 1	Case 2
$\mathcal{L}_l$ (MW)	3.47	3.47	3.47
$\mathcal{S}_l$ (MW/h)	0.35	0.35	0.35
$\mathcal{T}_{rs}$ (h)	0.16	0.16	0.16
$\mathcal{L}_{rs}$ (-)	0.81	0.14	0.26
$\mathcal{T}_{rp}$ (h)	0.00	0.00	0.00
ENS (MWh)	7.71	35.64	12.73

Table 4.4: The resilience metrics computed for the given case study summary.

The study highlights the vulnerability of MV networks to LBS failures and the necessity for robust preventive maintenance strategies. The developed simulator effectively quantifies resilience metrics and supports decision-making to mitigate potential failure risks.

4.2.1 Unavailability evolution analysis of LBS

Publication IX focuses also on optimizing preventive maintenance periods to reduce overall system unavailability. The study evaluates the evolution of LBS unavailability over a 25-year mission time. Figure 4.3 illustrates that optimizing preventive maintenance intervals significantly decreases system unavailability.

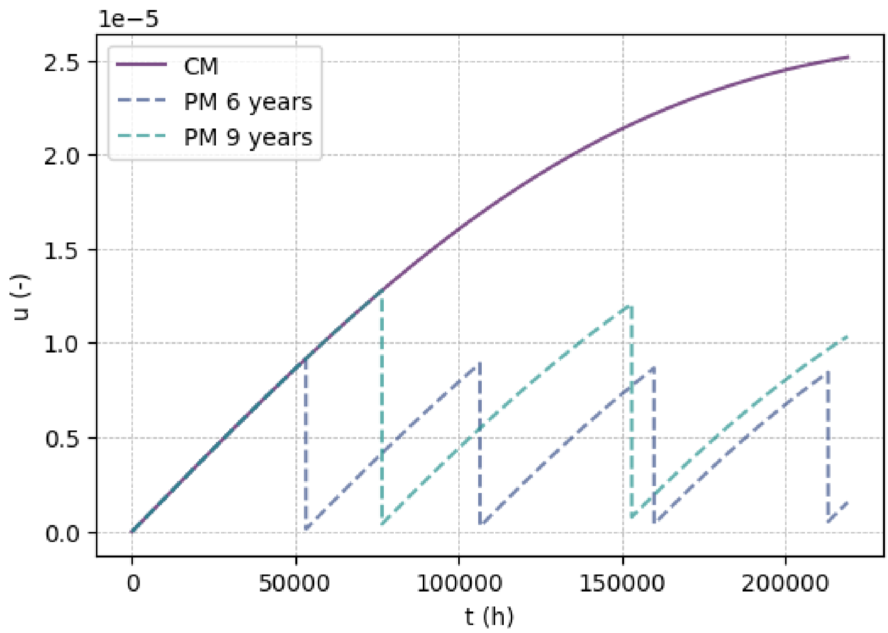


Figure 4.3: Unavailability evolution of the LBS within the mission time of 25 years.

The results suggest that refining preventive maintenance scheduling and establishing optimal maintenance intervals can greatly improve network reliability and resilience. Future work should further explore optimal scheduling of inspections and repairs to minimize ENS and operational risks. Through simulation-based testing, the study evaluates the consequences of LBS failures under different scenarios and highlights the importance of automated switching for power restoration. Additionally, preventive maintenance optimization is shown to be an effective strategy for reducing ENS and system downtime. By integrating renewal theory-based modeling, the study provides a robust framework for decision-making in network resilience planning.

4.3 System Maintenance Optimization

Publication VIII focuses on enhancing the resilience of smart grids by analyzing the unavailability of system components and optimizing maintenance strategies. The study aims to minimize operational costs while simultaneously improving system resilience. To achieve this, a multi-objective optimization framework is employed, combining cost and reliability metrics. The methodology is demonstrated on a simplified model of real critical infrastructure, presented in Section 2.1.4.

This publication presents the application of multi-objective optimization algorithms, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which were employed for a comprehensive analysis of the network's behavior. One of the key outcomes of applying these algorithms is the Pareto front of non-dominated solutions, along with proposed maintenance schedules for components identified as the most critical for ensuring system reliability.

For the purpose of the conducted analysis, the optimization objectives were defined as follows:

- minimize total maintenance cost, $\text{cost}_{\text{total}}$,
- minimize average system unavailability, $\frac{1}{T_m}\int_0^{T_m} U_{\text{sys}}(t)\,dt$.

The publication first provides a detailed description of the algorithm's implementation within the developed simulator module, followed by a discussion of the obtained results and their potential application in the analysis of resilience in interconnected critical infrastructures. The optimization process generates maintenance schedules that balance cost and reliability. The results are visualized through graphs illustrating the trade-off between operational costs and system unavailability. These insights serve as a valuable basis for informed decision-making in system maintenance planning. The most significant findings of the conducted analysis are presented in the following subsections.

The application of the multi-objective optimization algorithm NSGA-II enabled the evaluation of a large number of preventive maintenance scenarios. Figure 4.4 illustrates the resulting Pareto front, highlighting the trade-offs between cost (x-axis, logarithmic scale) and system unavailability (y-axis). The red dot represents the baseline case of corrective maintenance. The figure clearly demonstrates that certain combinations of preventive strategies can simultaneously reduce both unavailability and costs. Solutions located in the lower-right region of the graph correspond to strategies with frequent preventive maintenance, which result in lower unavailability but at the expense of higher operational costs. Such analysis, performed using the developed tool, can support system operators in selecting optimal maintenance strategies.

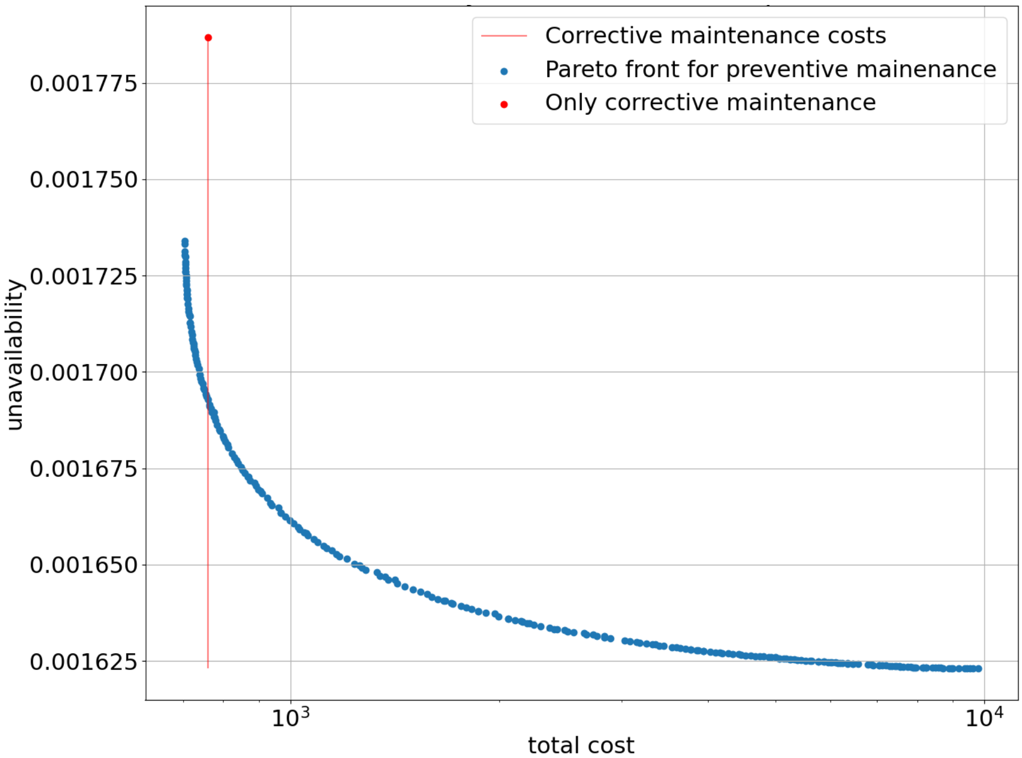


Figure 4.4: Pareto front composed of the variants proposed by the optimization algorithm. The red dot represents cost and unavailability for corrective maintenance only. The x-axis is logarithmic.

The figure presented above illustrates the analysis conducted at the level of the entire interconnected system under study. The publication further extends this analysis by focusing on maintenance strategies at the level of individual components.

4.3.1 Component-Level Maintenance Analysis

As an example of component-level analysis, transformer T1 was selected for the purposes of this publication, as it was identified as the component with the highest impact on overall system availability. Figure 4.5 shows the time evolution of unavailability for transformer T1. The graph compares several preventive maintenance schedules with the baseline strategy based solely on corrective maintenance. The three least effective preventive strategies correspond to maintenance intervals of 2.86, 1.66, and 0.72 years. In contrast, the most effective strategy involves a minimum preventive maintenance interval of one month, resulting in the lowest observed unavailability.

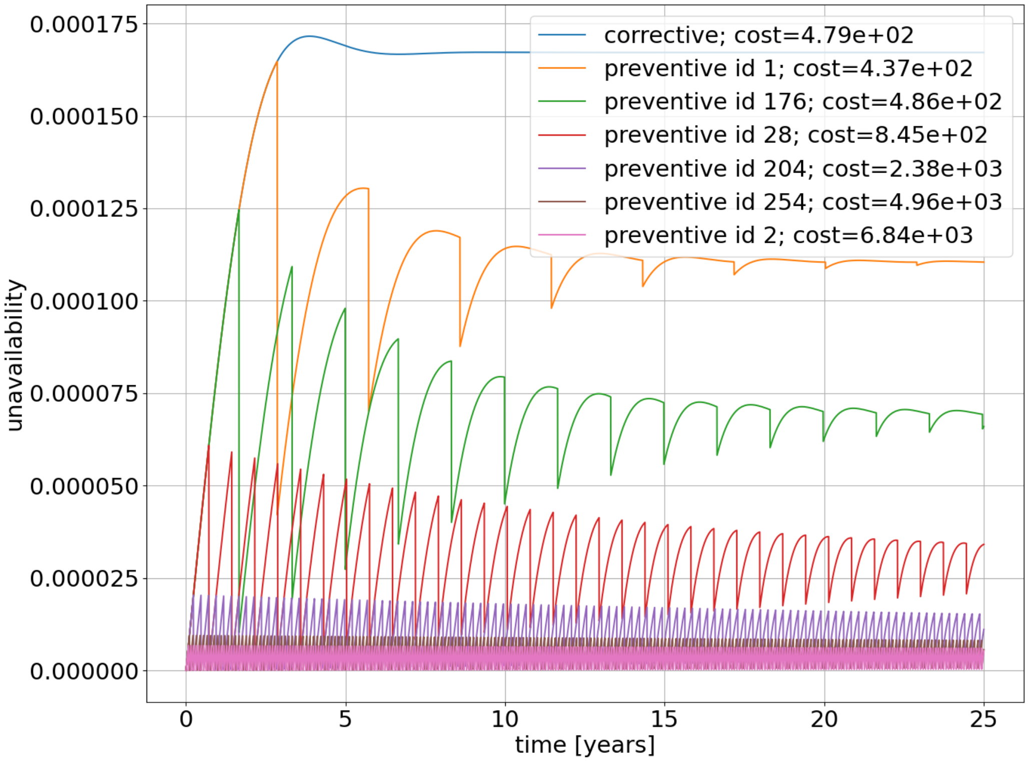


Figure 4.5: Time evolution of component T1 unavailability for several maintenance strategies compared to the corrective-only strategy.

This analysis demonstrates that appropriate adjustments to the preventive maintenance schedules of critical components such as T1 can have a substantial impact on overall system performance. Building upon these findings, the subsequent part of the study investigates the impact of maintenance optimization on the performance of the entire system.

Figure 4.6 illustrates the time evolution of overall system unavailability for selected maintenance strategies. These strategies are spaced according to their associated operational costs. The results indicate that while preventive maintenance reduces system unavailability, a significant portion of the remaining unavailability originates from communication system components, which are maintained by third parties and not included in the optimization framework. This finding underscores the necessity of focusing optimization efforts on components under direct management, such as transformers and switchgear, to maximize reliability improvements.

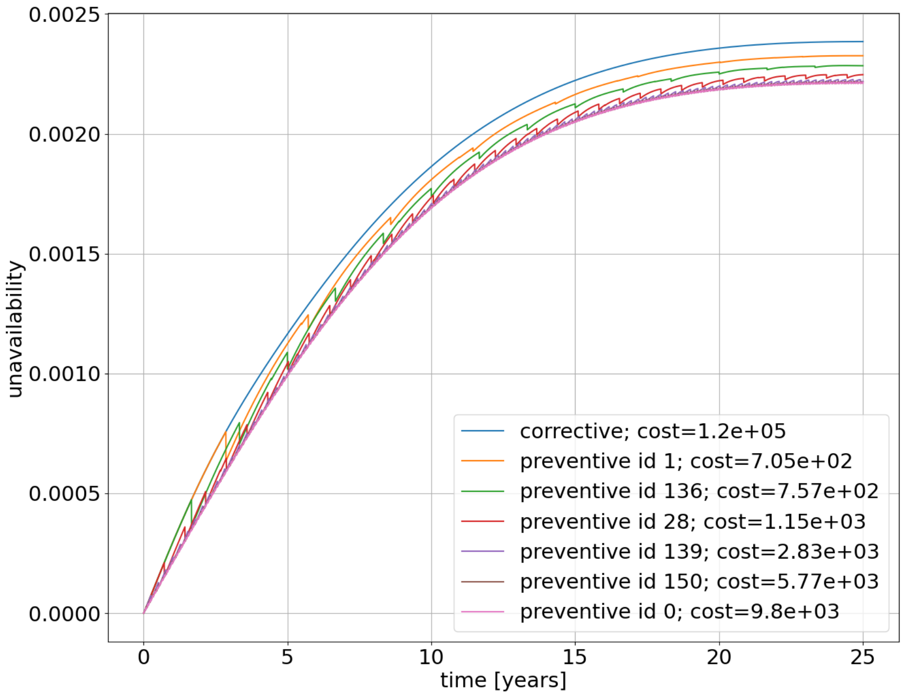
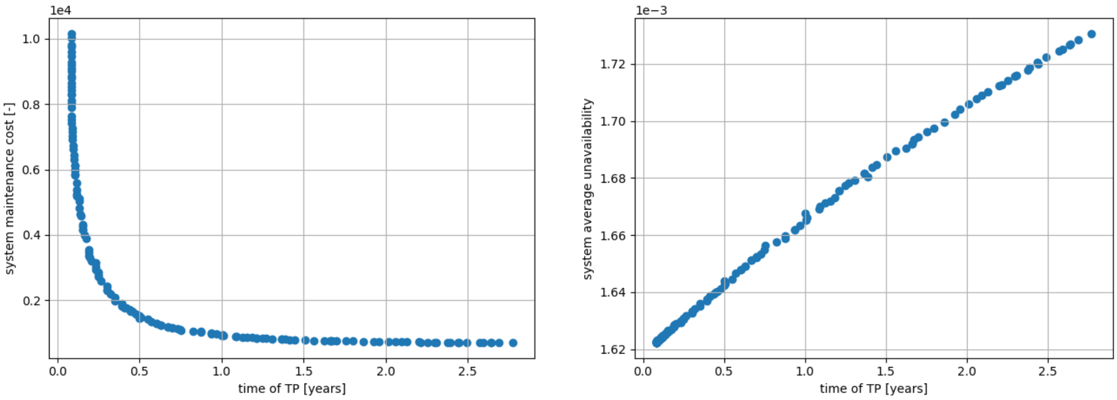


Figure 4.6: Time evolution of overall system unavailability for several maintenance strategies compared to corrective-only maintenance.

4.3.2 Extended Analysis of Critical Components

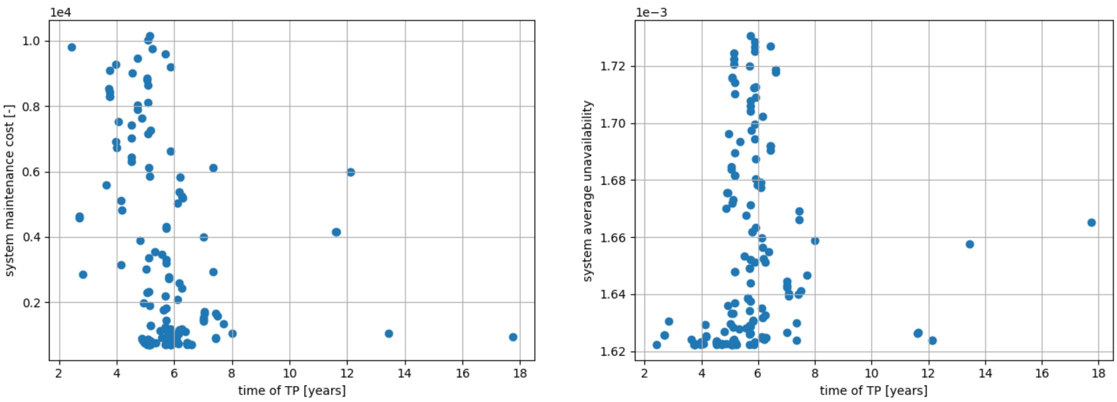
Beyond the results presented in **Publication VIII**, an extended study investigated the impact of preventive maintenance optimization on previously identified critical components (T1 and DT3). The influence of their preventive maintenance intervals on optimization objectives is depicted in Figures 4.7 and 4.8, illustrating solutions proposed by the NSGAII algorithm.

For transformer T1, the optimization algorithm suggests a continuous range of maintenance intervals, reflecting its substantial influence on system unavailability and cost. In contrast, transformer DT3, with an MTTF of 5 years, shows a clustering of proposed solutions just above 5 years (Figure 4.8). This pattern arises because corrective-only maintenance stabilizes around 10 years, beyond which preventive maintenance has minimal additional impact. Proposed DT3 maintenance intervals exceeding 10 years indicate that the algorithm recommends corrective maintenance, as this option was not explicitly included in the problem formulation. A similar trend is observed across other system components: some exhibit a single optimal cluster, similar to DT3, while others, like T1, present a trade-off spectrum.



(a) Impact on total system costs. (b) Impact on total system unavailability.

Figure 4.7: Proposed maintenance schedules for transformer T1 [83].



(a) Impact on total system costs. (b) Impact on total system unavailability.

Figure 4.8: Proposed maintenance schedules for transformer DT3 [83].

The study underscores the significance of preventive maintenance optimization in improving system reliability while controlling costs. The Pareto front analysis provides actionable insights for selecting maintenance strategies, while the component and system-level analyses highlight the importance of targeted interventions for critical assets.

4.4 Comparison Testing with Open-Source Tools

As part of the initial testing of the developed software, a comparison with competing open-source solutions was conducted to verify the suitability of the integrated method within the simulator. The results were published in **Publication VII**, which presents a comparative analysis of a Matlab-based method, integrated as a module for critical infrastructure contingency analysis within the developed simulator, against selected open-source alternatives. The comparison focuses on key parameters relevant to the applicability of each solution within the simulator framework. The development and validation of analytical tools for interconnected infrastructure systems are crucial for achieving accurate, efficient, and reliable simulations. This section evaluates the Matlab-based solution, serving as the core of the simulator, alongside open-source tools such as *FaultTree* and *ftaproxim*.

4.4.1 Overview of Fault Tree Analysis Tools

Reliable analysis of complex fault trees requires advanced software tools, as manual construction and validation of dynamic fault trees are time-consuming and prone to errors. Previous surveys, such as [85], reviewed available tools up to 2017, identifying OpenFTA as one of the few freely accessible options for critical infrastructure analysis.

However, many existing tools remain commercial, offering restricted functionality or limited access without a full license. These include solutions such as OpenAltaRica, Fault Tree Analyser, Isograph FaultTree+, and Item Toolkit. Matlab also provides FTA libraries, while Python-based solutions such as OpenErrorPro [30] for stochastic reliability modeling and the probabilistic model checker Storm [86] with its Python interface stormpy, offer flexibility for prototyping and interaction.

Given the broad applicability of FTA across multiple domains, emphasis was placed on identifying freely available tools that match the performance of commercial alternatives. The statistical computing environment R [87] emerged as a strong candidate due to its widespread adoption, continuous development, and robust security practices, making it an ideal platform for reliability modeling. Historically, R included the *Reliability* package for reliability and availability computations.

However, it has been deprecated and removed from Comprehensive R Archive Network (CRAN) due to a lack of maintenance. As alternatives, two R packages were identified and tested for their suitability in reliability analysis: *FaultTree* [88] and *ftaproxim* [89, 90].

The *FaultTree* package enables the creation of fault trees as dataframe objects, supporting logical nodes (e.g., AND, OR gates) and various event types, such as active failures (immediately detectable) and dormant failures (remaining hidden until inspection). It also supports probability-based and demand-based inputs, enhancing modeling versatility.

The *ftaproxim* package, in contrast, focuses on simulating discrete-state stochastic models, including queueing systems and stochastic Petri nets. It employs a numerical state-space analysis method known as Proxel (probability element), initially introduced in [91]. This approach approximates continuous stochastic processes using a discrete-time Markov chain framework, enabling efficient state-space traversal and probabilistic evaluations.

4.4.2 Methodology

The comparison focuses on analyzing the time-dependent unavailability of interconnected infrastructures, specifically a smart grid combining power and communication networks. The Matlab solution was benchmarked against *FaultTree* and *ftaproxim*, two widely used open-source tools implemented in R. The evaluation criteria were:

- accuracy - the capability to model the interconnected infrastructure and predict system unavailability,
- computation time The efficiency of the tools in handling complex scenarios,
- flexibility - the ability to incorporate time-dependent behaviors such as component aging,
- usability - the user-friendliness of the tools, including ease of configuration and accessibility for further research and development.

The test scenarios involved three configurations:

- power grids - modeling of transformers, feeders, and switching devices,
- communication network - analysis of RTUs and communication links,
- interconnected network - integration of both networks, with dependencies modeled using acyclic directed graphs.

Key reliability parameters such as MTBF and MTTR were obtained from experimental data. Weibull distribution with a shape parameter $\beta = 2$ was used to account for aging components. Additionally, mission times of 10,000 hours and 40,000 hours were chosen to evaluate long-term performance. The evaluation was conducted on the test network described in section 2.1.4.

4.4.3 Accuracy Evaluation

The accuracy of the evaluated tools was assessed by comparing their computed unavailability values with the results obtained from the commercial Matlab-based solution. The *FaultTree* package exhibited significant limitations due to its constraint to exponential distributions, which prevented it from accurately modeling aging effects inherent in critical infrastructure components such as transformers and communication devices. Consequently, its results deviated from the expected values, reducing its applicability to real-world scenarios involving long-term system operation.

In contrast, the *ftaproxim* package provided the capability to incorporate Weibull-distributed failure and repair times, offering a more flexible modeling approach. However, its accuracy was highly dependent on the chosen numerical parameters, particularly the tolerance value and time step size. For a mission time of 10,000 hours, *ftaproxim* achieved a minimum error of 0.8×10^{-4} with a tolerance of 10^{-5} and a time step of 1 hour. While this level of accuracy is acceptable for practical applications, increasing the mission time to 40,000 hours revealed greater discrepancies, with errors reaching up to 9.6×10^{-4} when suboptimal parameter settings were used.

The results indicate that while *ftaproxim* can closely approximate the Matlab solution under well-tuned conditions, it is sensitive to parameter selection, which may introduce significant computational overhead for achieving high accuracy. Table 4.5 summarizes the comparative accuracy results for different configurations.

Tolerance set (-)	Time step (h)	Unavailability (-)	Comp. time (h)	Error (-)
10-6	1	7.0e-4	26	0.0e-4
10-5	1	7.8e-4	0.25	0.8e-4
10-6	10	8.9e-4	0.58	1.9e-4
10-5	10	8.9e-4	0.05	1.9e-4

Table 4.5: Numerical results for a mission time of 10,000 hours comparing the unavailability estimation accuracy.

4.4.4 Computation Time and Scalability

The computational efficiency of the evaluated methods was analyzed by comparing their execution times under different parameter settings. The *FaultTree* package demonstrated the fastest computation times, as it relies on a simplified analytical approach with minimal computational complexity. However, this speed advantage comes at the cost of accuracy and flexibility, as *FaultTree* is constrained to exponential distributions and lacks support for time-dependent failure models.

The *ftaproxim* package, in contrast, allows for more complex modeling, including Weibull-distributed failure and repair times. However, its computation time is highly sensitive to two key parameters: the tolerance level and the time step size. For a mission time of 10,000 hours, an initial configuration with a time step of 1 hour and a tolerance of 10^{-6} resulted in a computation time of approximately 26 hours. Reducing the tolerance to 10^{-5} significantly improved performance, reducing the computation time to 15 minutes while maintaining an error of 0.8×10^{-4}. Increasing the time step to 10 hours provided further computational savings, bringing the total execution time below 1 hour, albeit with slightly reduced accuracy.

For longer mission times of 40,000 hours, the computational demands increased significantly. The initial setting with a 1-hour time step and a tolerance of 10^{-6} resulted in an impractically long execution time of 264 hours. Adjusting the tolerance to 10^{-5} reduced this to 8 hours, but with a higher error of 9.6×10^{-4}. The most efficient configuration, using a 10-hour time step and a tolerance of 10^{-5}, achieved a computation time of 5 hours while maintaining an acceptable accuracy level.

The results indicate that *ftaproxim* can achieve near-Matlab accuracy when properly tuned, but at a high computational cost. The trade-off between accuracy and computation time is a critical factor when applying this tool to large-scale network models. Further optimizations, such as parallelization or adaptive step-size control, could enhance its scalability for practical use in critical infrastructure analysis. Table 4.6 summarizes the computation times and associated accuracy levels for different configurations.

Tolerance set (-)	Time step (h)	Unavailability (-)	Comp. time (h)	Error (-)
10-6	1	NA	264	NA
10-5	1	9.4e-4	8	9.6e-4
10-6	10	20.0e-4	50	1.0e-4
10-5	10	17.5e-4	5	1.5e-4

Table 4.6: Numerical results for a mission time of 40,000 hours illustrating the computation time and accuracy trade-offs.

All obtained results, including graphical inputs in the form of fault trees and graphical outputs representing system unavailability, are presented in **Publication VII**.

5 Conclusion

This work addresses the domain of critical infrastructure analysis, with particular emphasis on the interdependence between power and data networks. The investigated issues are reflected through commentary on nine published research contributions, each focused on a different subtopic. Thematically, the contributions are grouped into three main categories: (i) development of a simulation tool for interconnected infrastructures, (ii) analysis of system unavailability and maintenance strategies, and (iii) practical deployment and testing of the simulation platform.

For the initial development and testing phase of the simulator, data were provided by municipal representatives, particularly concerning points of electricity delivery, the municipal data network, and the control infrastructure of traffic signaling. Consultations were conducted to assess the simulator's practical applicability. Based on these discussions, core functional requirements were defined. The simulator development was also consulted with the DSO, who provided network topology data for early development purposes. As a result, power and data infrastructures (including traffic light control) were integrated into a unified platform from the very beginning.

However, the early phase of development revealed challenges in presenting simulation results due to the sensitivity of critical infrastructure data. Some of the attached publications present simulations and platform development based on real anonymized datasets. Subsequently, efforts were made to develop solutions allowing for full-result presentations. A separate section of this work is therefore dedicated to the test networks employed during successive development stages, including tools for generating anonymized infrastructure topologies. The work also introduces a custom-designed test network that emphasizes the interconnectivity of separated infrastructures, highlighting cascading failures and domino effects.

The research methodology spans a wide range of techniques, including software engineering, stochastic modeling, graph-theoretical analysis, and time-dependent simulations of failure scenarios. Particular attention was devoted to developing an interactive simulation platform with a GUI and a scalable architecture capable of modeling cascading failures and enabling advanced infrastructure analysis. While only selected results are presented in the thesis, extended outcomes and broader evaluations can be found in the referenced publications.

5.1 Contribution and Outcomes

The research presented in this work has yielded several key findings, structured around the major thematic areas defined in the introduction of the thesis.

- A fully functional simulator was designed and implemented, capable of modeling the behavior of power grids and communication networks simultaneously. Its modular architecture, supported by virtualization and containerization technologies, enables scalable simulations and allows future extension to additional infrastructure layers. A novel state matrix concept was introduced to track and visualize cascading failures.
- Time-dependent unavailability computations were integrated into the simulation platform, allowing for a detailed assessment of system resilience under varying maintenance strategies. The results confirmed that preventive maintenance scheduling, based on stochastic modeling, significantly reduces long-term unavailability and operational risks, particularly for critical infrastructure components.
- Multiple test networks were developed and validated. A new interconnected smart grid test network was constructed to capture mutual dependencies between power and communication infrastructures, supporting reproducible failure propagation studies and resilience metric evaluation.
- The simulator was adapted for deployment on supercomputing infrastructure. Computational performance was optimized through input data preprocessing and parallelization techniques, resulting in a substantial reduction in simulation times and enabling large-scale scenario analysis.
- The analysis of key performance indicators introduced a standardized methodology for defining and quantifying reliability parameters. The results emphasize the role of RTUs in fault detection and service restoration, with a direct impact on reliability indices such as SAIDI and SAIFI.

These contributions support a deeper understanding of the behavior, vulnerabilities, and optimization opportunities of interconnected critical infrastructures within smart grids and complex urban systems. In addition to the simulation platform development and methodological framework, the thesis also reports practical findings presented in the attached publications, particularly the following.

- The study on graph theory application in critical infrastructure analysis demonstrated the use of graph-based algorithms for modeling, analyzing, and optimizing interconnected energy and communication networks. By representing distribution networks as graph structures, this approach enabled the identification of critical components and optimization of network topologies. Validation experiments confirmed the feasibility of the methodology for urban distribution networks, proving its potential to enhance reliability and operational efficiency.
- The reliability and resilience analysis of MV distribution systems evaluated the impact of LBS failures across various outage scenarios. The study showed that LBS malfunctions critically degrade network resilience, as quantified by

metrics such as ENS. The results confirmed the importance of automated switching and preventive maintenance in mitigating long-duration outages and economic impacts. Furthermore, optimizing LBS maintenance intervals was shown to improve both reliability and resilience by reducing downtime and accelerating restoration processes.

- Further research into maintenance optimization addressed the trade-off between reliability and operational cost using a multi-objective optimization approach. The study applied advanced techniques, including the NSGAII genetic algorithm, to identify optimal maintenance schedules. The findings highlighted that preventive maintenance substantially lowers unavailability when compared to corrective-only approaches.
- A comparative evaluation of the simulation platform against open-source reliability tools, namely *FaultTree* and *ftaproxim*, confirmed the superiority of the developed platform in both computational accuracy and performance. The platform proved to be the most suitable tool for modeling unavailability in interconnected infrastructures.

The developed simulator and associated methodologies offer a wide range of practical applications and are primarily aimed at two key user groups: DSOs and municipalities. The simulator provides a tool for risk assessment, outage prediction, and reliability optimization. It supports DSOs in evaluating maintenance strategies and investment prioritization. Municipalities can employ the tool for scenario-based planning in smart city projects that integrate energy and communication systems.

5.2 Limitations and Future Research

Despite the demonstrated capabilities of the developed simulator, several limitations remain, which should be considered when interpreting the results.

- The accuracy of simulations is highly dependent on the availability and quality of input data. In many cases, particularly for the communication infrastructure, data access is restricted. As a result, the communication layer simulations are based on simplified assumptions and do not reflect the full dynamic behavior of real-world telecommunication protocols.
- Although performance optimizations were applied, extremely large-scale simulations involving thousands of nodes may still encounter computational bottlenecks, even within an HPC environment. The simulator currently operates in batch mode; real-time simulation or integration with live infrastructure monitoring systems has not yet been implemented.
- Some results presented in the referenced publications are based on synthetic test networks, which may limit the direct applicability of findings to specific

real-world infrastructures without additional calibration and validation.

The increasing share of digitalized and decentralized technologies in energy and communication networks elevates the importance of simulating cyber-physical interactions and assessing risks related to cybersecurity, synchronization delays, and system-wide coordination failures. Future research will address the following areas:

- Expanding the simulator to cover additional infrastructure domains (e.g., water supply, transportation) and modeling their interdependencies.
- Further work will focus on integrating the simulator with flood zone models, enabling more comprehensive resilience analysis with respect to the physical location of critical assets (e.g., transformer stations).
- Improving the realism and parameterization of communication network models, particularly for latency-sensitive applications and cybersecurity threat propagation scenarios.
- Further integration of predictive maintenance scheduling techniques, incorporating machine learning approaches trained on historical failure and maintenance data.
- The optimization framework will be extended to incorporate advanced models of component ageing and predictive maintenance. Initial age and degradation rates will be considered to enable realistic, cost-effective scheduling. Condition monitoring data will be integrated to refine failure probability estimates, supporting the transition to condition-based maintenance strategies.

In conclusion, the resilience and reliability of interconnected infrastructures remain an essential research domain. This work has introduced tools and methodologies that advance the understanding and management of complex interdependent systems and provides a foundation for continued academic and applied research in this field.

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Symbols and abbreviations

A	Availability
C_c	Corrective maintenance cost
C_p	Preventive maintenance cost
$F(x;\lambda,\beta)$	Weibull cumulative distribution function
$f(x;\lambda,\beta)$	Weibull probability density function
$\mathcal{L}_l$	Expected maximum load loss
$\mathcal{L}_{rs}$	Automatic restoration load ratio
$n_{\mathbf{prev}}$	Expected number of renewals during the mission time
$\mathcal{S}_l$	Load interruption rate
ΣT	Total operational time of a system
T_m	Mission time
T_P	Time of preventive maintenance
$\mathcal{T}_{rp}$	Post-restoration time
$\mathcal{T}_{rs}$	Automatic restoration time
ΣT_{res}	Total time required for restoring components
$U(t)$	Unavailability function over time
λ_p	Failure rate of a component
λ_r	Repair rate of a component
Σn_f	Total number of failures
Σn_r	Total number of repairs

AG	Acyclic Graph
AMM	Automated Metering Management
API	Application Programming Interface

CDF	Cumulative Distribution Function
CIGRE	International Council on Large Electric Systems
CIRED	International Conference on Electricity Distribution
CRAN	Comprehensive R Archive Network
DiNeMo	Distribution Network Model
DSO	Distribution System Operator
ENS	Energy Not Supplied
FTA	Fault Tree Analysis
FR	Functional Requirement
GUI	Graphical User Interface
HPC	High-Performance Computing
IEEE	Institute of Electrical and Electronics Engineers
JSON	JavaScript Object Notation
JRC	Joint Research Centre
KPI	Key Performance Indicator
LBS	Load Break Switch
LV	Low Voltage
MTBF	Mean Time Between Failures
MTTF	Mean Time To Failure
MTTI	Mean Time To Incident
MTTK	Mean Time To Known Issue
MTTRep	Mean Time To Repair
MTTRes	Mean Time To Restore Service
MTTV	Mean Time To Validate
MV	Medium Voltage

NIST	National Institute of Standards and Technology
NSGAII	Non-dominated Sorting Genetic Algorithm II
NS-3	Network Simulator 3
PDF	Probability Density Function
RCM	Reliability-Centered Maintenance
REST	Representational State Transfer
RTU	Remote Terminal Unit
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	Supervisory Control and Data Acquisition
SS	System State
VPN	Virtual Private Network

A Publication Summary

This appendix provides a list of publications referenced throughout the thesis, forming an integral part of the submitted work. It also includes a description of the author's contribution, including authorship share and indexing information. At the time of submission, Publications VI and VII were still undergoing the indexing process and are expected to be included in both the Scopus and Web of Science databases.

I. Matej Vrtal, Jan Benedikt, Radek Fujdiak, David Topolanek, Petr Toman, and Jiri Misurec. Power grid and data network simulator. *2022 22nd International Scientific Conference on Electric Power Engineering (EPE)*, pages 1–4, Kouty nad Desnou, Czech Republic, 2022.
doi:10.1109/EPE54603.2022.9814104.

   Author's contribution: conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization (40 %)
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   Licensing: Subscription
   Indexed in: Scopus, Web of Science

II. Matej Vrtal, Jan Benedikt, Radek Fujdiak, David Topolanek, Petr Toman, and Jiri Misurec. Investigating the possibilities for simulation of the interconnected electric power and communication infrastructures. *Processes*, 10(12):2504, 2022. doi:10.3390/pr10122504.

   Author's contribution: conceptualization, validation, writing—original draft preparation, visualization (50 %)
   Available from: https://doi.org/10.3390/pr10122504
   Licensing: Open Access
   Indexed in: Scopus, Web of Science

III. Matej Vrtal, Vit Krcal, and Petr Toman. Application of graph theory in urban infrastructure analysis. *27th International Conference and Exhibition on Electricity Distribution (CIRED 2023)*, pages 3954–3957, Rome, Italy, 2023. doi:10.1049/icp.2023.0505.

   Author's contribution: conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization (60 %)

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IV. Matej Vrtal, Radek Fujdiak, Jan Benedikt, David Topolanek, Michal Ptacek, Petr Toman, and Jiri Misurec. Determination of critical parameters and interdependencies of infrastructure elements in smart grids. *2023 23rd International Scientific Conference on Electric Power Engineering (EPE)*, pages 1–6, Brno, Czech Republic, 2023. doi:10.1109/EPE58302.2023.10149250.

Author's contribution: conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—original draft preparation, writing—review and editing, visualization (40 %)
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V. Matej Vrtal, Radek Fujdiak, Jan Benedikt, Pavel Praks, Radim Bris, Michal Ptacek, and Petr Toman. Time-dependent unavailability exploration of interconnected urban power grid and communication network.
Algorithms, 16(12):561, 2023. doi:10.3390/a16120561.

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Indexed in: Scopus, Web of Science

VI. Matej Vrtal, Jan Benedikt, Radek Fujdiak, Pavel Praks, and Petr Toman. Computation time optimization strategies for critical infrastructure simulator. *Proceedings of the 12th International Scientific Symposium on Electrical Power Engineering (ELEKTROENERGETIKA 2024)*, pages 123–130, Stara Lesna, Slovak Republic, 2024.

Author's contribution: conceptualization, methodology, validation, formal analysis, investigation, writing—original draft preparation, writing—review and editing, visualization (60 %)
Licensing: Subscription

VII. Matej Vrtal, Michal Beloch, Pavel Praks, Radek Fujdiak, Jan Benedikt, Petr Toman. Comparative evaluation of open-source tools for infrastructure reliability analysis. *Proceedings of the 12th International Scientific Symposium on Electrical Power Engineering (ELEKTROENERGETIKA 2024)*, pages 131–138, Stara Lesna, Slovak Republic, 2024.

Author's contribution: conceptualization, methodology, validation, investigation, writing—original draft preparation, writing—review and editing, visualization (60 %)
Licensing: Subscription

VIII. Matej Vrtal, Daniel Krpelik, Pavel Praks, Radim Bris, Radek Fujdiak, and Petr Toman. Improving smart grid resilience using unavailability analysis and maintenance optimization. *IET Conference Proceedings CP882*, 2024(27):212–216, 2024. doi:10.1049/icp.2024.2600.

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IX. Matej Vrtal, Vit Krcal, Jan Koudelka, Daniel Krpelik, Radek Fujdiak, and Petr Toman. Resilience analysis in medium voltage distribution system: case study. *IET Conference Proceedings CP882*, 2024(27):217–221, 2024. doi:10.1049/icp.2024.2601.

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