UNIVERSIDADE FEDERAL FLUMINENSE
ESCOLA DE ENGENHARIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA ELÉTRICA E DE TELECOMUNICAÇÕES

CAROLINA CUNHA DE MENEZES

Metaverse Framework for Power Systems: Proposal and Case Study of a Solar Power Plant

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Dissertação de Mestrado apresentada ao Programa de Pós-Graduação em Engenharia Elétrica e de Telecomunicações da Universidade Federal Fluminense como requisito parcial para a obtenção do título de Mestre em Engenharia Elétrica e de Telecomunicações. Área de concentração: Sistemas de Energia Elétrica.

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CAROLINA CUNHA DE MENEZES

METAVERSE FRAMEWORK FOR POWER SYSTEMS: PROPOSAL AND CASE STUDY OF A SOLAR POWER PLANT

Dissertação de Mestrado apresentada ao Programa de Pós Graduação em Engenharia Elétrica e de Telecomunicações da Universidade Federal Fluminense como requisito parcial para a Obtenção do Grau de Mestre em Engenharia Elétrica e de Telecomunicações.
Área de concentração: Sistemas de Energia Elétrica.

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To all the women in science who defied the status quo and led the way forward, inspiring many others.

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Resumo

À medida que o setor elétrico evolui em direção à sustentabilidade, métodos convencionais de gestão de energia, baseados em sistemas centralizados, apresentam dificuldade em aproveitar a incorporação acelerada de fontes alternativas de energia na rede. Em particular, a introdução de usinas solares no sistema implica em mudanças no perfil do consumidor, bem como complexidades relacionadas a configurações distribuídas e padrões intermitentes de geração de energia. Consequentemente, uma mudança correspondente nas estratégias de gestão de energia faz-se necessária. Neste contexto, soluções como gêmeos digitais e metaversos industriais são capazes de fornecer um ambiente digital integrado para experimentação e análise de sistemas de potência. Não obstante, o desenvolvimento de tais aplicações no setor elétrico ainda é preliminar, exigindo maiores investigações. Em vista disso, este trabalho propõe uma nova arquitetura para o desenvolvimento de metaversos industriais de sistemas de potência. Esta arquitetura adota a modularidade como um princípio fundamental, permitindo a expansão da aplicação de acordo com os serviços desejados. Em seguida, para ilustrar a viabilidade da arquitetura proposta, uma aplicação de um metaverso industrial é apresentada, utilizando o Unity como plataforma de desenvolvimento e OPC-UA (do inglês, *Open Platform Communications - Unified Architecture*) como o principal protocolo de comunicação de dados. Para isso, uma usina solar, localizada no Centro Experimental da Universidade Federal Fluminense (UFF) em Iguaba Grande, é considerada. A aplicação demonstra a eficácia da arquitetura proposta, fornecendo uma visualização 3D do sistema, dados em tempo real do sistema SCADA (do inglês, *Supervisory Control and Data Acquisition*), além da integração com um sistema de detecção de falhas em Python. Deste modo, este trabalho busca inspirar a adoção de metaversos industriais e gêmeos digitais na gestão de sistemas de potência, promovendo uma abordagem mais moderna e digitalizada.

Palavras-chave: Gêmeo Digital, Metaverso, Realidade Aumentada, Realidade Virtual, Sistemas de Potência

Abstract

As the energy landscape evolves towards sustainability, conventional energy management methodologies, primarily designed for centralized power systems, struggle to harness the full potential of renewable energy production. In particular, the expansion of solar power plants introduces changes in the energy consumer profile, as well as complexities related to managing their distributed settings and energy production patterns. As a result, a corresponding change in energy management strategies becomes critical. In this context, the energy metaverse provides stakeholders with an integrated digital ecosystem that allows for experimentation and analysis of complex power systems. However, developing and implementing such applications within the energy sector still requires further research. This work raises this discussion and proposes an architectural framework for developing specialized metaverse applications of photovoltaic power plants. The framework embraces modularity as a core principle, allowing the expansion of the application according to diverse services and needs. In the following, a case study is presented to illustrate the feasibility of the proposed framework using Unity as a development platform and *Open Platform Communications - Unified Architecture* (OPC-UA) for data communication. A power plant located in the UFF Experimental Center of *Iguaba Grande* is considered. The application demonstrates the efficacy of the proposed framework by providing a 3D visualization of the system, real-time data from *Supervisory Control and Data Acquisition* (SCADA), a fault detection system, and weather forecasts. This way, this work aims to inspire further exploration and adoption of the metaverse and digital twins in photovoltaic systems, fostering a more modern and digitalized approach to energy management and development.

Keywords: Augmented Reality, Digital Twin, Metaverse, Power Systems, Virtual Reality.

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REST	Representational State Transfer	40
SEL	Schweitzer Engineering Laboratories	49
SCADA	Supervisory Control and Data Acquisition	6
SLAM	Simultaneous Localization and Mapping	17
SDK	Software Development Kit	24
TCP/IP	Transmission Control Protocol/Internet Protocol	40
UFF	*Universidade Federal Fluminense*	2
UML	Unified Modeling Language	41
VR	Virtual Reality	1
XR	Extended Reality	1

Contents

Chapter 1

Introduction

The convergence of digitalization, decentralization, and decarbonization of the energy sector has prompted a paradigm shift in power systems' infrastructure [1]. While the introduction of renewable energy sources into the grid has been paramount in decarbonization goals, their integration into existing systems has brought unique challenges related to their decentralized and intermittent nature. At the same time, digitalization has become a strategic enabler in managing and optimizing these fluctuations. By bridging the gap between physical and virtual worlds, technologies like Internet of Things (IoT) and Machine Learning (ML) opened up previously unimaginable possibilities and opportunities for the energy sector [2]. For instance, advanced IoT can collect data from solar panels, while ML algorithms can help optimize energy usage and identify areas of energy waste. Going ahead, there is an increasing interest in developing solutions that leverage these technologies to provide accurate representations of reality, such as industrial metaverses and Digital Twins (DTs) [3, 4]. These applications can provide a dynamic and interactive way to monitor, analyze, and simulate the behavior of power systems. In light of this, this dissertation explores the application of industrial metaverses in the energy sector, aiming to establish a new methodology for their development and implementation.

An industrial metaverse application is a virtual environment where DTs, Extended Reality (XR), and IoT technologies can converge to provide a collaborative platform for enhanced decision-making processes. Nonetheless, developing metaverse and DT applications in power systems remains relatively unexplored. Details about the specific software, hardware, communication protocols, and methodology employed in such implementations are missing. Moreover, research and development in this area is also challenging due to its multidisciplinary nature and the blurred boundaries between concepts like the metaverse, DT, XR, Augmented Reality (AR), and Virtual Reality (VR).

Given the above, the primary objectives of this dissertation are twofold. First, it seeks to develop a framework for creating industrial metaverse applications for power systems. This framework embraces modularity as a guiding principle, breaking down the application into smaller and manageable packaged business capabilities. Second, the dissertation aims to demonstrate the feasibility of this framework through a practical case study. To this end, it considers a solar power plant located in the *Universidade Federal Fluminense* (UFF) Experimental Center of *Iguaba Grande*. In addition to testing the framework, this case study has an educational purpose. It aims to give students a practical learning tool to understand solar power generation and operating behavior remotely within a virtual environment.

The methodology employed in this work consists of an extensive review and analysis of the literature followed by the development of the new framework. Eighty-five studies meticulously selected from a pool of 1523 records are investigated. The subsequent analysis maps article distribution across different application fields, identifies current software and development tools, and examines barriers and motivations for adoption. In the following, considering the findings derived from this review, a new framework for developing industrial metaverse applications for power systems is proposed. Finally, the implementation of the case study comprises developing a project plan and applying the suggested framework.

Finally, the significance of this work lies in promoting the adoption of industrial metaverses and DTs in the energy sector and contributing to the ongoing digitalization of the grid. It considers a scenario of increased complexity and demand for advanced tools to manage and optimize modern power grids.

1.1 Background

To better understand the unique value and capabilities of industrial metaverses in power systems, it is essential to investigate and clarify their differences from other similar concepts that have gained significant attention in recent years, such as DT, XR, AR, and VR. Given this context, this section provides a preliminary overview and brief historical context of industrial metaverses and related concepts to facilitate a more informed engagement with the subsequent chapters.

The term "metaverse", which once was restricted to gaming and science fiction, has gained attention from various distinct sectors, especially after the Facebook rebrand as

Meta [5]. According to [6], although the metaverse is usually associated with entertainment applications, many analysts have debated that the metaverse's true transformative potential is more likely to be achieved in the industrial context. An industrial metaverse can be understood as a virtual, interconnected digital platform where people can interact with mirrored real-world machines and systems through avatars and immersive tools. In the energy sector, for example, energy companies can use the metaverse to simulate and optimize their operations, while researchers and policymakers can experiment and evaluate new regulatory frameworks and business models before their practical implementation in the physical world [3].

In contrast, a DT is a digital replica that mirrors the physical characteristics and behavior of real-world equipment by reading and interpreting data from various sources [7]. They provide a high degree of fidelity to a reference model and allow bidirectional interaction flows, often aiming for focused optimization efforts of an individual component or equipment, such as a solar panel or inverter. More specifically, considering the challenges posed by the variability and uncertainty associated with renewable energy sources, DTs can enable easier identification and response to grid disturbances, optimization of energy usage, and efficient demand management [2].

Finally, XR is an umbrella term for technologies that allow users to have immersive experiences either by completely entering a virtual environment (VR) or simply by providing a merged view of real and virtual elements (AR) [8]. In this sense, both VR and AR can provide a more intuitive and immersive way for training and education purposes, enabling operators to practice handling complex situations in a safe and controlled environment [9]. In addition, AR may also support on-field decision-making processes by providing an enhanced view of reality with superimposed real-time data from equipment.

Given this context, it is possible to say that these technologies converge in the sense that a DT may be a type of content found in an industrial metaverse, whereas AR and VR technologies may be used as a means to access the metaverse or even a DT [10]. Moreover, it is essential to highlight the relevance of these technologies, particularly considering the following years, as they are likely to continue shaping how we live, work, and interact with one another [10]. In this sense, although these ideas are not entirely new, only in recent years have technological advancements allowed us to move away from an imagination era, in which concepts were theorized and conceptualized, to a new era of implementation and adoption.

Fig. 1.1 summarizes some key milestones related to these technologies. It can be ob-

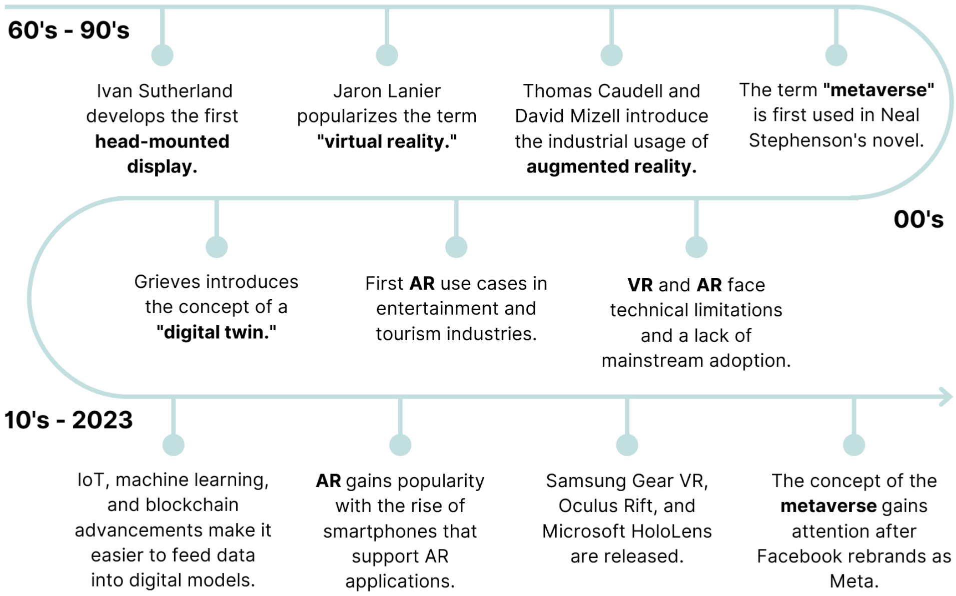


Figure 1.1: Milestones of the metaverse, DTs, and XR technologies over the decades.

served, from earlier years, the development of experimental VR headsets, the theorization of virtual and augmented realities, and the ideation of the metaverse in Neal Stephenson's science novel [8, 9]. In the following years, up until the 2010s, the technical foundations started to be built. However, technical limitations and lack of social acceptance led to a lack of mainstream adoption and a trough of disillusionment with AR and VR [9]. Despite that, recent democratization and developments in several important areas for the evolution of these technologies have sparked a new wave of innovation and acceptance [8].

1.2 Motivation and Related Work

The implementation of industrial metaverses and DTs in power systems can serve multiple purposes, from energy management to load scheduling and performance monitoring. Since studies on industrial metaverses are still preliminary and mostly conceptual, this section overviews relevant articles on DT case studies for solar power systems and emphasizes the distinctive features that set this study's approach apart.

Addressing the intricacies of microgrid energy management, studies such as that by [11] and [12] emphasize the use of DTs for managing the integration of various distributed energy resources, like solar panels, wind turbines, and energy storage, to meet local demand within a microgrid. In [11], the authors propose a DT-based distributed energy management system for formulating and solving optimal power flow problems. Unlike traditional methods, which assume accurate load predictions, the system proposed by [11] considers stochastic loads and employs probabilistic models. Simulation results demonstrate the system's effectiveness in both grid-connected and islanded modes, providing resilience to communication failures. Similarly, [12] uses an improved pigeon-inspired optimization algorithm to solve the cost-effective daily dispatch scheme for hybrid energy production, optimizing energy storage charge and discharge planning. Lastly, [13] focuses on smart home communities, proposing a fog-driven energy management system DT to optimize power sharing among users, reducing costs and reliance on imported power.

Considering demand response programs and small domestic consumers utilizing photovoltaic power, [14] proposes a multi-layered DT that uses reinforcement learning to solve decision-making problems in load scheduling, taking into consideration aspects such as user satisfaction, stochastic parameters, and tariffs. Furthermore, a series of case studies focusing on load forecasting were also found in the literature. For example, [15] proposes a rapid and precise short-term load prediction layout for smart grid market applications, addressing the challenge of predicting electrical loads due to users' nonlinear and random behavior. In contrast, [16] proposes a novel evolving-based prediction model for accurate short-term load forecasting in solar-based smart grids that aims to support decisions about the deployment of photovoltaic energy systems in a smart grid and maximize energy production.

Moreover, still concerning prediction capabilities, [17] proposes a solar irradiance forecasting model using Artificial Intelligence (AI) and ML techniques, taking into account factors like temperature, cloudiness index, and relative humidity. Besides demonstrating high accuracy and potential for enhancing solar irradiance predictions, the authors suggest that the proposed solution could support the development of DT models for positive energy districts and smart buildings. However, specific details on the implementation and integration of the model within DT frameworks are not provided. Lastly, a fault diagnosis DT for photovoltaic energy systems is proposed by [18]. The solution leverages the sensing, computation, and actuation capabilities of the converter and uses a real-time model-based estimation of the system to compare the estimated and measured outputs for fault diagnosis.

Despite the innovative strategies for solving the current challenges the photovoltaic energy sector faces, the existing literature presents gaps concerning development frameworks of DT and industrial metaverse for photovoltaic power systems. For example, details about the specific software, hardware, and communication protocols used in DT implementations and a more holistic approach are missing. Moreover, the current literature focuses on the model-based design and simulation algorithms tailored to solving scoped issues. Other characteristics, such as integration with spatial and graphical models and streaming real-time data, were not addressed. In this regard, this work distinguishes itself from the existing literature by focusing on a framework for developing a holistic metaverse of photovoltaic power systems. Therefore, while previous studies have laid the groundwork for improving the representation of photovoltaic power systems in specific domains, the tailored framework described in Chapter 3 aims to provide the big picture of how these isolated systems can communicate to form a high-level digital representation of photovoltaic power systems.

1.3 Research Scope and Objectives

The scope of this work encompasses the development and application of industrial metaverses within the context of power systems. This proposal is inherently multidisciplinary. Collaboration between professionals in electrical engineering, computer science, data analytics, and cybersecurity is crucial. Delving deeply into all aspects that compose these applications exceeds the scope of this study. In this sense, this work's main focus is on defining key components and laying the foundation for future exploration of industrial metaverses in power systems. To provide a structured approach to this work, the objectives are divided into two main categories: primary and secondary objectives.

1.3.1 Primary Objectives

- Provide a framework for developing metaverse applications for power systems.
- Demonstrate the feasibility of the proposed framework through a practical case study, considering the solar power plant located in the UFF Experimental Center of *Iguaba Grande*, and therefore provide an educational and controlled platform for monitoring and testing the system.

1.3.2 Secondary Objectives

- Integrate real-time data from the Supervisory Control and Data Acquisition (SCADA) system into the industrial metaverse application, facilitating ongoing monitoring and analysis.

- Integrate a fault detection system within the industrial metaverse application to enhance operational reliability and test the framework's modularity capability.
- Provide a 3D scene, allowing stakeholders to interact with a virtual representation of the solar power plant.
- Provide an administrator panel as a central hub for system management.
- Employ open-source tools and adhere to standardized protocols to ensure interoperability within the application.
- Make the application public on Github [1] and employ open-source practices to provide a resource that supports and advances future research and learning in the field.

1.4 Dissertation Structure

This dissertation is organized into six chapters, as described below:

- **Chapter 1 - Introduction:** Provides an overview of the research background, problem statement, and the objectives of the study. It also outlines the scope and significance of the research and presents the structure of the dissertation.
- **Chapter 2 - Literature Review:** Identifies gaps in the literature and provides the theoretical foundations that underpin the new framework.
- **Chapter 3 - Industrial Metaverse Framework:** Introduces the new framework for developing industrial metaverse applications for power systems. It details the components, design, architecture, and key features of the framework.
- **Chapter 4: Case Study:** Presents the methodology and application of the case study. It provides an introduction to the case study and implementation details.
- **Chapter 5: Results and Analysis:** Evaluates the framework based on its application in the case study. It presents the results and findings and analyzes the framework's suitability.
- **Chapter 6: Conclusion:** Summarizes the key findings of the research, highlights the contributions to the field, and discusses the practical implementation of the framework. It also outlines potential directions for future research and offers concluding remarks.

[1] Available at `https://github.com/FriendsLabUFF/industrial-metaverse`

Chapter 2

Literature Review

This chapter delves into the theoretical foundations and main concepts of industrial metaverses and related technologies, such as DTs and XR. In the following, the results of a systematic literature review, named "A Survey on Extended Reality, Digital Twins, and Metaverse Applications in Power Systems," submitted to the "IEEE Internet of Things" journal, are presented. More details about the specific methodology and search selection are available in Section III of the paper. The systematic literature reviews 85 relevant studies selected from an initial pool of 1523 records. Further analyses of the selected articles provide an overview of current advancements, challenges, and gaps in the application of these technologies in the energy sector.

2.1 Theoretical Foundations and Concepts

Industrial metaverses, DTs, and XR are terms often confused due to their similarities in providing virtual representations of reality. These technologies, however, offer different immersion and interaction levels, each with unique features and benefits that make them more suitable for specific types of power system applications. For example, a complex platform such as the metaverse may not be necessary to solve a particular problem that a more straightforward AR implementation could solve. Hence, carefully considering the requirements of each application and selecting the most appropriate technology can save both time and resources. The following subsections cover the foundation of each technology mentioned in more detail.

2.1.1 Metaverse

While the idea of the "metaverse" emerged in science fiction and gained initial attention in the gaming and social media sectors, its potential is increasing traction across several industries [5]. With an emphasis on facilitating social interactions and collaboration, interconnected virtual environments, ranging from highly realistic simulations to fantastical realms, are central to the metaverse's architecture. In this context, avatars play a significant role as digital personas that reflect a user's appearance, preferences, and personality [8]. Another defining feature of the metaverse is its continuity and persistence, meaning that alterations and interactions between avatars and assets have lasting effects over time [8]. This characteristic also allows a new, intricate economic landscape where transactions are facilitated by virtual currencies and blockchain [19].

Moreover, in [6], the authors further compare the idea of industrial metaverses with the "consumer metaverse." According to the authors, the "consumer metaverse" focuses on entertainment and socialization and is not populated with data from the physical world. Industrial metaverses, in contrast, mirror real elements, such as machines, grids, cities, and logistics processes, to provide detailed analysis and simulations, and support decision-making processes. In this sense, Fig. 2.1 presents the enabling technologies necessary to

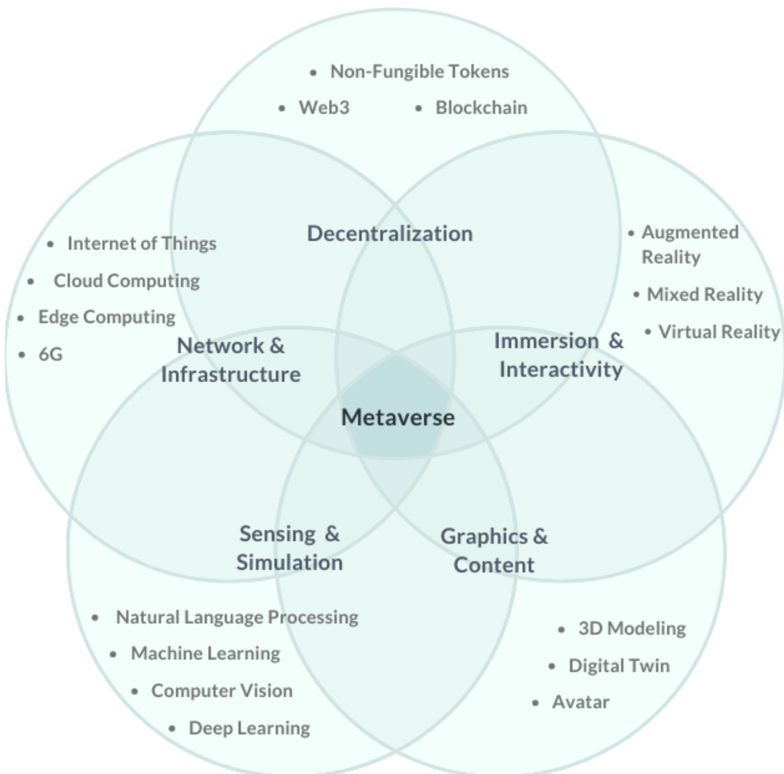


Figure 2.1: Venn diagram presenting the enabling technologies for the metaverse.

advance and catalyze the adoption of metaverse applications within the industrial sector.

Enabling technologies for industrial metaverses include:

- **Decentralization** - Refers to the distribution of control and decision-making across a network of participants rather than being concentrated in a single entity. Web3, the next generation of the internet, is closely tied to this concept of decentralization. Built on blockchain technology, Web3 provides the infrastructure for creating decentralized applications and services. Unlike previous generations of the internet, Web3 uses decentralized networks to enable peer-to-peer transactions and interactions. This means that in a Web3-powered metaverse, users can have ownership of their digital assets and participate in governance and decision-making processes without needing intermediaries. As such, Web3 decentralization technologies are closely tied to establishing a more transparent and secure digital economy and data privacy for the metaverse by supplying the necessary tools for managing and exchanging digital assets [5]. Non-Fungible Tokens (NFTs), for example, allow users to prove ownership and authenticity of virtual assets, whereas blockchain provides a consistent way for recording transactions (or blocks) across devices, ensuring that related transactions cannot be altered retroactively without affecting the following blocks [8]. Considering the energy sector, Web3 decentralization can provide a blockchain-based peer-to-peer energy marketplace, where energy producers and consumers could buy and sell energy in real-time, using Non-Fungible Tokens (NFTs) to ensure the security and transparency of transactions, as proposed by [20].

- **Sensing and simulations** - Sensing technologies and IoT are essential for providing a greater understanding of the environmental context [19]. By collecting real-time data from physical assets, these tools allow monitoring diverse aspects of equipment and systems. Moreover, the combined usage of sensing with AI technologies will allow for highly personalized interactions inside the metaverse. In this regard, as virtual worlds become more complex and dynamic, AI will become increasingly important in supplying the intelligence required to generate accurate simulations of realistic behaviors [8]. Technologies like ML, deep learning, and natural language processing will not only be able to generate isolated content but also enable a more natural integration between virtual and digital [19]. In an industrial metaverse for power systems, for example, the combined use of AI with real-time data can help recognize patterns and predict future issues in a system [6].

- **Network and infrastructure** - Advances in network capabilities, including the development of 6G, edge, and cloud computing, are crucial to providing faster speeds, improved bandwidth, and reduced network latency [19, 20]. According to [5], the metaverse will change the requirements for mobile and stationary broadbands with respect not only to an increase in the number of devices but also to the volume of the data throughput of the individual devices. Hence, the development of these technologies is imperative to enable a more seamless connection between devices and improve internet connectivity in remote areas, guaranteeing seamless experiences and allowing more people to benefit from the digital world and the metaverse.

- **Graphics and content** - As an immersive environment, 3D graphics, avatars, and other types of content are essential for providing visual and audio cues that facilitate the user's navigation and interpretation of virtual surroundings. Besides unrealistic elements, the metaverse can also contain complex digital representations of the real world, such as DTs, which can be further used for planning, testing, optimizing, and predictive analysis of real-world systems and processes [19].
- **Immersion and interactivity** - According to Mark Zuckerberg, the concept of a metaverse is tied to an "embodied internet," where users will be in the experience rather than just looking at it [21]. In this regard, immersive and XR technologies will be the primary way to access metaverse applications. Users will be able to experience the metaverse via different devices and interfaces, but XR technologies, such as AR and VR, will provide the most immersive, interactive, and comprehensive experiences [8].

2.1.2 Digital Twin

DTs have emerged as a promising technology for controlling, planning, and simulating complex systems and processes across different industries. The idea, which has its roots in aerospace engineering, was first used by NASA to model and simulate aircraft and spacecraft [22]. However, it was not until the publication of its whitepaper by Grieves in 2014, [7], that the concept of a DT was fully articulated. The whitepaper served as a foundational document that established the core principles and technical specifications of DTs, helping to drive the adoption and further development of this technology.

In its first definition, a DT is referred to as a model composed of "[...] three main parts: (a) physical products in real space, (b) virtual products in virtual space, and (c) the connections of data and information that tie the virtual and real products together"

[7]. Considering the above, [23] highlights that although all these attributes are essential for creating a sophisticated DT, the level of fidelity required by each of them may vary depending on the intended purpose and application of the DT. As such, DTs encompass many different variations and possibilities. This broad definition allows researchers to approach DTs from different perspectives and make unique contributions to their development [24]. For example, a researcher in control engineering might focus on the automation aspects, while a researcher in data mining might concentrate on different ML approaches to support informed decision-making. In this sense, [25] proposes a distinction between digital models, digital shadows, and DTs. The first consists of a digital representation of an entity that does not use any form of automated data integration between the physical and the digital objects. In contrast, the digital shadow combines a digital model with an automated one-way data flow, meaning that a change in a state of the physical object leads to a change of state in the digital object, but not vice versa. Finally, a DT allows for fully integrated data flows in both directions. In this scenario, the digital object can act as a controlling instance of the physical object.

This suggests that, as the virtual and physical worlds become increasingly linked to each other, DTs are likely to gain increased attention, with growing interest from both academia and industry [24]. In particular, advancements in sensor technology, data analytics, and IoT have enabled the development of more complex and comprehensive DTs solutions in recent years. These transformations have also driven the development of several DTs architectures, such as the five-dimensional model proposed by [26] and the four-layer DTs proposed by [27].

Fig. 2.2 presents the interplay between the maturity of the twinning process and the

TWINNING PROCESS	DIGITAL MODEL	DIGITAL SHADOW	DIGITAL TWIN
Static data	Provides **static** metadata from model.	Introduces dynamic **parametric** data that enhance accuracy and relevance.	Has access to broad metadata, parametric, and **historical** data.
Visual representation	Provides basic visuals, limited to static **3D models** and **point clouds**.	Incorporates **GIS** layers, detailed **BIM** components, and animated 3D models.	Evolves to **real-time interactive graphics** and may also provide **immersive** experiences.
Real-time data integration		Provides real-time data for specific elements.	Actively integrates real-time data, including continuous **streams from IoT** devices.
Control		Presents limited **unidirectional** control features.	Incorporates advanced **bidirectional** control mechanisms, such as IoT-based control.
Simulation and prediction		Simulates basic interactions and predicts **scoped scenarios**.	Incorporates robust simulation of **complex scenarios** and prediction features, **driven by AI**.

DIGITAL REPRESENTATION LEVEL

Figure 2.2: Twinning process considering different levels of digital representation.

corresponding level of digital representation, using a matrix structure with the horizontal axis denoting various levels of digital representation and the vertical axis representing different stages of the twinning process. Given this scenario, this work assumes that a DT is not only a virtual model that looks and behaves like a real-world object but a virtual replica that is dynamically interconnected with its physical counterpart and capable of advanced bidirectional interactions [23].

A high-level representation of a DT is shown in Fig. 2.3. The physical asset, represented in the figure by a wind turbine, is equipped with various sensors, actuators, and other monitoring devices responsible for capturing real-time data, such as 3D scans. Sensors include instruments that detect and measure physical properties, converting these measurements into signals. Actuators, in turn, include devices that respond to these signals by performing actions, such as adjusting a setting based on the sensor data. Lastly, 3D scanning involves specialized equipment, such as laser scanners and Light Detection and Ranging (LiDAR), responsible for capturing and processing spatial data. Finally, additional data sources, such as historical, design, and geospatial data, can also be incorporated into the DT.

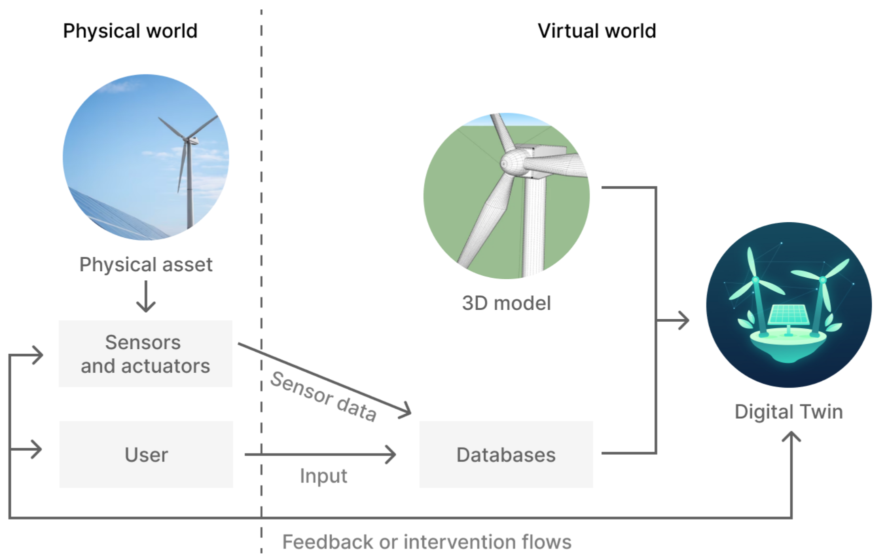


Figure 2.3: A high-level representation of a DT.

By combining the mathematical model of the asset with its corresponding 3D model or Building Information Modeling (BIM) and related data, the DT can provide advanced and visual simulations of the behavior and characteristics of its physical counterpart. In this sense, real-time sensor data can be used to continuously update and refine the DT, ensuring its accuracy and relevance. More robust DTs may also use AI models and prediction algorithms to simulate and evaluate different scenarios, such as the impact of different operating conditions and changes to the physical object.

Finally, it is important to highlight that, besides replicating and monitoring the state of its physical counterpart, a complete DT solution can also actively influence and control it, either by user input or automatic intervention flows. For that, the DT must also include advanced control capabilities that allow for a dynamic feedback loop where real-world inputs from sensors can update the DT, which can, in turn, inform decisions and trigger actions in the physical system.

2.1.3 Extended Reality

XR is an umbrella term used to describe any technology capable of providing a sense of presence and immersion in a virtual or augmented world [8]. Considering the reality-virtuality continuum introduced by [28] and presented in Fig. 2.4, XR encompasses all technological possibilities within this spectrum, including all current technologies, such as AR and VR, as well as those yet to be developed.

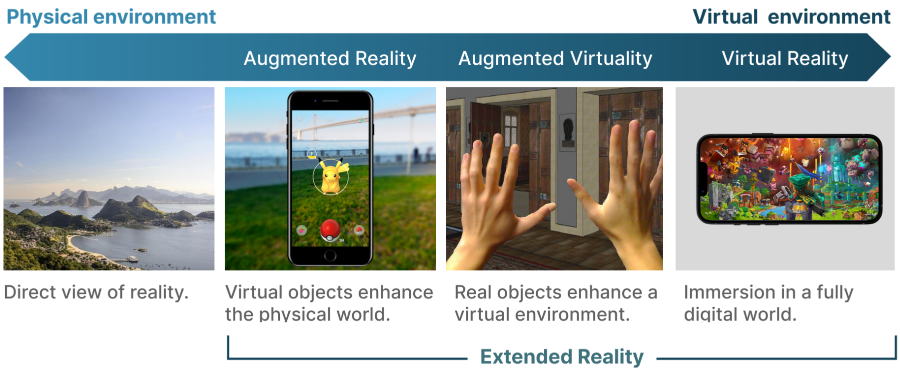


Figure 2.4: Simplified representation of a reality-virtuality continuum (adapted from [8]).

VR, the most immersive XR technology, creates an effect of spatial presence by replacing the user's view of the real world with computer-generated graphics [9]. By immersing the user in a fully synthetic environment and isolating them from the real world, VR provides a safe environment for planning, learning, and training. In this sense, it presents a singular opportunity to visualize, simulate, and test strategies before their implementation, as well as to recreate dangerous scenarios without putting people in danger.

In contrast, AR is an XR technology that superimposes virtual information onto the physical world while preserving a multi-sensory coherence concerning the observed scene [29]. [9] highlights that an AR system must fulfill three main requirements: (a) combine real and virtual content; (b) be interactive in real-time; and (c) be able to anchor virtual content in the real world. Moreover, digital overlays can range from simple graphics, such as annotations and images, to complex 3D objects that appear to be completely blended into the real world. In more modern applications, it may also go beyond the sense of sight by incorporating spatial audio and haptic feedback [30].

It is worth noting that, in addition to commonly used terms such as AR and VR, the term Augmented Virtuality (AV) is also found in the literature to refer to an environment where real-world elements are overlaid on top of computer-generated content to create a mixed reality experience. The key difference between AV and AR is that in AV, virtual content composes the primary landscape, and physical world elements are added on top of it [30]. In AR, the opposite is true. For simplicity, the term AR will be employed to denote any form of overlaid real and computer-generated elements in this work, as it is a well-established and widely recognized term.

Furthermore, both AR and VR applications are typically experienced through input devices equipped with a display, computer vision algorithms, camera, and other optical sensors [30]. However, given the differences between both technologies, the complexity required by each may differ. For example, viewpoint tracking in VR does not require the same accuracy relative to the real world as AR since, in this type of application, the user can no longer see the real world [9]. On the other hand, to create a realistic sense of immersion, the need for high-quality graphics is more significant for VR.

Specifically, the visual display is a critical component in XR as it affects the user's perception of the virtual environment. Display options for XR include handheld devices such as smartphones and tablets, Head-mounted displays (HMDs), and large-scale projection systems [30]. Among these, HMD currently provides the most enhanced sense of presence and depth, as well as hands-free interactions. Considering AR, the characteristics of these displays may vary in terms of the underlying technology employed to combine the real and virtual images, notably between video see-through and optical see-through displays, as presented in Fig. 2.5 [9]. Moreover, VR HMDs are a more affordable alternative for experiencing VR. However, this type of HMD blocks out the real-world environment entirely, replacing it with computer-generated visuals and simulations and not allowing for AR experiences.

In contrast, although video see-through displays, such as Samsung Gear VR, also employ opaque screens that block the direct view of the physical world, these displays can also provide AR experiences. In this case, the user is presented with a digitally combined image on the screen, with the graphics processor blending computer-generated

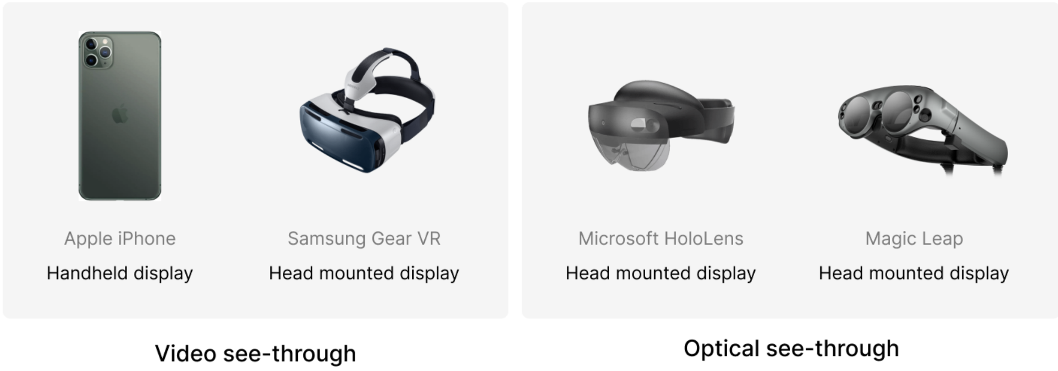


Figure 2.5: Examples of video see-through and optical see-through AR displays.

images with videos of the real world captured by a camera [9]. Both VR and video see-through HMDs usually require high-resolution screens with a wide field of view and low latency to avoid motion sickness. In addition, eye-tracking algorithms are also necessary for adjusting the virtual environment based on the user's gaze.

Moreover, AR can also be experienced via optical see-through displays, such as Microsoft's HoloLens and Magic Leap. These displays maintain a direct view of the real world and use a transparent optical combiner, such as a half-silver mirror, to superimpose computer-generated elements onto the real-world scene [30]. This way, the AR experience is perceived more naturally, in real resolution, and free from parallax. Despite that, video see-through displays have increased in popularity due to a wide range of software libraries that facilitate AR implementation, besides being more affordable [31, 32].

Finally, it is also worth noting that depending on the method used to trigger and anchor the visual elements, AR systems can be classified into two main groups, as illustrated in Fig. 2.6. The first group is marker-based, which relies on visual cues and patterns, such as fiducial markers and QR codes, to trigger and anchor virtual objects. This type of AR tracking system became a popular approach due to its simplicity of use and high accuracy of detection [9, 29, 31, 33, 34]. In marker-based AR, the tracking algorithm recognizes and calculates the location and orientation of the virtual objects with respect to the real world by using a camera to identify a predefined pattern. Since these patterns are highly distinct from the existing elements in the scene, the computing effort required to calculate the correct spatial orientation in an AR environment is reduced [30].

The second category is markerless. Markerless AR is a broad category that encompasses different techniques for tracking the physical world without the need for predefined markers. Instead, it might be (1) sensor-based, for example, by applying GPS, magnetometers, accelerometers, and gyroscopes to help determine the relative pose of

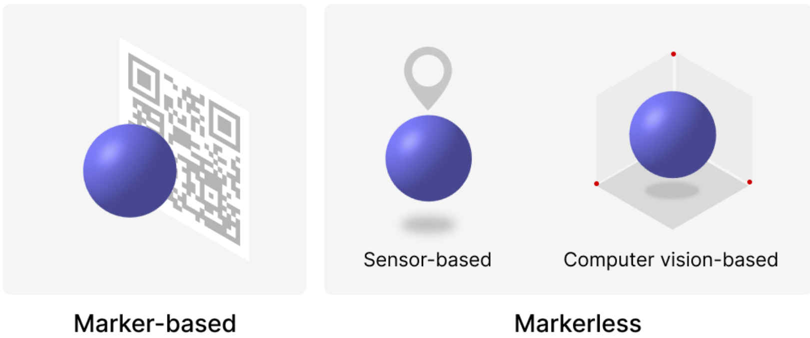


Figure 2.6: Examples of marker-based, sensor-based, and computer vision-based AR tracking methods.

the tracked object [9]; or (2) computer vision-based by detecting unique natural feature points of the environment, such as corners, blobs, and edges, for anchoring virtual objects to specific locations in the real world [30]. Computer vision-based markerless AR lacks prior knowledge of the environment. Hence, more computational cost and sensors may be necessary for great accuracy in object recognition and motion tracking [35]. In this regard, Simultaneous Localization and Mapping (SLAM) is commonly employed to continuously map the real-world environment and estimate the device's relative position within that map [36, 37, 35]. With SLAM, all found feature points are used to create a 3D map of a room and accurately place a virtual object within that room in real time.

It is worth noting that, in order to overcome the drawbacks of individual tracking methods, AR applications can also use a hybrid tracking system that combines data from multiple sensors and computer-vision techniques [9]. Hence, the application and intended user experience will determine the most appropriate types of AR technologies to be employed.

2.1.4 Comparative Analysis Between Technologies

In light of the preceding discussions, this section examines how these technologies fit into the broader picture and how they interact with one another. It also explores how their interconnected usage can lead to new and innovative solutions to address real-world challenges. Fig. 2.7 presents the relation between the technologies discussed in this work.

It is possible to observe that XR behaves as an interface between the user and the virtual world. In summary, XR relates to technologies that allow users to have immersive experiences either by completely entering a virtual environment or simply by experiencing an enriched reality from the merge of real and virtual elements. In this regard, the

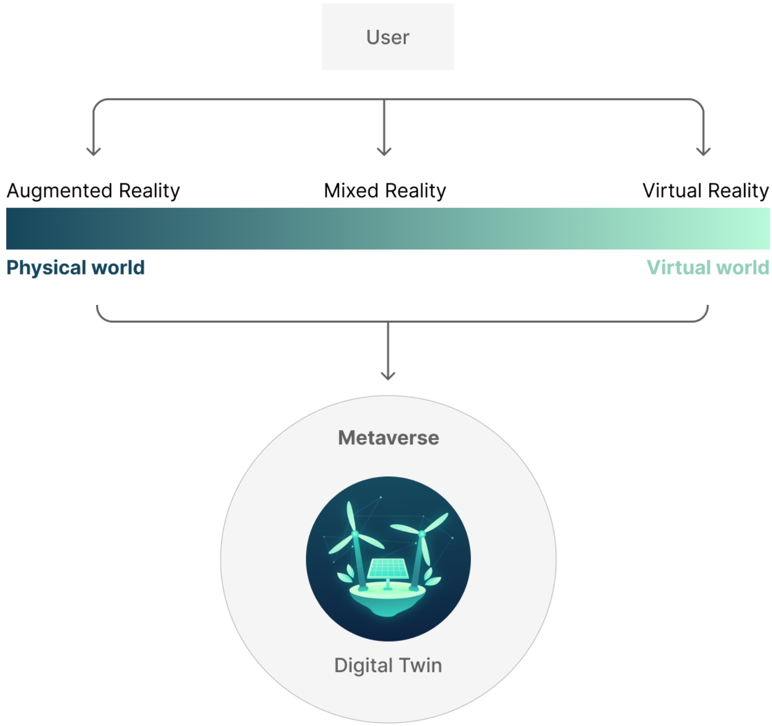


Figure 2.7: Relationship between the metaverse, DT, VR, and AR technologies.

metaverse, as a shared virtual space, can be accessed in a three-dimensional way, with varying degrees of immersion, via these different XR technologies.

Still, confusion may arise between VR and the metaverse due to their similar ability to provide complete immersive digital experiences. However, one key point to consider is that, unlike VR, which focuses on providing a way to enter isolated virtual worlds, the metaverse is expected to be an interoperated persistent platform built upon the convergence of various virtual worlds, social platforms, and other types of advanced content.

Given the above, it is important to highlight the differences between metaverse and DTs. In summary, although these technologies may converge on some levels, the key difference is that the metaverse is not necessarily tied to a physical asset nor requires sensor data. It may even include unrealistic representations that do not exist in the physical world. In addition, while the metaverse is a virtual space usually focused on providing creative and collaborative experiences, DTs focus on mutually communicating, promoting, and co-evolving with their physical counterparts through bidirectional interactions [24].

It is also worth noting that, as the current technology stands, the metaverse experience may be largely limited to passive observation. For instance, while it may be possible to see and explore the physical layout of a given device via its 3D model in the metaverse, it may not be possible to interact with or operate its corresponding physical entity. On the other hand, by incorporating DTs into the metaverse, it is possible to envision industry-specific metaverses, such as the energy metaverse or the healthcare metaverse [3]. Moreover, considering the benefits of DTs, the metaverse may achieve a higher level of realism with enhanced real-time and bidirectional interactivity.

Finally, via XR technologies, users will be able to enter the metaverse and experience and operate machines and systems via their DTs as if they were in the physical world. This, however, will only be possible via the continuous development of the enabling technologies previously discussed in this section. In light of the above and based on the key features identified throughout this work, Table 2.1 presents a comparison of the technologies discussed in this section.

2.2 Applications in the Energy Sector

The potential applications of industrial metaverses, DTs, and XR were reviewed and analyzed, considering how they can address current challenges in power systems. As a result, the 85 papers investigated in the systematic literature review previously mentioned were classified into the following categories:

- **Energy Market and Demand Management:** applications related to strategies to optimize energy supply and consumption. It involves monitoring, analyzing, and forecasting energy market trends and prices. This category focuses on balancing energy supply and demand techniques and enhancing the energy trade market.
- **Training and Occupational Safety:** applications related to enhancing the knowledge, skills, and awareness of electric utilities' personnel. It includes training programs and courses designed to educate employees on safety protocols and best practices. This category aims to prevent workplace accidents, injuries, and hazards by providing appropriate training, promoting a safety culture, and ensuring compliance with relevant Occupational Health and Safety (OHS) regulations.
- **Maintenance and Inspection:** applications related to assessing and preserving the operational condition and reliability of systems and equipment. It focuses on identifying potential issues, defects, or malfunctions through routine inspections, preventive maintenance, and corrective actions. This category aims to ensure the smooth functioning and longevity of assets by detecting and addressing problems promptly, reducing downtime, and minimizing the risk of accidents or failures.

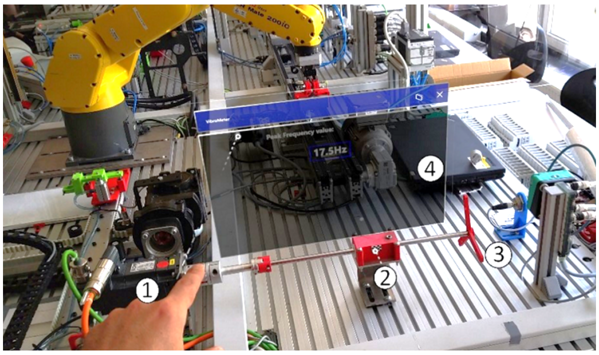
	3D visualization	Fully immersive virtual environment	Real-world interactivity	Interactive virtual environment	Object recognition	Simulation of physical systems	Digital object interactivity	Shared virtual space for user interaction	Enhanced view of the real world	Typically mobile-based	Experienced via wearable HMDs	Blockchain and NFT-based	Real-time data from physical objects	Remote access	Predictive capabilities	Persistence	Avatar-based
Metaverse	✓	✓	O	✓	O	O	✓	✓	O		✓	✓	O	✓	O	✓	✓
Digital Twin	O		✓		O	✓	✓		O		O		✓	✓	✓		
Augmented Reality	✓		✓		✓		✓		✓	✓	✓		✓				
Virtual Reality	✓	✓		✓			✓	O			✓	O		✓		O	O

Table 2.1: Feature comparison of the metaverse, DTs, AR, and VR technologies. ✓indicates an inherent functionality of a given technology. *O* indicates an optional feature, meaning its absence does not define the essence of that particular technology. The empty spaces indicate that the given technology does not characterize or provide that feature.

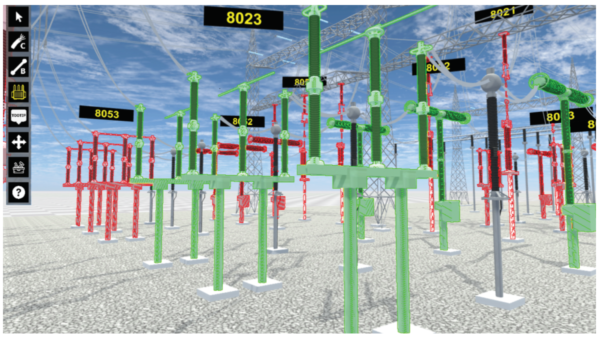
- **Project Planning:** applications related to the systematic and strategic process of managing power system projects. Simulation techniques are used to model and predict project outcomes, allowing stakeholders to assess different scenarios and make informed decisions.

- **Performance and Real-time Control:** applications related to the continuous observation, measurement, and management of power systems. It involves gathering and assessing real-time data, as well as providing insights into corrective actions to maintain desired operating conditions. This category focuses on performance monitoring, detecting deviations, and implementing control mechanisms to maintain the system's stability and performance.

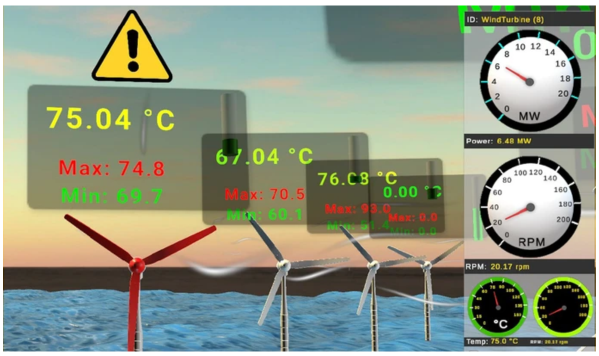
Fig. 2.8 provides a visual snapshot of the diverse and practical applications explored in the reviewed articles. Fig. 2.8 (a) shows an application where AR is employed for predictive maintenance of a wind turbine model, detecting unequal weight distributions in wind turbine propellers. Fig. 2.8 (b) illustrates how VR can be utilized for training and supervision of an electric power substation. Fig. 2.8 (c) depicts a use case of a DT



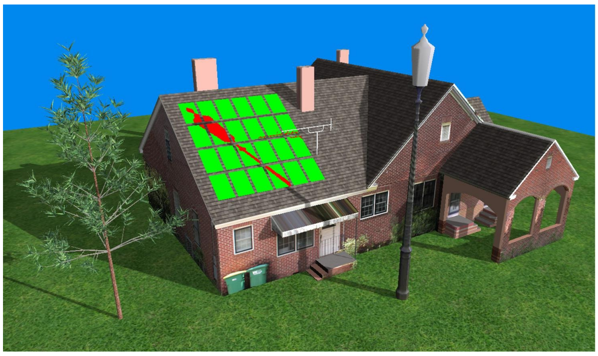
(a) Predictive maintenance of rotating machines and AR view from HoloLens [34].



(b) Supervision of an electric power substation through a VR application [38].



(c) Monitoring of an offshore wind farm through its DT [39].



(d) Shadow evaluation on the photovoltaic array installed on the roof of the house [40].

Figure 2.8: Examples of XR and DT applications in power systems.

for predictive maintenance of offshore wind farms. Lastly, Fig. 2.8 (d) shows how VR can be used in project planning to assess shadow in photovoltaic installations.

Furthermore, the radar chart presented in Fig. 2.9 indicates the number of papers classified in each application field, providing a quick and easy-to-read overview of trending applications related to each technology reviewed in this work. It is possible to observe that AR is more commonly employed in *Maintenance and Inspection*, being mainly used to overlay information about equipment performance and status onto the user's view. This allows operators and maintenance personnel to quickly identify potential issues and take corrective action. VR, in turn, is predominantly employed for *Project Planning* and *Training and Occupational Safety* purposes since this technology's immersive and interactive nature facilitates realistic training experiences and enhances project planning by providing stakeholders with an in-depth understanding of scenarios that would otherwise be too difficult to convey.

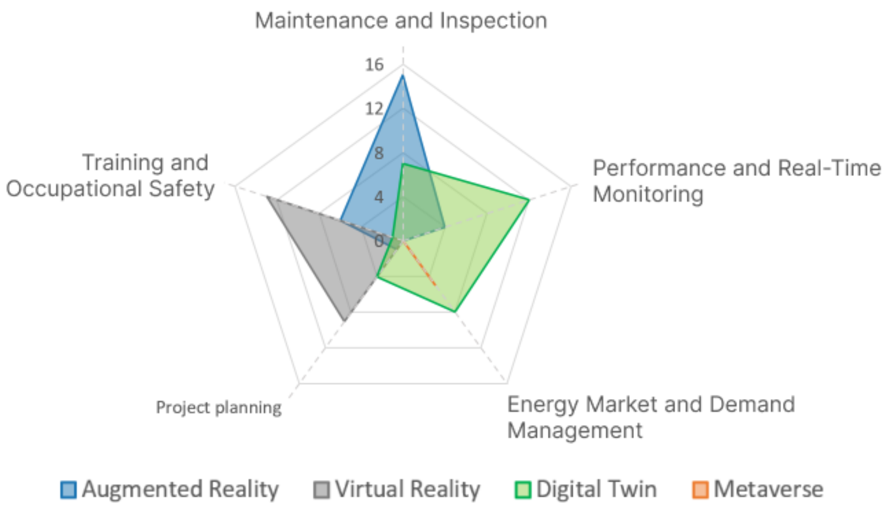


Figure 2.9: Radar chart mapping article distribution across application fields.

It is also possible to observe from Fig. 2.9 that the scope of DTs applications is more extensive, with their primary usage being in the area of *Performance and Real-time Control*. In this regard, DTs are mainly used to provide insights into the behavior and efficiency of their physical counterparts. By comparing DT-generated data with real-world data, operators can detect deviations and anomalies in the physical asset's performance. Moreover, the simulation capabilities of DTs can help operators predict how changes in certain variables will affect the behavior of the physical asset, allowing for informed decisions and adjustments in real-time.

Finally, despite the limited number of studies on the metaverse, the radar chart indicates a growing inclination towards utilizing this technology in *Energy Market and De-*

mand Management applications. In this scenario, users could engage in trading activities using digital avatars and exchange digital representations of energy assets.

2.3 Software and Development Tools

The development of industrial metaverses, DTs, and XR applications usually requires a combination of software and hardware components. The stack employed may also vary depending on the specific goals, available budget, and intended functionalities of the application. For example, a marker-based AR solution focused on precise object tracking may require a different set of software than a markerless AR solution focused on flexibility and natural user experience. In the case of industrial metaverses and DTs, specifically, the choice of tools and technologies is also driven by the complexity and completeness of the solution. For instance, if the primary focus of a DT is to simulate and optimize energy consumption in a smart grid, Geographic Information System (GIS), renewable energy modeling platform, and integration with IoT devices may be essential for capturing and analyzing real-time data. On the other hand, if the DT focuses on aspects that are not related to geography or physical location, integrating GIS into the DT may not be necessary.

Through the systematic literature review conducted, it was possible to identify and classify the development tools mentioned in the reviewed publications as in the following:

- **CAD and 3D modeling:** Software for creating technical drawings and detailed digital representations of objects and structures. These tools usually offer features such as precise measurement, object placement, and comprehensive control over shapes, sizes, and textures. Autodesk® Revit and Autodesk® Infraworks 360 were the most common tools cited in the reviewed literature. Autodesk® Revit is a BIM software for creating 3D models of buildings and infrastructure projects. Autodesk® Infraworks 360, on the other hand, is a specialized software for creating 3D infrastructure projects in a real-world context.
- **Game engine and animation:** Software platforms for developing simulations and interactive experiences. These tools usually offer features such as advanced graphics rendering, physics simulation, asset management, and visual scripting. Since they allow the creation of sophisticated 3D objects with realistic lighting, shading, and texture effects, these tools are commonly employed to build 3D animations in

XR applications and DTs that include high-fidelity visualization and real-time interactivity. Besides Autodesk® 3Ds Studio Max, a 3D animation and rendering software, game engines such as Unity and Unreal were mentioned.

- **Programming language:** Programming languages were used for diverse reasons in the reviewed literature. In general, they were mainly employed either to facilitate the implementation of complex algorithms and mathematical models or to support the integration and interoperability of various elements within services and systems. The most common programming languages mentioned in the reviewed literature include MatLab, C#, and Python. Notice that MatLab was classified as a high-level programming language, mainly used to implement mathematical models in DTs.

- **Computer vision Software Development Kits (SDKs):** Sets of pre-built functions and algorithms that assist developers in building computer vision applications. These tools usually offer features for image and video processing, object detection, and motion tracking. The most common tools within this category include OpenCV, YOLO, and Vuforia.

Fig. 2.10 presents the technologies employed in the development of XR and DTs solutions in the context of the reviewed publications, systematically categorized and accompanied by their corresponding references. Lastly, although most of the reviewed publications on DTs did not explicitly mention a specific development tool related to data acquisition, data management, and data analysis, they consistently emphasized the significance of these aspects in their proposed solutions. Therefore, a brief explanation of these elements is provided in the following:

- **Data acquisition:** Involves acquiring real-time and historical data related to parameters, variables, and environmental conditions that influence the behavior and performance of the system. This data is used to update and synchronize the DT, allowing for accurate and dynamic representations of the physical system. The data acquisition layer includes hardware and software that collect data from various sources, including sensors, IoT devices, SCADA systems, GIS, and other data streams. SCADA services are mentioned in [39, 41, 42, 43, 44, 45, 46, 47], IoT is mentioned in [39, 41, 42, 48] and GIS in [41, 49].

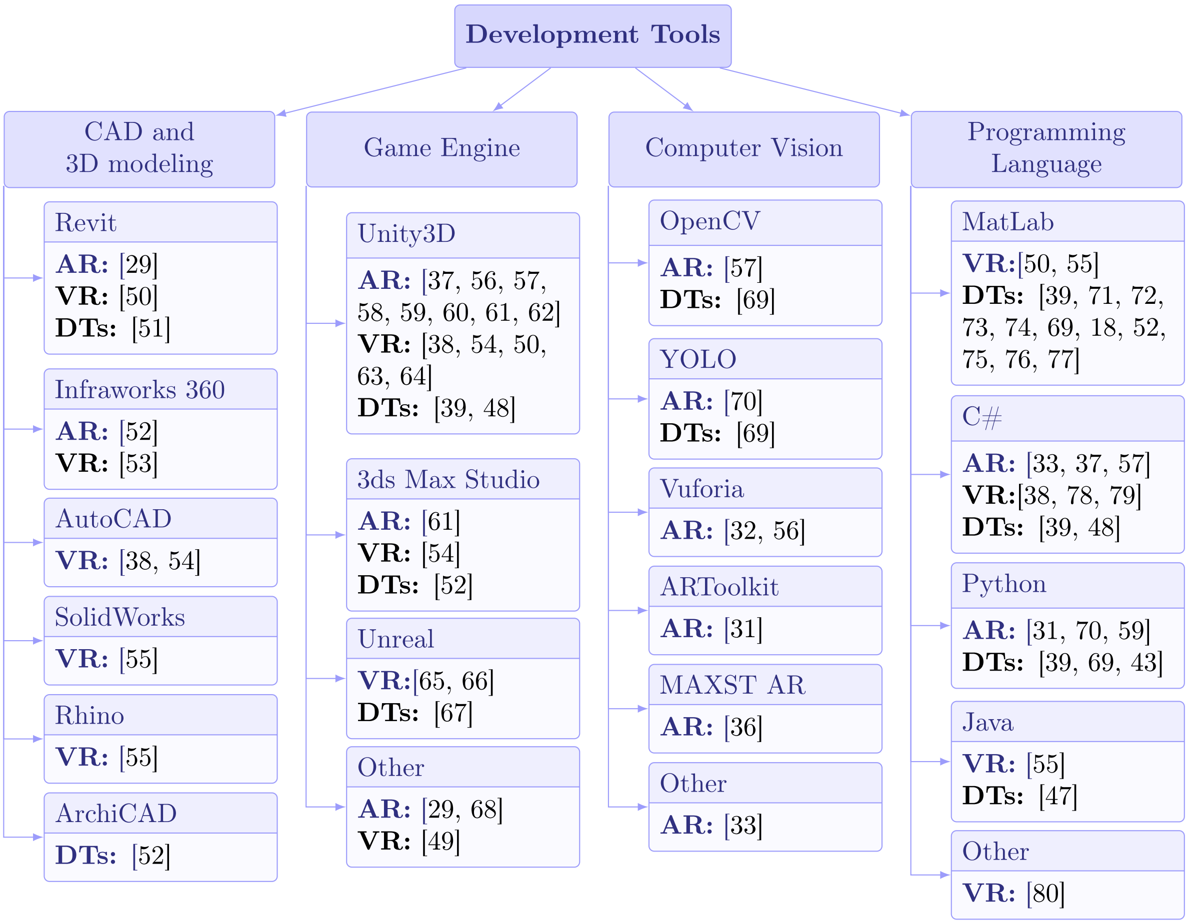


Figure 2.10: Overview of development tools employed in the reviewed publications for developing AR, VR, and DT solutions.

- **Data management:** Ensures that the DT has access to the relevant historical and real-time data required for accurate modeling and analysis. It involves storing and processing the large amount of data generated by the digital model and its physical counterpart. The data management layer encompasses data storage solutions, such as databases and cloud-based platforms, capable of handling the volume and variety of data produced by the whole system. MongoDB non-relational database is mentioned in [67]. Relational databases, such as MySQL and SQLite, are mentioned in [81, 48, 82], and SAP Hana in [47].

- **Data generation and analysis:** Involves simulating the behavior of the DT and generating synthetic data that mimics the responses and performance of the physical system. It also involves applying AI, statistical techniques, and ML models to identify patterns, predict system behavior, optimize performance, and support decision-making processes. AI and ML algorithms are mentioned in [39, 72, 73, 83, 48, 82, 77, 75].

It is worth noting that the diverse range of tools and technologies employed in the development of XR and DTs reflects the multidisciplinary nature of these fields. Moreover, the lack of specific tool references in publications related to the metaverse can be attributed to the predominantly conceptual nature of these studies. Because the metaverse is still in its early stages, the reviewed publications mainly focus on proposing novel methodologies rather than particular hardware and software.

2.4 Technical Challenges and Literature Gaps

The technical challenges observed throughout the reviewed studies are summarized in Fig. 2.11. They were categorized into three main groups intended to present a more nuanced understanding of the current state of the art and provide insights into areas that require further investigation and development:

- Hardware limitations
- Development limitations
- Lack of specialized solutions

2.4.1 Hardware limitations

The development of immersive technologies heavily relies on hardware devices with advanced capabilities. Consequently, current limitations faced by these devices may affect the implementation of reliant industrial metaverses, DTs, and XR solutions.

To simulate real-world scenarios and accurately provide real-time functionality, DTs usually require significant computational power. In practice, high-speed processing and communication capabilities are necessary in order to handle the workload of processing and updating data in real time. Hence, if there is a delay between the data transfer and the simulation software processing that data, latency issues may arise, leading to inaccuracies in the DT and impacting the effectiveness of the simulation [42, 43, 84]. Moreover, the complete hardware related to the sensing layer of the DT's physical counterpart may be complex and include various equipment, particularly considering specialized solutions. For example, in [44], the hardware requirements for a multi-turbine DT include wind speed, wind direction, temperature, and humidity sensors.

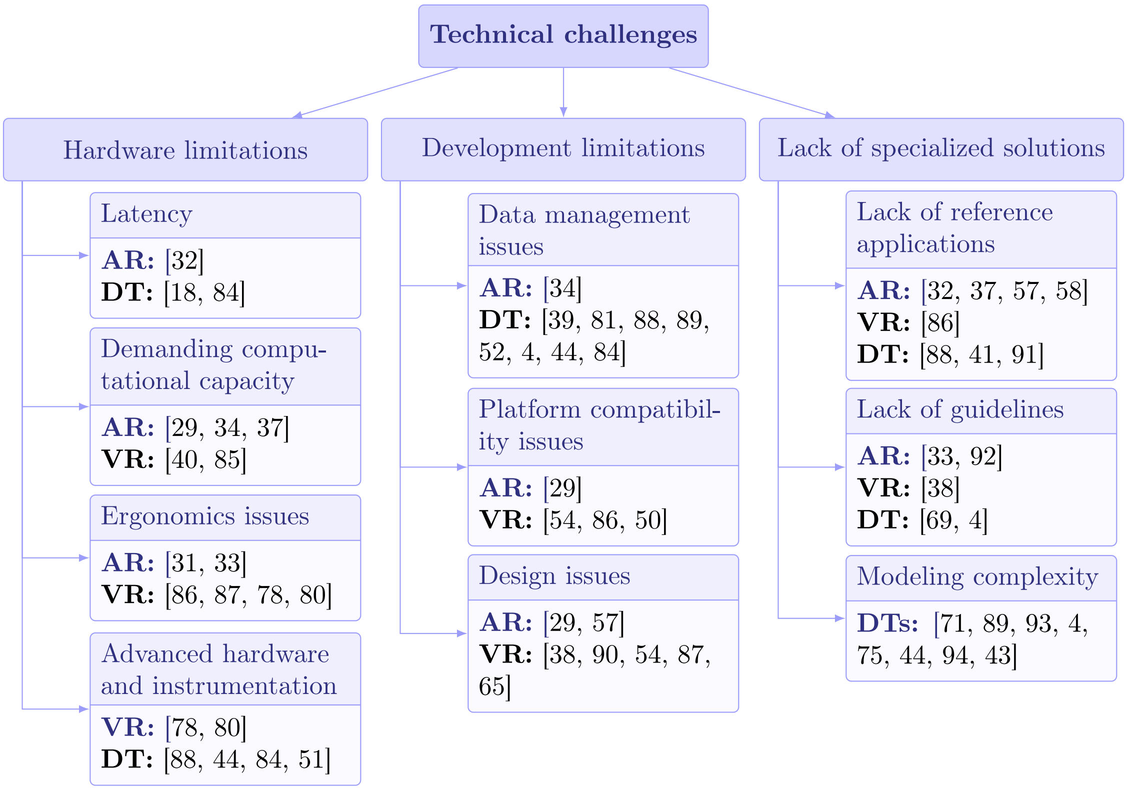


Figure 2.11: Overview of technical challenges found in the reviewed publications for developing AR, VR, and DT solutions.

Concerning XR technologies, despite significant advancements over the past few years, its development also faces hardware limitations. The literature reveals continuous challenges relating to ergonomics, processing capacity, and graphics performance.

Since maintenance and training tasks often involve prolonged periods of usage, ergonomics factors are critical. Heavy or uncomfortable devices, such as popular HMDs, can lead to user fatigue, eye strain, and headaches, consequently reducing adoption rates [29, 33, 86, 78, 80]. Nonetheless, alternative approaches using less immersive experiences, such as handheld displays, come with their own limitations, particularly the inability to provide a hands-free experience and an unobstructed view of the surroundings.

Another critical requirement of XR applications concerns the processing capacity required to render high-quality graphics, track virtual content, and maintain real-time interactivity [29, 34]. According to [40], the complexity of objects and structures that VR can handle is limited by the processing power of the CPU, and therefore, some practical applications remain out of reach. Finally, since limited internet connectivity can hinder real-time interactions, it is important to consider if the XR solution relies on cloud-based services for processing and content delivery [32]. Otherwise, applications aiming for remote assistance may be ineffective.

2.4.2 Development limitations

The development of DTs and XR applications presents various challenges and considerations that demand careful planning and execution, mainly related to data management, platform compatibility, and design issues.

Developing DTs requires careful consideration of specific limitations in terms of data management, primarily concerning the quality, volume, and availability of the data. First, it is important to consider that DT applications usually generate a large volume of data, demanding robust storage and data processing strategies to handle the workload efficiently.

According to [52], as the number of parameters under consideration increases, the analytical data volume also increases, consequently leading to time-consuming and complex data analysis processes. Also, because modeling accuracy depends on the model parameters, this connects to another technical difficulty in building DTs, which is properly modeling the physical system being duplicated in the DT [77]. This process requires extensive knowledge of the system's behavior and access to high-quality data. Moreover, noise data, biased models, and neglected aspects may also affect the twinning process of DTs. In this regard, it is important to consider that not all parameter data may be readily available or compatible with the DT's requirements.

According to [4], insufficient data availability can create dead spots, which may introduce biases and limit the ability of DTs to accurately represent certain aspects of the system, such as social and environmental factors. One of the contributing factors to the absence of data is the potential inaccessibility of certain data sources, which may be attributed to concerns surrounding privacy and security restrictions. In addition, historical data may be either non-existent or incomplete. For example, in [93], the authors mention that the monitoring capabilities of older nuclear power plants may have limited sensor sets, and historical data may not be rich enough to support data-driven algorithms. In [81], it is highlighted the absence of data due to the fact that some meters are not equipped with smart technology.

Moreover, [4] highlights that available data may also affect twinning since noise data is easily measurable and readily available. In [44], for example, the authors discuss how sensor failures may generate outliers and negatively affect the accuracy of the prediction model. Finally, since experts designing DTs have the authority to select datasets, [4] raises an ethical concern regarding data privacy and ownership, especially considering the bias and influence of dominant manufacturers.

Furthermore, given that DTs deal with multi-temporal, multi-dimensional, and heterogeneous data from various sources, data compatibility, and integration issues may arise [88]. For example, in [81], the authors mention the current knowledge gaps regarding the combination of energy-related data with geospatial data. In [51], the challenges related to data fusion with 3D models are highlighted. The authors cite inconsistent standards in 3D model creation, which hinder their reusability. Additionally, difficulties in updating changes in design and manufacturing prevent these models from accurately reflecting the real-world scenario.

Concerning XR technologies, developers must be aware of software concerns related to platform compatibility, accuracy, user experience, and tracking [29]. Platform compatibility is a crucial consideration in the development of XR applications, as it directly impacts the accessibility and usability of the product across various devices, operating systems, and the industrial environment [29, 86, 50]. Limitations related to platform compatibility may result in significant constraints for users, excluding a large portion of the potential audience and hindering widespread adoption. Yet, ensuring cross-platform support can be challenging due to differences in hardware capabilities and software APIs.

Moreover, the development of XR applications requires specialized cross-functional teams [38]. However, given the complexity and costs involved in these projects, some aspects of the development are often neglected. One point of attention is the design of accessible and user-friendly interfaces since these applications should be easy to navigate and manipulate without extensive training. In [38, 90], the authors discuss how existing authoring tools lack data integration and are desktop-oriented, disconnecting the creation process from actual immersive user experiences. In this regard, it is important to acknowledge that a poorly designed interface may lead to frustration and disengagement among users, affecting their overall experience with the solution.

2.4.3 Lack of specialized solutions

The implementation of industrial metaverses, DTs, and XR in power systems also faces significant limitations due to the absence of clear guidelines and prior references. Researchers often face the daunting task of adapting generic approaches to suit their particular requirements, leading to potential inefficiencies and limitations in the outcomes [32].

The development of specialized DTs for power systems is confronted with particular technical challenges. The literature reveals difficulties in modeling complex power systems, including representing unknown parameters and effectively incorporating physical constraints into prediction models [89]. Considering wind energy systems, the authors in [44, 75] mention the difficulties in dealing with spatially correlated turbines, as well as modeling these systems due to their nonlinear characteristics and uncertainty in data related to wind fluctuating patterns. In [77], the authors reveal the challenges in identifying unknown parameters of photovoltaic cells, including the diode quality factor, series resistance, shunt resistance, and temperature coefficients, necessary to build a reliable DT. Also, according to [91], the lack of design specifications for certain components, such as wind turbines, may hinder the development of high-fidelity DTs. This problem primarily arises from the proprietary nature of these designs, with many manufacturers guarding design specifications as intellectual property.

The absence of established guidelines, standards, and frameworks for developing DTs is another significant obstacle. [88] highlights that, while some initial efforts have been made, the transition from theory to practical DT applications requires further development related to addressing technical limitations, architecture standardization, and interface specifications. In [69], the authors mention that the lack of guidelines complicates the implementation of DTs and integration into existing infrastructures, making it time-consuming and expensive. Similarly, in [41], the authors highlight that, although DTs are expected to have a growing impact on the energy sector, their effective implementation requires additional efforts to enhance the current tools in integrated DT frameworks.

Comparable concerns are also observed in the context of XR since most applications are not industry-specialized and offer only generic data visualization solutions [32, 86]. Each application domain, however, presents distinct needs and prerequisites. When it comes to AR applications, for example, it is crucial to take into account environmental factors. This is because the unique intricacies presented by substation facilities may pose challenges for AR implementation as an assisting tool in maintenance and operation tasks. According to [37], the fact that substation facilities share similar scene structures and geometrical features makes AR challenging in terms of image processing. Such geometrical similarities can easily result in perceptual aliasing or failures in continuous ego-motion estimation. Another concern relates to detecting point features in substation facilities, since these settings are more susceptible to illumination changes, perspective shifts, and low-textured scenes.

In [57, 58], although a different set of AR technologies is used, the authors express similar concerns as those explored in [37]. It is said in [57] that lighting is a challenge for image-processing-based object detection algorithms in real operation courtyards. Moreover, according to [58], traditional methods commonly employed in AR, such as markers, are not appropriate for industrial environments since equipment is continuously powered on in these sites, limiting workers' mobility to a minimum safe distance. This poses a challenge not only for installing the markers but also for their visibility. In this regard, their applicability is limited in scenarios where pipes and equipment obstruct their visibility or when the worker's viewing angle does not include the fiducial marker. In addition, factors such as dust, which is common in power plants, can also hinder the detection of fiducial markers.

Finally, according to [95, 57], the existing literature lacks substantial focus on the potential applications of XR in power systems. For example, the integration of XR with power systems data, such as SCADA systems, has not yet been widely investigated. [61] also highlights that, although AR can be used to overlay BIM data onto a physical site with real-time data, there are significant gaps in the literature regarding the integration of BIM models with energy consumption and generation data. According to the authors, such limitations restrict the development of new immersive experiences in the sector.

Another literature gap in the development of XR applications for power systems relates to a lack of design methodologies that facilitate the creation and distribution of XR applications for training purposes [33, 38, 92, 90]. For example, the current authoring tools for creating immersive educational experiences lack integration with existing data and are primarily desktop-oriented. These characteristics detach the pedagogic process of creating the immersive experience from experiencing it in a situated context [90].

2.5 Barriers and Motivations for Adoption

To better understand the barriers and motivations for the adoption of the studied technologies, two main steps were undertaken: assessing academic interest in the reviewed topics throughout the years and mapping the motivations and barriers described in the existing literature. Academic interest was considered in order to evaluate future trends of the subjects under review. For that, a Scopus search encompassing only journal publications with titles containing the terms "augmented reality," "mixed reality," "virtual reality," "digital twin," and "metaverse " was conducted. The gathered data was then

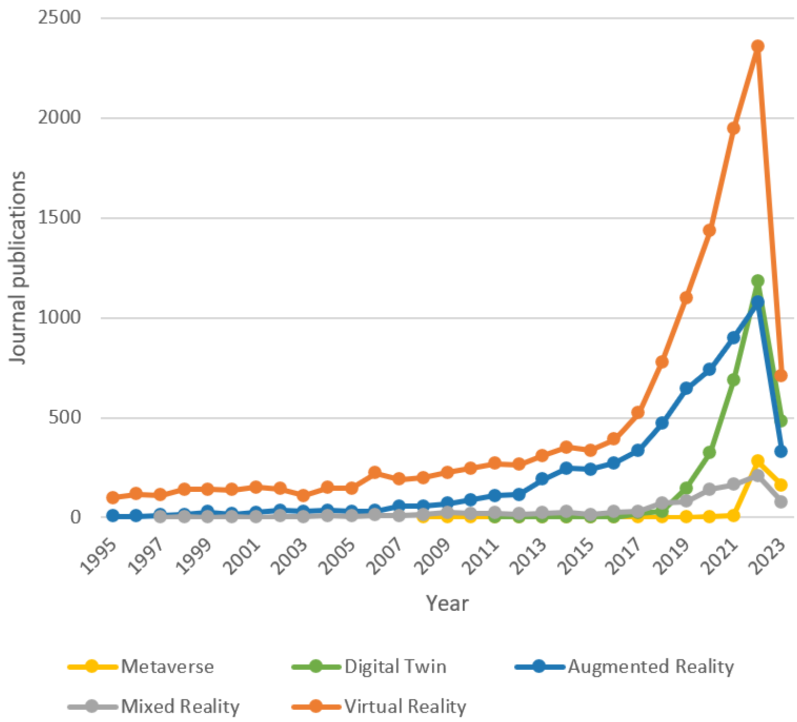


Figure 2.12: Number of journal publications containing the terms "augmented reality," "mixed reality," "virtual reality," "digital twin," and "metaverse" by year. Cut-off date: April, 2023.

examined over the years, as presented in Fig. 2.12.

The graph shows that although XR and DT technologies are not entirely new, the number of studies in these areas has increased significantly in recent years. This behavior may be an indicator of increased funding and investment in research and development for these technologies, suggesting a growing recognition of their perceived potential to address critical challenges in various industry sectors. Moreover, this surge in research interest may also be related to the evolution and democratization of enabling technologies, such as AI and IoT, which may have facilitated the exploration of formerly inaccessible solutions. Consequently, it is possible to anticipate new market opportunities and the maturation of these technologies in the following years.

In regard to the metaverse, it is possible to observe that studies on this subject have been experiencing rapid growth since 2021. In [3], the authors describe the motivation for building an Energy Metaverse as a means to facilitate the exploration of innovative "what-if" scenarios that would be too costly or difficult to investigate in the physical world. In addition to cost savings and improved resource utilization, the proposed Energy Metaverse would lead to faster discoveries and more efficient energy technologies and solutions development [96]. Nevertheless, the Energy Metaverse faces its own set of obstacles.

The persistence of user-generated actions introduces intricate challenges related to data management, privacy issues, and ethical responsibilities in preserving users' digital footprint [97]. In this regard, studies such as [20] are actively exploring the use of blockchain in the metaverse. However, challenges lie in the diversity of blockchain transaction formats, which can hinder efficient information exchange between different blockchain systems. Moreover, establishing an energy trading ecosystem with blockchain requires transaction regulations, which are difficult to enforce in public and decentralized systems with no central authority, such as the metaverse [20].

Additionally, ensuring the accuracy and reliability of virtual simulations poses an ongoing challenge that needs to be addressed for the Energy Metaverse to gain widespread acceptance and application [96]. In this sense, the development and maintenance of comprehensive simulation models demand significant computational resources and expertise, making it a resource-intensive endeavor. For example, according to [96], terminal nodes in the energy system present highly nonlinear operating characteristics; hence, creating DT models for all components can be costly. Furthermore, advanced solutions, as those proposed in [20, 98], face regulatory uncertainties, lack of interoperability, and the need for high financial investments. Therefore, it is important to acknowledge that the Energy Metaverse, as proposed in the reviewed literature, remains largely conceptual and not yet feasible in its entirety. To summarize these findings, Fig. 2.13 showcases an Ishikawa diagram, which elucidates the underlying requirements for the widespread adoption of the metaverse in power systems.

Moreover, when analyzing the academic interest in DT, it is possible to observe a similar pattern as that described for the metaverse, but with an earlier starting point in 2017. The motivations for implementing DTs in the energy sector are rooted in the benefits they offer in terms of real-time monitoring, advanced simulation, and improved decision-making capabilities. However, despite the current academic interest, several barriers hinder the widespread adoption and successful implementation of DTs. Challenges related to understanding their scope, data handling, and adaptability were found in the literature.

In terms of costs, the DT implementation is usually described as a cost-effective solution [88, 45, 91]. Nonetheless, a comprehensive analysis by [43] reveals that the implementation and maintenance costs of DTs can be high, especially for large and complex physical systems. The authors further underscore that most DT implementations exhibit restricted applicability and that the final implementation of a full and one-to-one DTs remains elusive. Moreover, lacking a standardized understanding of what DTs truly entail and how they function is mentioned in [4] as a challenge that hinders research investigation and creates misalignment between project goals and expectations. In general, different requirements for DTs were perceived in the reviewed literature. While certain studies placed particular emphasis on the mathematical model of the physical counterpart, others explored prediction models. It was also observed that the field of 3D visualization, especially concerning interactive features, requires further investigation. [4] also cautions against overly equating DTs with reality and emphasizes the importance of transparency and understanding the limitations of these tools for policymaking.

Another barrier lies in the efforts involved in integrating DTs into the existing power grid infrastructure. As stated by [43], existing DT frameworks for power systems do not consider the adaptability of the solution nor its scalability. This restricts the potential benefits of the application to just one type of end user. Another type of infrastructure limitation is mentioned in [84], where the massive data of the twin system is presented as a considerable challenge to power communication infrastructure. In this sense, current wireless technologies face limitations in terms of time delay, latency, massive connectivity, ultra-low power consumption, and deep coverage [84].

Finally, Fig. 2.12 shows that research and development in XR technologies have been ongoing since the 1990s. However, it was not until around 2016 that academic

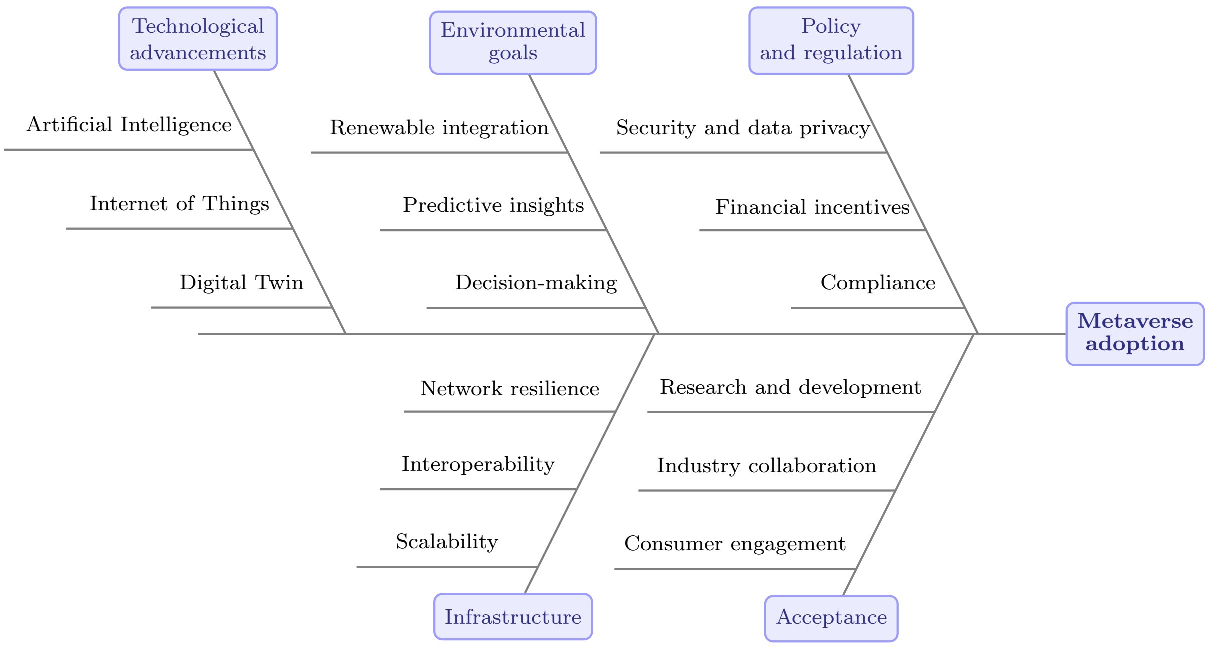


Figure 2.13: Ishikawa diagram illustrating the requirements for the widespread adoption of the metaverse in power systems.

interest in this subject grew significantly. Despite the large body of work in this field, its widespread adoption is yet to happen. Considering the power systems sector, the motivations for implementing XR include mainly improved safety, enhanced real-time support, cost reductions related to personnel displacement, and enriched user experiences both in training and maintenance.

Nonetheless, although these technologies may be valuable to the industry, the cost-effectiveness of XR in power systems still needs to be assessed [29, 58]. According to [29], no exhaustive study confirms that AR prototypes offer substantial gains for the industry in terms of investment costs and operational efficiency. Moreover, high costs and ergonomics concerns related to immersive hardware, such as HMDs, limit the widespread adoption of XR technologies [86, 78, 80]. This not only makes it difficult for vendors to build a solid business case for their products, but regulators may also be unwilling to endorse the usage of these technologies since they have yet to be improved and increase adoption. In this regard, [29] stresses that companies have been cautious in adopting AR into their processes since these solutions are not competitive yet. Furthermore, literature gaps, few practical examples, and technical constraints are cited as challenges in [29, 33, 37, 57]. For example, [90] highlights the complexity of creating VR experiences, as software development expertise is required and existing authoring tools lack integration with organizational data. In [38], the initial design and development of VR scenes are also considered time-consuming and resource-intensive processes, as they often involve manual methods and specialized teams. For example, the VR-based training system presented in [99] took thirty-six months, involving more than 40,000 person-hours of work.

Finally, it is important to highlight that, despite these challenges, the use of XR, DTs, and metaverse is likely to increase adoption as technology advances and more success stories emerge from early adopters.

Chapter 3

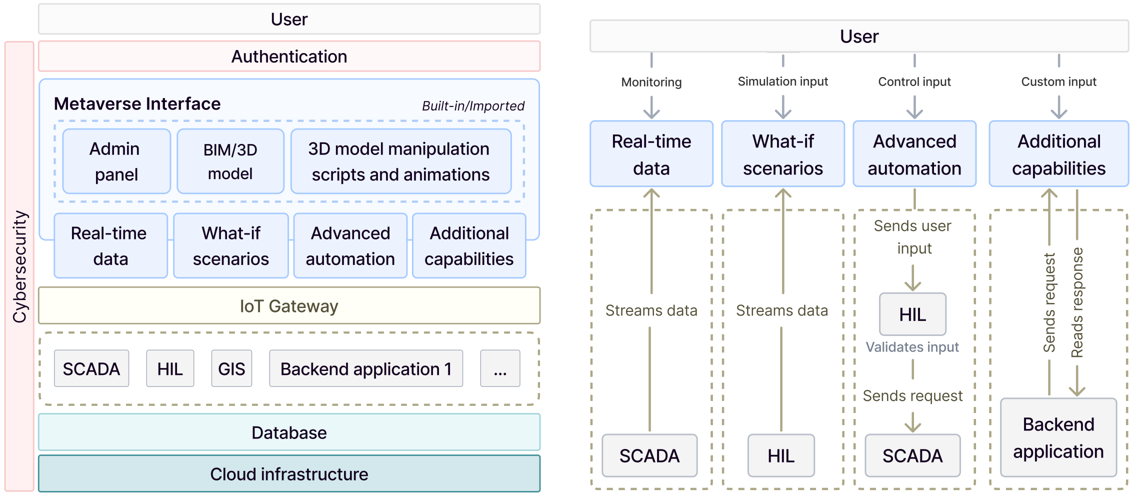
Metaverse Framework Proposal

Building on the insights gained from the literature review, this chapter presents a framework proposal for the development of industrial metaverse applications in power systems. The framework is designed to address specific needs and challenges identified in the literature review, such as the lack of specialized solutions and interoperability issues.

Central to this framework proposal is the following definition: An industrial metaverse application for power systems is a collaborative virtual platform that allows stakeholders to interact with each other and digital models in real time. It provides insights into the overall operation of power plants or systems, focusing on their collective performance rather than highly specific elements. The platform integrates a realistic 3D environment, administrative controls, real-time data, and simulation capabilities, allowing it to adapt and adjust itself to mirror the current state of the system. It leverages standard communication protocols and modular services to ensure interoperability and enhance its relevance.

A high-level representation of the proposed framework is presented in Fig. 3.1. At its core, the framework embraces modularity as a guiding principle. Modularity concerns the application's capacity to break down the system into smaller, manageable components, facilitating integration with diverse services and functionalities. To this end, the framework prioritizes standardized communication protocols, a decoupled interface, and a data-centric architecture. These characteristics facilitate various user flows, as those presented in Fig. 3.1(b). Possible user flows within the metaverse application include:

- Monitoring real-time data from the SCADA system.
- Sending input values to perform simulations. These inputs can be passed to a



(a) Architecture of the industrial metaverse framework.

(b) User flows facilitated by communication protocols and APIs.

Figure 3.1: Proposed industrial metaverse framework for power systems.

Hardware-in-the-Loop (HIL) system, which streams the simulated data back to the metaverse application. This interaction allows for testing and analyzing potential outcomes without impacting the actual system.

- Sending input values to perform advanced automation tasks. These inputs can be sent to the HIL system, which processes the requests and sends them to the SCADA system. This closed-loop interaction may help validate inputs before sending them to the actual system.
- Requesting data from a backend service. This user flow can be implemented for less time-sensitive tasks.

The following subsections dive deeper into the core aspects of the proposed framework.

3.1 Real-Time Data Integration and Interoperability

The proposed framework is built upon several pillars, among which interoperability stands out as a critical part. Interoperability ensures that different components, including hardware and software, can successfully work together. Moreover, the use of proprietary protocols limits the system's applicability as it hinders communication and integration with non-compatible components [100]. Hence, besides facilitating integration and optimizing processes, interoperability can reduce costs by avoiding the need to replace existing infrastructure due to proprietary constraints. In this sense, data exchange via standard communication protocols, such as Open Platform Communications - Unified Architecture (OPC-UA) and International Electrotechnical Commission (IEC) 61850, serves as the backbone of the framework.

Given the above, standard communication protocols define the rules and conventions for data exchange between different parts of the application, enabling interactions such as those presented in Fig. 3.2. The figure illustrates the application's modular design and integration points between its different components.

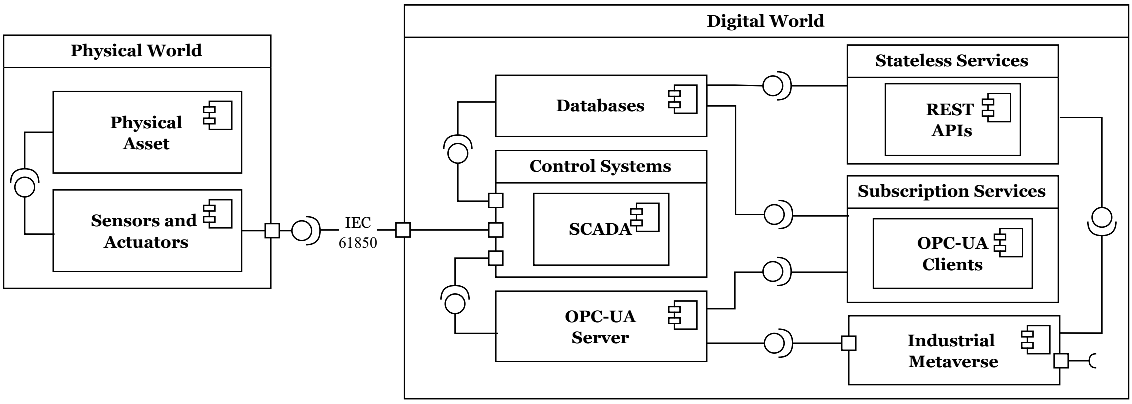


Figure 3.2: UML component diagram illustrating the architectural structure of the system, indicating the interactions and dependencies between key components.

3.1.1 OPC-UA

OPC-UA is an interoperability standard (IEC 62541) that allows the continuous data flow between devices from different vendors and suppliers. The standard provides flexible information modeling, allowing it to represent various devices and systems as well as adapt to existing smart grid data models [101]. Another key feature that makes OPC-UA an essential part of industrial metaverse applications is that it supports real-time data transmission with high precision and redundancy mechanisms. These mechanisms facilitate data availability and improve the application's resilience, ensuring that data is not lost or corrupted due to technical failures.

The OPC-UA architecture usually includes servers responsible for managing the data and an OPC-UA client, which, given adequate access rights, read and write data, can invoke methods, and subscribe to alarms [101]. The architecture also supports peer-to-peer communication with direct data transfer between servers. Moreover, data modeling in OPC-UA is based on a hierarchical structure of nodes, with each node having a unique identifier called a NodeId and attributes that provide additional information about it, such as value, data type, and access level. The structure that organizes all nodes in the OPC-UA server is called an Address Space, and it is how clients can browse and navigate the OPC-UA server [102].

3.1.2 IEC 61850

While OPC-UA provides a general approach for industrial automation, the IEC 61850 standardizes communication within substations. Therefore, implementing OPC-UA and IEC 61850 can be highly beneficial to achieving greater interoperability and efficient communication for successful smart grid applications, as investigated in [101, 102].

The IEC 61850 standardizes communication for digital devices in power systems by following an object-oriented data modeling approach, which defines a common language for describing power system assets, their functions, and data exchanged between them [100]. In this sense, data exchange is facilitated not only between physical devices such as substations, transformers, and switchgear but also between these devices and the broader systems responsible for managing and analyzing operational data.

3.2 Decoupled Interface

A decoupled interface implies minimizing the interdependencies between the frontend solution and the underlying business logic. This approach offers several advantages, including the ability to evolve individual systems without affecting the metaverse's core functionalities. For this purpose, game engines, such as *Unity*[1] and *Unreal*[2], are suggested.

In such architecture, the decoupled interface does not rely on internal details or dependencies of other backend services. Besides reducing the risk of one component breaking due to changes in another, decoupled interfaces promote a modular design, where each component focuses on specific tasks without being tightly coupled to other parts of the system. The following sections explore the development of decoupled user interfaces through game engines.

[1] Available at `https://unity.com/`.
[2] Available at `https://www.unrealengine.com/`.

3.2.1 Connectors

Although the suggested engines are renowned for their capabilities in game development, their flexibility also allows for the creation of interactive applications, simulations, and virtual reality experiences that require complex backend integrations and networked functionalities. Moreover, since these engines typically use C# and the .NET framework in their underlying processes, it is possible to leverage a wide range of libraries and tools that are compatible with these technologies to establish connections. For example, through C# scripting, it is possible to integrate industry-standard communication protocols such as OPC-UA and Transmission Control Protocol/Internet Protocol (TCP/IP) to establish reliable data transmission and allow real-time updates between a server and a client.

These scripts work as connectors, i.e., specialized scripts that facilitate communication and interaction between different parts of the application. These connectors can be further understood as bridges that enable data exchange, event triggering, and behavior synchronization between various elements of the application. In the context of industrial metaverses and DTs, a script that configures an OPC-UA client can be especially useful in order to enable subscriptions to data nodes from IoT sensors and SCADA. Moreover, once the connection is established with the real-time data communication layer, simulation capabilities can also be integrated into the solution, utilizing either an independent backend service or a HIL application. A recommended approach involves streaming the outputs of the system's HIL, possibly based on Simulink, to the real-time data communication layer, as presented in [103, 104, 105].

In addition to streaming and subscribing to data, the industrial metaverse application can also integrate additional Hypertext Transfer Protocol (HTTP) Representational State Transfer (REST) Application Programming Interfaces (APIs) to create stateless interactions that do not require maintaining a connection session. A REST API is a software architectural style for creating web services that allow different systems to communicate with each other using the HTTP protocol. In this scenario, it is important to highlight that HTTP is request-based and stateless, designed primarily for discrete data exchanges rather than continuous streams. Nonetheless, integrating with such APIs allows for enriching the application's capabilities and providing users with a comprehensive suite of tools and information. Moreover, HTTP APIs also allow for bi-directional communication between Unity and external systems. Commands can be sent from Unity to trigger actions and request external data. For instance, integrating the application with a specialized ML load forecasting API could enable users to provide input data and the application to utilize the retrieved results to enhance simulation results. Another example involves fetching historical data or configuration settings from a centralized database. This data can then be used to enrich the simulation environment and provide contextual information to users.

Fig. 3.3 presents the Unified Modeling Language (UML) sequence diagram for the interactions between the metaverse application and the SCADA system, enabled by the OPC-UA communication layer. In the figure, the SCADA system initializes communication with both the IEC 61850 driver and the OPC-UA server. The metaverse application, in turn, subscribes to data nodes and updates the simulation scene considering the data fetched from the centralized communication layer.

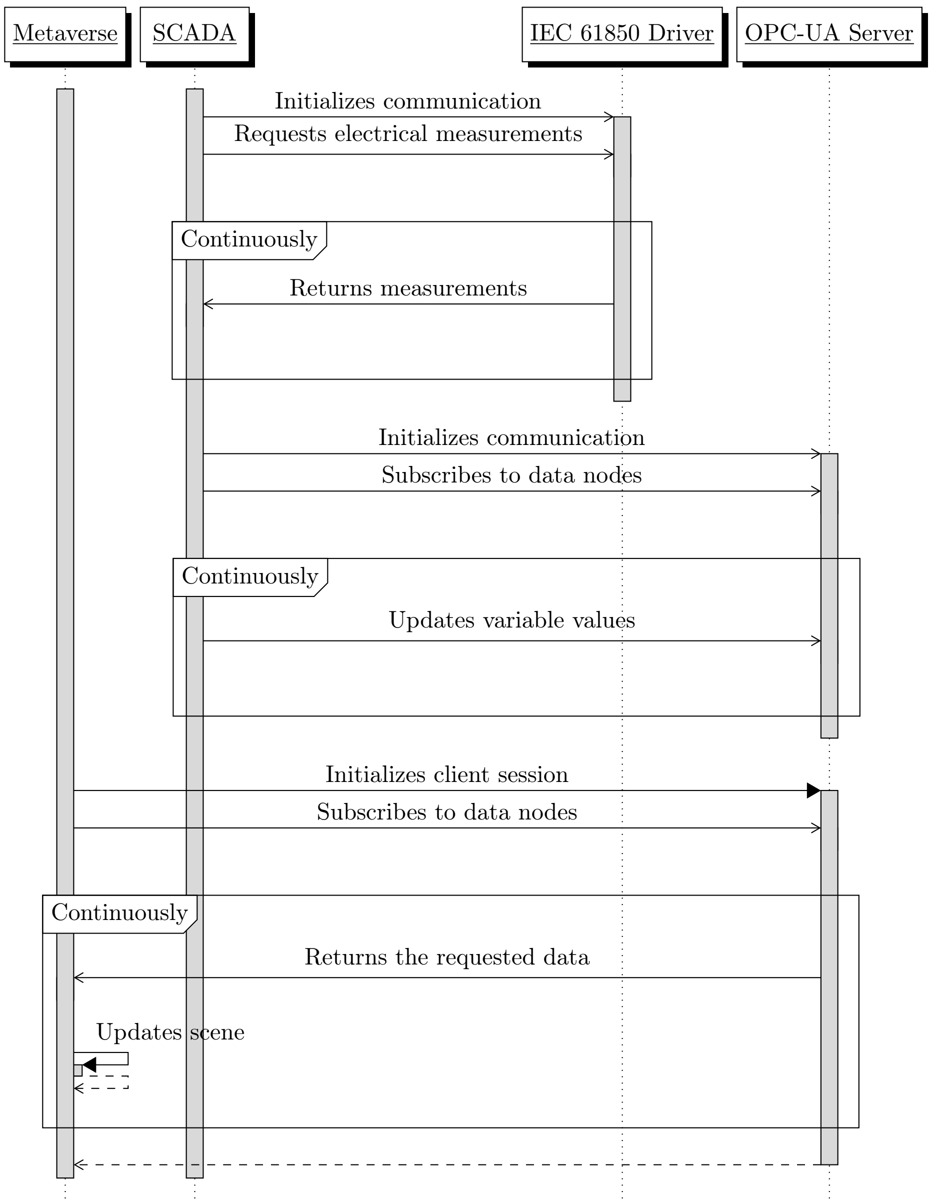


Figure 3.3: UML sequence diagram illustrating the interactions between the SCADA system, the IEC 61850 driver, the OPC-UA server, and the metaverse application.

Similarly, in Fig. 3.4, the interaction with a backend application is presented. The application works as an OPC-UA client, subscribing to data nodes and processing the received data to send alarms and events to the OPC-UA server.

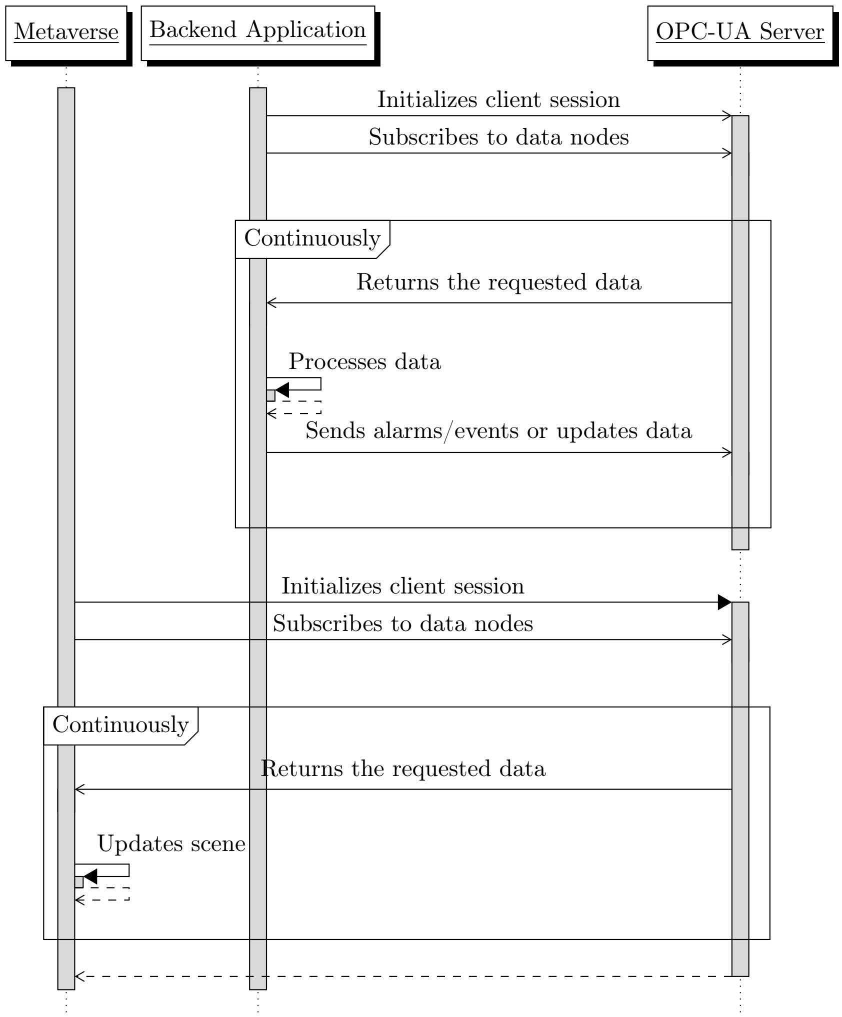


Figure 3.4: UML sequence diagram illustrating the interactions between the OPC-UA server, a backend service, and the metaverse application.

3.2.2 User Experience Design

By implementing script connectors to retrieve data, the user interface components remain independent and responsive to changes in real-time data. As a result, the design of administrative interfaces and heads-up displays, as well as the creation of interactive 3D scenes, can be done separately, with the objects adapting their behavior according to the attached scripts. For example, when the OPC-UA server receives an alert, the application can present a warning on top of a specific component. Additionally, animations based on native flow-based animators can also be implemented to enhance user interactions.

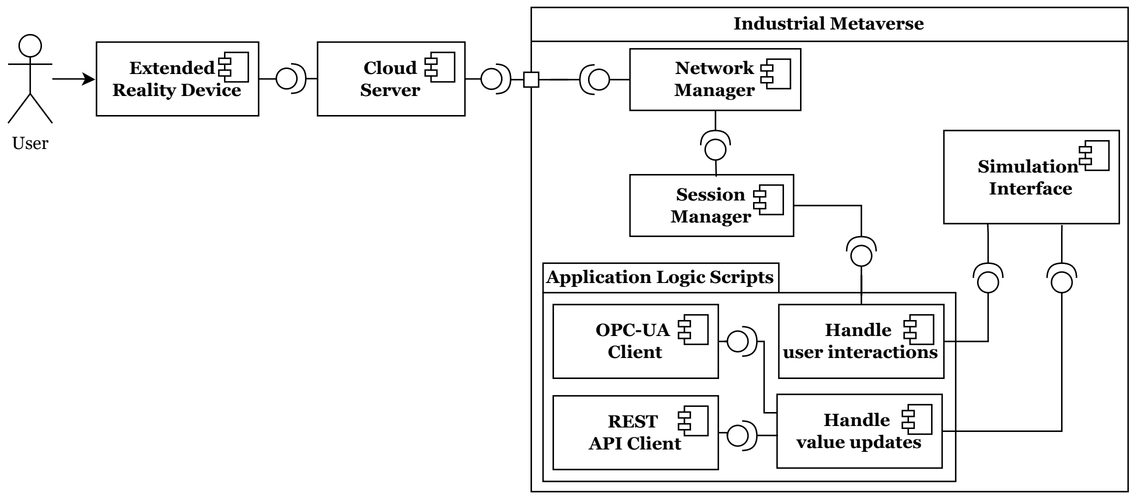


Figure 3.5: UML component diagram for a multi-user industrial metaverse application accessible via XR devices.

Other valuable features to create engaging user experiences concern configuring an immersive and multi-user environment. Enabling immersive experiences through XR devices allows users to explore the power plant within a 3D perspective, increasing user engagement and facilitating the understanding of complex information. It may also enable deeper analysis, realistic simulations, and more effective remote collaboration.

Moreover, enabling a multi-user experience is possible through a server-client architecture, where one application instance acts as the server and coordinates client sessions. A network manager is necessary to manage the low-level networking tasks necessary for connecting users' devices to the simulation servers. Complementing the network manager, the session manager enables the high-level management of the clients' sessions by synchronizing states across all connected clients. This synchronization is critical for ensuring that every user has a consistent experience. Moreover, cloud servers are also necessary to provide the infrastructure to host the application, as well as a way for the XR device or computer to access the application. These interactions are illustrated in the UML component diagram presented in Fig. 3.5.

3.3 Observability

While decoupling enhances the flexibility of the metaverse application, it is also important to guarantee that the system is observable. Observability refers to the system's ability to provide real-time insights into its internal states. This suggests that a system can be virtually recreated more or less faithfully, given how observable it is. Therefore, heightened observability correlates with enhanced comprehensibility of the system, facilitating the creation of a more faithful virtual replication thereof. As such, the continuous operation of a DT or industrial metaverse application may heavily rely on sensor data. In this regard, depending on the complexity of the system's sensing layer, IoT gateways, such as ThingsBoard and Node-RED, are advised to accommodate a diverse range of devices and sensors. Nonetheless, directly leveraging SCADA can be a more straightforward option, depending on the application's desired functionalities and maturity level.

Still, synchronization requires careful configuration of sensor sampling times and data transmission rates. Sensors embedded within solar panels, inverters, weather stations, and other components must be synchronized to capture relevant data, such as solar irradiance levels, temperature, panel orientation, and electrical output, in real-time. This is essential for the metaverse application to receive timely and accurate information about the current operating conditions of the photovoltaic power plant. Furthermore, synchronization extends beyond data acquisition to encompass the integration and processing of data within the metaverse platform.

Finally, real-time data collected from the physical equipment can directly feed the decoupled user interface. Furthermore, the proposed framework also suggests consuming the gathered data into modular packaged capabilities that target different aspects of the solution. Examples include a fault detection and diagnostics application, a predictive maintenance alert service, and a weather forecasting service. Each service is responsible for providing specific functionalities and adding intelligence to the metaverse application in a particular way. These applications can evolve independently from one another while still sharing interdependencies and consuming shared data from databases, SCADA, and the IoT gateway. As a result, the metaverse platform adopts a modular, data-centric approach, where every facet of the industrial metaverse operation revolves around collecting, analyzing, and utilizing relevant data points.

3.4 Cloud-infrastructure and Cybersecurity

A fundamental layer of the metaverse framework includes the cloud infrastructure responsible for providing the computational power and storage necessary to create, simulate, and analyze the system on a massive scale. In this context, the Infrastructure as a Service (IaaS) model can be employed to handle the high computational power, storage, and network demands required by such applications. IaaS is a cloud computing model that provides virtualized computing resources over the internet, allowing one to rent computing resources as needed without the necessity for physical hardware investment or maintenance.

Such technologies offer, therefore, scalable computing power, high performance, and flexibility, ensuring that metaverse platforms can efficiently manage fluctuating user activity and complex data while focusing on delivering engaging experiences. Lastly, it is also important to highlight that achieving synchronization in power systems metaverses requires a balance between precision and computational efficiency. Developers must consider factors such as model complexity, synchronization accuracy, and computational resources to ensure that the metaverse application remains responsive to changes in the physical system.

The engine used for the development of the application may also offer features and frameworks for implementing multi-user experiences. For an industrial metaverse, multiple stakeholders may need to interact with the virtual environment simultaneously. In this sense, the networking capabilities of game engines can enable developers to create collaborative experiences where users can view and interact with the virtual environment together in real-time.

Nonetheless, although the communication layer enabled by OPC-UA and IEC 61850 already offers native security measures, including features like authentication, authorization, confidentiality, and data integrity, the cloud-based and interconnected nature of the industrial metaverse presents particular cybersecurity concerns. Integrating the metaverse platform with other systems, such as enterprise networks, may expand the attack surface, heightening the risk of cyber intrusions. Moreover, malicious actors may exploit vulnerabilities within interconnected systems to gain unauthorized access and launch coordinated attacks. Therefore, cybersecurity must be ingrained into every layer of the metaverse architecture to protect sensitive data, ensure operational continuity, and mitigate the risk of cyber threats and attacks. These include encryption methods to protect data at rest and in transit, robust access controls and authentication mechanisms to prevent unauthorized access, regular software updates and patches to address vulnerabilities, blockchain for immutable data recording, continuous monitoring for suspicious activities or anomalies, and incident response plans.

Chapter 4

Case Study

To validate the framework proposed in Chapter 3, this chapter presents a case study of the industrial metaverse application, considering a solar power plant located in the UFF Experimental Center of *Iguaba Grande*. The case study centers on providing a 3D virtual environment integrated with real-time data from the SCADA and fault detection systems. This educational application serves as a practical example of how the framework can be implemented, offering insights into its feasibility, effectiveness, and potential benefits. Moreover, as the solar power plant is in its initial design phases, a testbed, described in Section 4.3.1, is used to provide a controlled and adaptable testing environment for the system.

4.1 Case Study Specification

The solar power plant under analysis is presented in Fig. 4.1. It has a nominal power output of 150kW and operates with inverters that convert the generated Direct Current (DC) power from the solar panels to a primary Alternating Current (AC) voltage of 400/230V. The plant is designed to maximize energy capture and efficiency through the use of a tracker structure. It comprises three 50kW inverters (Sineng SN50PT) connected to the main distribution busbar, rated at 320A.

The inverters receive AC power from solar panels (Vertex TSM-DE21) arranged in strings, with each string composed of 20 panels rated at 660Wp. The AC output from each inverter is connected to the main busbar via 100A circuit breakers. This AC power is then routed through a bi-directional meter and protection devices before being stepped up to 13.8 kV for grid integration via a three-phase transformer.

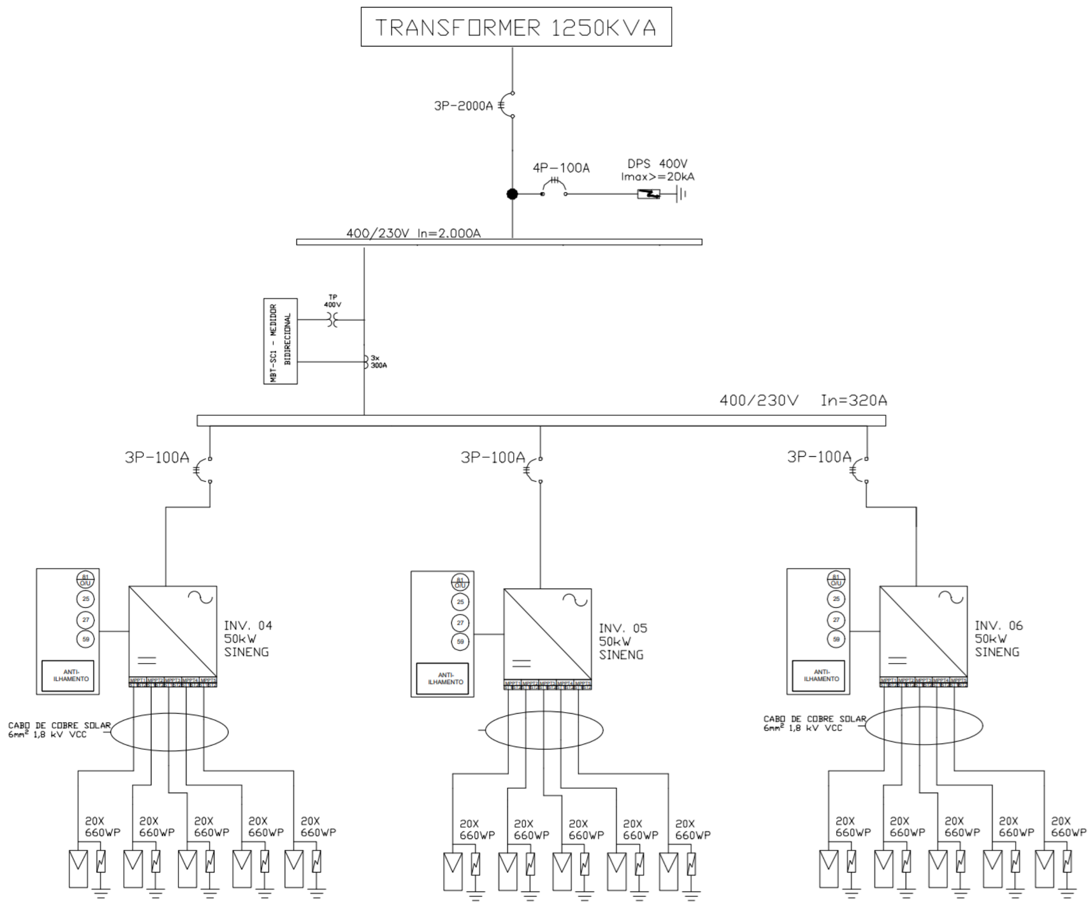


Figure 4.1: Single-line diagram of the photovoltaic power plant

4.2 Methodology

The proposed methodology for the implementation of the case study follows a well-defined workflow comprising planning, project development, execution, and deployment stages, as presented in Fig. 4.2. During the planning phase, specific objectives were meticulously outlined, feasibility was thoroughly assessed, and resources were allocated in alignment with the project goals. For instance, although control and behavior modeling were desired features, it was not feasible to implement them due to resource and time constraints. This limitation was acknowledged, and the focus was placed on the other aspects.

Subsequently, the project development stage involved specialized contributions from each discipline. One team worked on the SCADA system, another on the 3D model of the power plant, and a third one on the fault detection system. It is important to acknowledge that the 3D model presented is still under development. For the current construction of the 3D scene, free online assets have been used. As a result, the positioning of key components such as the solar panels, trackers, inverters, transformer house, and weather

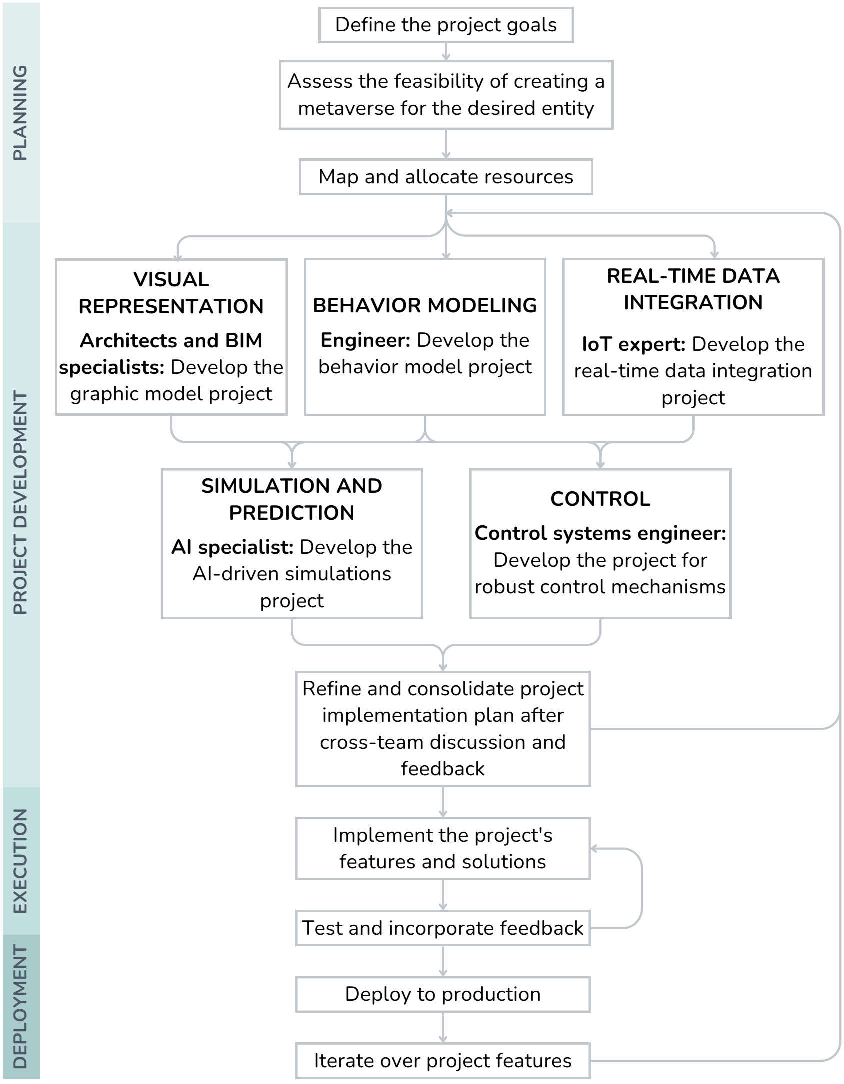


Figure 4.2: Metaverse project implementation process.

station may not accurately represent their real-world counterparts. The development team plans to address these discrepancies in future iterations of the model.

Moreover, details regarding the fault detection system, which is also in progress, are beyond the scope of this work. Given the above, this work focuses on demonstrating how these various modules can be integrated to create a modular metaverse application.

A refinement step follows, with the multidisciplinary team validating the entire project plan. Next, the execution phase begins with the practical implementation and development of the metaverse application. This phase involves coding, integrating various modules, and thorough testing to ensure the application meets all specified requirements.

Finally, the next steps involve transitioning the application into production and starting a continuous refinement workflow for iterative feedback and improvement. This stage is critical as it marks the application's entry into a real-world environment, where it must perform reliably and efficiently. Regular updates and maintenance are planned to address any issues and implement enhancements based on user feedback.

4.3 Industrial Metaverse Application Architecture

This section provides an overview of the architecture of the developed application, considering both hardware and software aspects. Subsection 4.3.1 presents the hardware requirements and the infrastructure of the testbed used to represent the actual solar power plant. Meanwhile, Subsection 4.3.2 presents the tools implemented to orchestrate data and visualization within the application.

4.3.1 Hardware

The development and digitization of physical photovoltaic power plants require a controlled and flexible environment for testing the system's design and infrastructure. To address this need, a testbed, serving as a surrogate of the power plant, is employed. This allows assessing and testing the industrial metaverse application before implementation in real-world settings.

A testbed consists of a combination of hardware and software that provides a controlled environment for conducting experiments. In this case study, an Intelligent Electronic Device (IED) is employed along with a relay test set to simulate power generation. An IED is a specialized microprocessor-based controller used to perform protective functions such as monitoring, control, and protection of electrical equipment and power lines. IEDs are also more sophisticated than traditional electromechanical relays since they offer features such as digital signal processing and support to the IEC 61850. Moreover, a relay test set is a specialized device used to generate controlled electrical signals and check how the relay responds.

Figure 4.3 presents the configuration of the employed testbed. In this testbed, the test set, an OMICRON CMC 356, is used to simulate the electrical output of the power plant. The IED Schweitzer Engineering Laboratories (SEL) 421, connected to the test set, receives and processes these signals as it would in a real-world scenario. In the following, communication between the IED and the SCADA system is enabled by an Ethernet switch, governed by the Manufacturing Message Specification (MMS) protocol of the IEC 61850 standard.

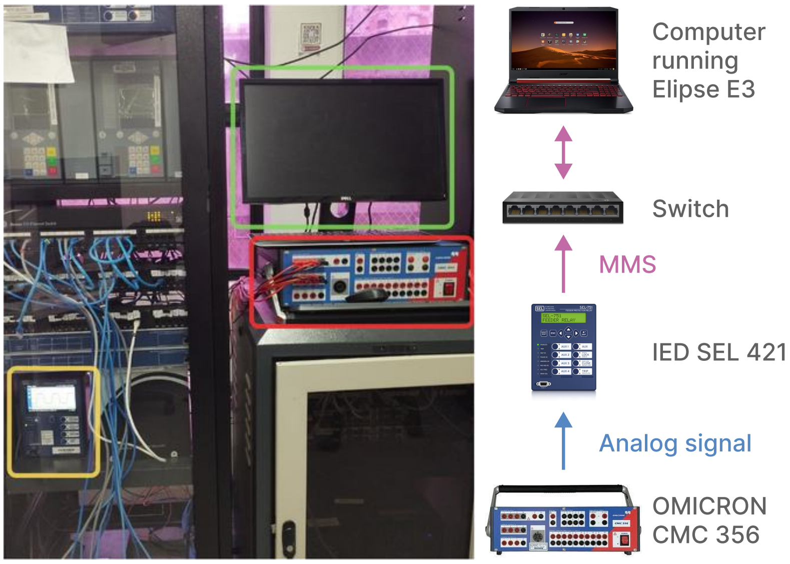


Figure 4.3: Topology of the testbed environment.

Once the direct communication between the IED and the computer is enabled, the SCADA system is configured to retrieve vital sensor readings, operational parameters, and status updates in real-time. Further details on the implementation of the SCADA system are presented in Section 4.4.1.1. Lastly, the digitized data is used within the industrial metaverse application, as further described in Section 4.4.

It is also important to highlight that the development of this case study required a robust computer setup capable of handling the computational, graphical, and data-intensive requirements to run the necessary software for developing the proposed industrial metaverse application. The computer setup used for this implementation included a multicore processor, Intel i7, 16 GB of RAM, a dedicated graphics card - NVIDIA GTX 1650, and an SSD with at least 50GB of free space.

4.3.2 Software

The development of the proposed application utilized a suite of software tools, as presented in Fig. 4.4. The software architecture is structured around the Elipse-based SCADA system collecting real-time data from the testbed, representing the actual power plant. Moreover, the fault detection system, enabled by a Python service, actively monitors the SCADA database, identifying anomalies and triggering alerts when necessary. Both the SCADA and fault detection systems transmit the data to the OPC-UA server, which is configured through Node-RED. The Unity application, set up as an OPC-UA client, subsequently receives real-time data and fault alerts, providing stakeholders with a virtual view of the system. In summary, the following tools and software are used in this case study:

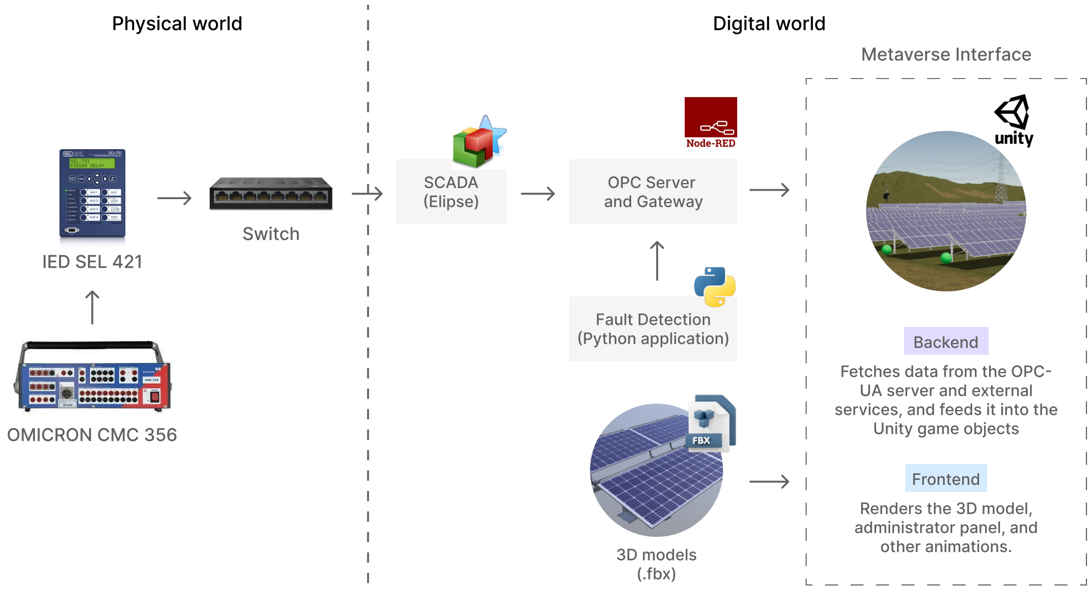


Figure 4.4: Architecture of the industrial metaverse application.

- **Elipse E3:** A platform for creating SCADA systems. It acts as a central control hub for the solar power plant, collecting real-time data from sensors and providing an interface for monitoring the plant's operations.

- **Python:** The chosen programming language for developing the fault detection system. The decision to employ Python for the fault detection system is driven by its extensive libraries and support for ML, which provide significant advantages in developing advanced detection algorithms.

- **Node-RED:** An open-source flow-based development tool that facilitates communication between hardware devices, APIs, and online services. It is used to set up an OPC-UA server and also functions as a gateway for data integration and communication. The decision to use Node-RED stems from its widespread adoption in IoT applications, particularly those leveraging OPC-UA for communication.

- **Unity:** A game engine for creating 3D and 2D games, as well as interactive simulations. The final solution with Unity provides a scene of the power plant and an administrator panel. The decision to utilize the Unity game engine is based on its prevalence in related applications, as evidenced by the systematic literature review in Chapter 2.

- **C#:** The primary programming language for scripting within the Unity game development engine. It allows for handling user inputs and responding to dynamic changes in the virtual environment.

Furthermore, the **OMICRON Test Universe** is employed to inject data into the OMICRON CMC 356 test set. This allows various test procedures to be executed and further analysis of the measurement data. Finally, it is also worth mentioning that **Simulink** was employed in the fault detection mechanism to generate the training data.

4.4 Implementation Process

This section presents the main aspects of the practical implementation of the industrial metaverse application, explaining how the software and development tools described in Section 4.3 were employed to build the proposed solution. This section is divided as follows. Section 4.4.1 details the configuration of the real-time data communication layer and Section 4.4.2 explains the development process within the Unity game engine.

4.4.1 Real-time Data Communication Layer

The effective integration of real-time data from various sources within the application requires a robust communication layer that facilitates interoperability. To this end, a Node-RED application, presented in Fig. 4.5, was designed. The application works as an OPC-UA server and gateway for data ingestion and processing. This layer interfaces with critical data sources responsible for delivering real-time data, such as the SCADA and the Python fault detection system.

To set up the OPC-UA server within Node-RED, the `node-red-contrib-opcua` package was utilized. This package provides OPC-UA capabilities and nodes within Node-RED. Moreover, the configuration involved setting up the `OPC-UA - Server` node and further defining the port number and resource path where the server would listen. Security configurations could also be established at this stage; however, a formal security policy was not implemented for the purposes of this case study.

In the following, the data points from the SCADA system and the Python service were created in the OPC-UA server. Fig. 4.6 illustrates the hierarchical structure of the OPC-UA data points. Each data point, represented as a node, is configured with properties such as namespace, identifier, and data type. With the OPC-UA server already running,

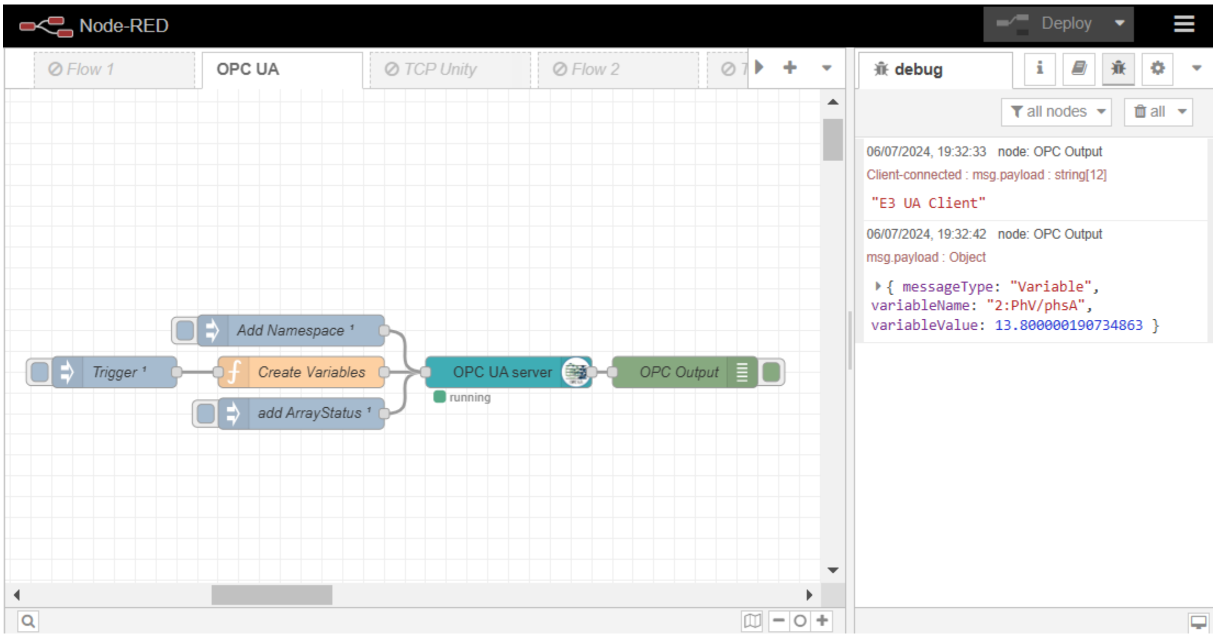


Figure 4.5: Node-RED flow used to set up an OPC-UA server.

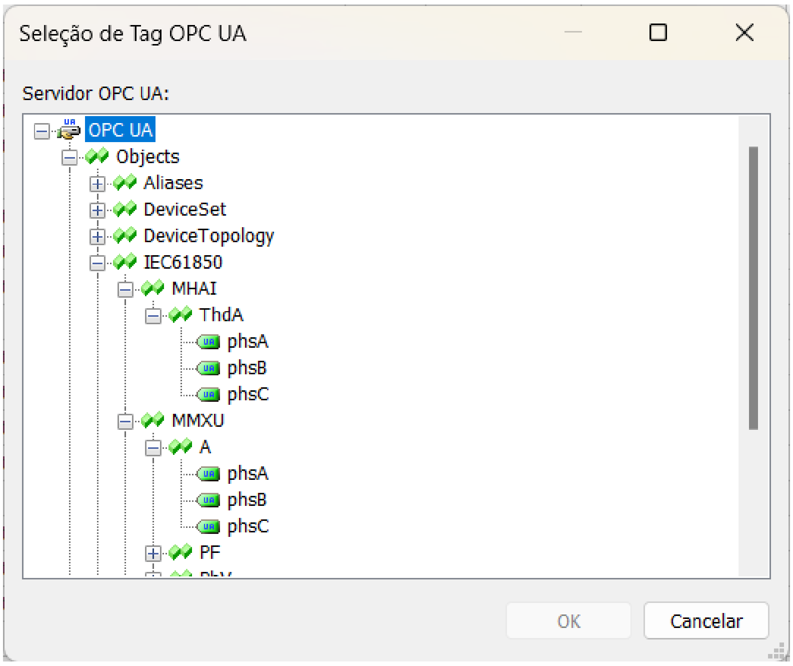


Figure 4.6: IEC 61850 data mapped into OPC-UA.

the Elipse-E3 SCADA and the fault detection systems are configured as OPC-UA clients responsible for sending data to the OPC-UA server. After subscribing to the relevant nodes, these systems respectively update the monitored variable values and send alerts whenever a faulty state is detected in one of the solar panel strings. Further details are presented in subsections 4.4.1.1 and 4.4.1.2.

4.4.1.1 SCADA System

The foundation of the real-time data monitoring rests upon the SCADA system, which serves as the central hub for communication with the IED. The SCADA, built on Elipse E3, is grounded in adherence to the IEC 61850 standard and modeled using the functional hierarchy presented in Fig. 4.7. This hierarchy comprises (1) the Physical Device, which represents equipment with an associated network address; (2) the Logical Device allocated to the physical device; (3) the Logical Node, which represents a piece of equipment or function from the system; (4) the Data Object, which encapsulates specific sets of information and parameters; and (5) the Attribute, which is the data to be acquired and processed. This standardized approach ensures consistency and compatibility within the system architecture, facilitating integration between components from different vendors and simplifying data management.

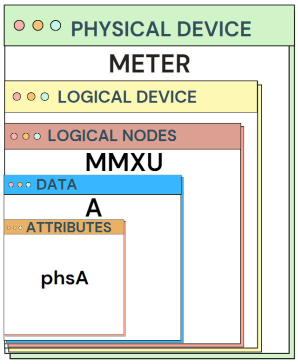


Figure 4.7: Node modeling for the SCADA system.

Since the testbed is designed to simulate the values delivered after the DC output from the solar panels has been converted to AC by the inverters, this work focuses on integrating with the AC data and ensuring that the simulations accurately reflect the operational conditions that are most relevant for analyzing the output delivered to the grid. To this end, the following logical nodes were used in this case study:

- **MMXU:** Three-phase measurement data;
- **MHAI:** Harmonics and interharmonics;
- **MSQI:** Sequence and imbalance.

With the SCADA system modeled and running on Elipse E3, the Elipse E3 was configured to send node data to the OPC-UA server. To this end, an OPC-UA driver was created within Elipse E3 considering the appropriate associations to the IEC 61850 attributes, as presented in Fig. 4.8

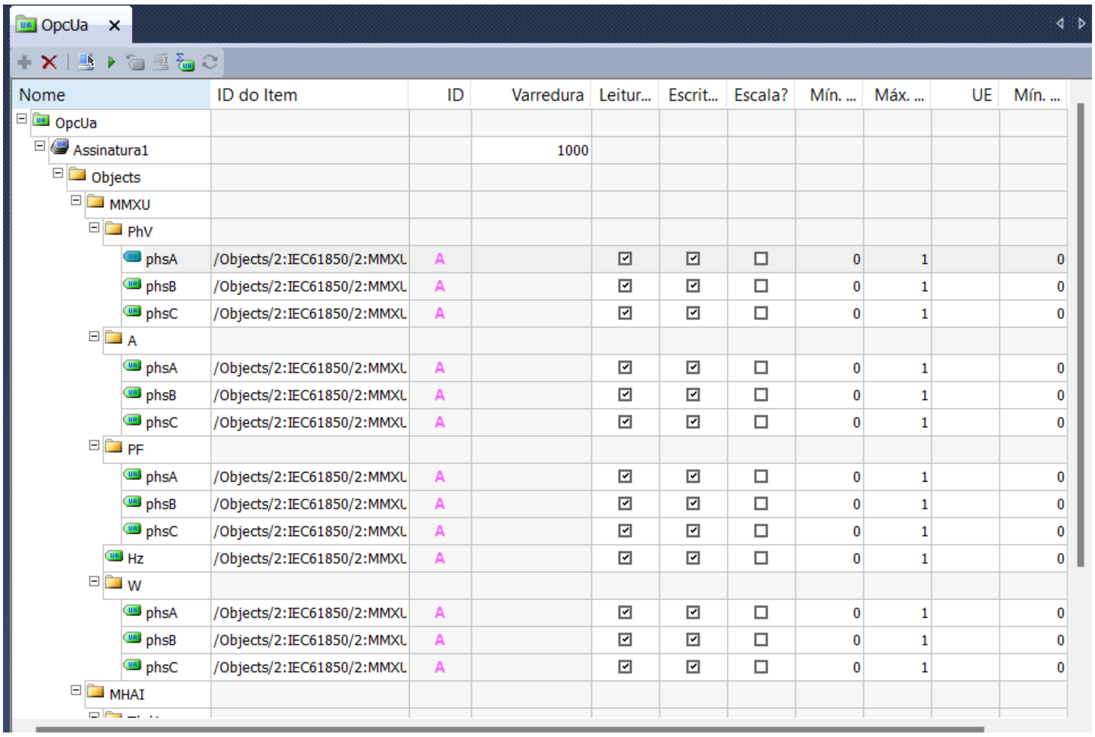


Figure 4.8: Design of the OPC-UA driver within Elipse E3

While IEC 61850 defines Logical Nodes, Data Objects, and Data Attributes for information modeling, OPC-UA usually defines Objects, Variables, and Methods to represent entities and relationships within a system. For example, in OPC-UA, `MMXU/A/phsA`, `MMXU/A/phsB`, and `MMXU/A/phsC` are mapped into separate Variables within a nested object representing `MMXU/A`, as presented in Fig. 4.9. This ensures that the hierarchical structure and relationships defined in IEC 61850 are maintained in OPC-UA, facilitating data integration and interoperability.

Finally, testing procedures using the OMICRON Test Universe were conducted to validate and provide input data for the SCADA system and, accordingly, for the OPC-UA server.

4.4.1.2 Fault Detection System

To showcase the framework's versatility and underscore its potential to strengthen operational efficiency and reliability in real-world scenarios, integration with a fault detection system was performed. The system identifies three main types of faults in the DC side of the photovoltaic plant: open-circuit faults, short-circuit faults, and mismatch faults.

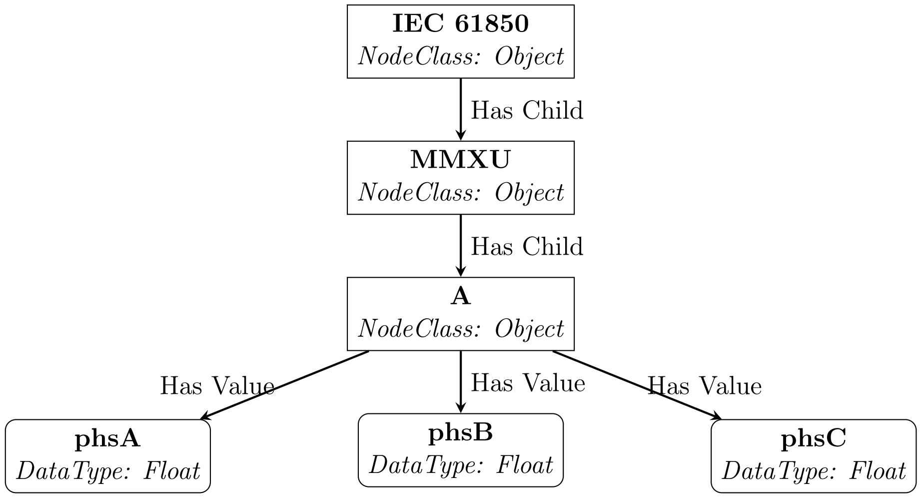


Figure 4.9: OPC-UA data modeling for IEC 61850 current values.

Open-circuit faults occur when a disconnection within the system interrupts the flow of electric current, potentially impacting anything from a single string of modules to the entire system. Short-circuit faults arise when a low-impedance path forms within the system, which can happen between module terminals, within a string, between distinct strings, or between a string and the ground. Lastly, mismatch faults are caused by significant differences in the electrical properties of cells or modules. These faults can be temporary, caused by factors such as dust accumulation, snow coverage, or shading. Nonetheless, they can also be permanent when there is degradation or physical damage to the cells and modules.

To achieve these functionalities, the Simulink software was used to simulate normal and fault scenarios and generate training data that includes electrical and environmental variables. The electrical variables include the current and voltage, while the environmental variables comprise the temperature, global solar irradiation, irradiation in the module plane, and reflected radiation. The training data has 100,000 samples, and a neural network with 2 hidden layers with 50 neurons was employed. Moreover, the Rectified Linear Unit (ReLU) activation function was implemented in the hidden layer and Softmax in the output layer. It is important to emphasize that the fault detection subsystem is an ongoing work, and a detailed discussion on its implementation falls outside the scope of this present work.

The fault detection subsystem utilizes data from the SCADA database to predict if a certain solar panel string is at fault. Lastly, an additional script connects to the OPC-UA server, hosted in Node-RED, and sends alarms based on the statuses of the solar panel strings.

Once the communication with the OPC-UA server is established, the system continuously checks the status of the panels via the `get_string_status`. This function determines the status of each string based on a pre-defined probability. It returns a dictionary where keys represent different solar panel strings, and values indicate whether each string has a fault (`True`) or not (`False`). This process runs in an infinite loop, with a delay of one second between each check. In practice, whenever a change is detected in the new string status, a function responsible for sending alarms is invoked to send the updated values to the server.

Since the fault detection system is under development, the script enters an infinite loop, where checks are simulated via the `get_string_status` function, constantly generating a dictionary with boolean values. It is important to highlight, however, that this is done for demonstration and simulation purposes. In an actual application, events can react to specific changes in the monitored variables. Still, the integration of the Python application with the industrial metaverse application and OPC-UA server is still valid.

4.4.2 Unity Development

The user interface of the industrial metaverse application is built upon Unity, a game development engine integrated with C# scripting. Unity offers a wide range of functionalities, with key parts including the following:

- **Scene:** Allows visual construction of the simulation environment by placing and arranging objects (`GameObjects`) such as 3D models, terrain, cameras, lights, and other elements. It's the primary workspace for designing the spatial layout of the application. It also allows building user interfaces through canvas elements, such as text, images, and buttons.
- **Hierarchy:** Provides a hierarchical representation of all the objects currently in the scene. It shows the parent-child relationships between objects and can also be used to select and manipulate objects.
- **Inspector:** Shows detailed information about the currently selected object in the Hierarchy tab. It allows viewing and editing of various properties such as position, rotation, scale, attached scripts, materials, and additional options that define the object's behavior and appearance.
- **Game:** Provides a real-time preview of how the application will look and behave

when it's running. It facilitates debugging and testing, allowing to see the simulation as it would be presented to the end user.

- **Console:** Displays messages generated by scripts attached to `GameObjects` and Unity, such as errors, warnings, and debug logs.

The Unity interface, including the Scene, Hierarchy, Inspector, Game, and Console tabs, is presented in Fig. 4.10. Lastly, it is also worth mentioning that Unity scripts are written separately in C# (`.cs` files) and attached to `GameObjects` via the Unity Inspector. For example, Fig. 4.10 shows the `Panel Status` script attached to the `ArrayStatus` `GameObject`. Each script can encapsulate specific functionality, such as controlling movement, interactions, or other complex behaviors.

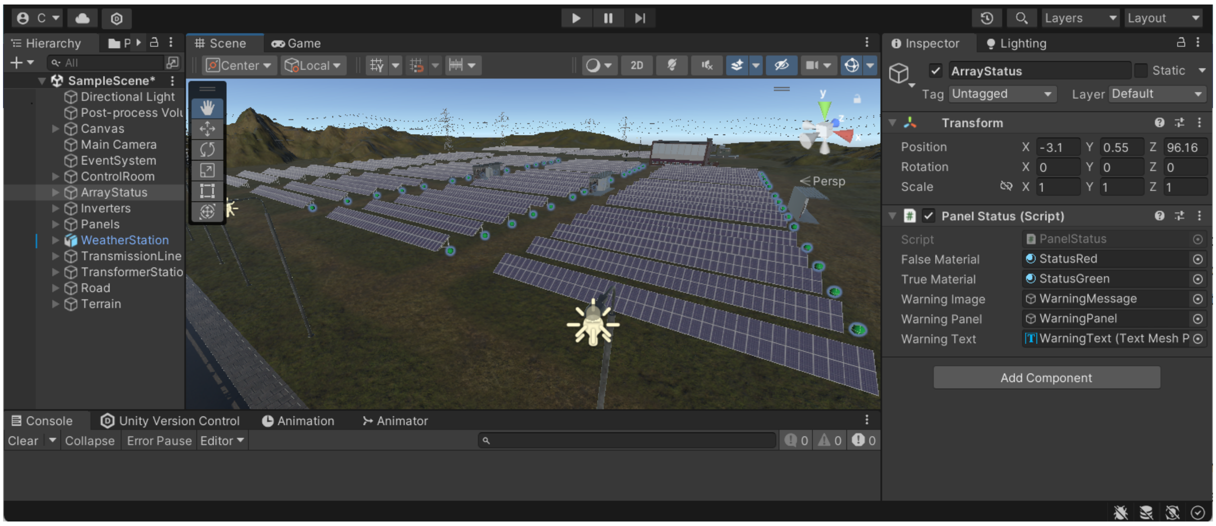


Figure 4.10: Interface of the Unity game engine.

The following sections dive deeper into the Unity scripts developed for this application and implementation details on the user interface. Moreover, the source code of the Unity application is publicly available on a GitHub repository [1].

4.4.2.1 Simulation Scene

The simulation scene used as a representation of the photovoltaic plant is composed of 3D models, imported from Filmbox (FBX) files. These 3D models are encapsulated as `GameObjects` and are responsible for composing the "game" scene. As such, each `GameObject` represents a distinct element of the photovoltaic power plant, forming a

[1] Available at `https://github.com/FriendsLabUFF/industrial-metaverse`

cohesive structure that mirrors the real-world. To create the scene, free assets from the Unity Asset Store[2], as well as FBX files from Sketchfab[3] were employed.

In addition to the game scene, the metaverse application includes an administrator panel, which is built using Unity's Canvas. Canvas allows the placement of user interface elements like buttons, sliders, and input fields to build interface layouts. Moreover, C# scripts are employed to add functionality and handle user interaction within the game scene and administrator panel. The application includes the following panels: (1) real-time data from SCADA, (2) weather data from the OpenWeather APIs, (3) historical data from the system's database, (4) simulation panel, (5) single-line diagram representation of the system.

4.4.2.2 C# Scripting

Through C# scripting, `GameObjects` can be animated to represent the behavior and real-time changes in the solar power plant's operation, acting as a bridge between the 3D models, the internet, and real-world data. These scripts can be implemented to continuously fetch and interpret data, dynamically modifying the visual elements of the administrator panel and 3D scene based on the received updates. For instance, changes in energy production, environmental conditions, or equipment status can be reflected in the virtual solar power plant through animations, color-coded indicators, and other visual cues.

The following scripts were developed for this case study to facilitate various functionalities and interactions within the system:

- `OpcUaClientScript.cs` - Configures the connection with the OPC-UA server ensuring real-time data synchronization. It also updates the appropriate text `GameObjects` on the Canvas with the latest data.
- `WeatherAPIConnection.cs` - Connects with the OpenWeather APIs. It retrieves and parses weather data and updates the corresponding text `GameObjects` on the Canvas.
- `ImageChanger.cs` - Dynamically updates the weather panel image based on the current weather conditions obtained from the OpenWeather API.

[2] Available at `https://assetstore.unity.com/`.
[3] Available at `https://sketchfab.com/`

- `WindDirectionArrows.cs` - Fetches wind direction data from the OpenWeather API and updates the wind direction arrow accordingly.
- `LightingManager.cs` and `LightingPreset.cs` - Responsible for changing the sun `GameObject` position according to the current hour.
- `SliderMenu.cs`, `TabGroup.cs`, and `TabButton.cs` - Configure the interactive behaviors of the administrative slider panel, including changing tabs, and opening and closing the panel.
- `DateAndTime.cs` - Retrieves the current date and time to display a real-time clock in the administrator panel.
- `PanelStatus.cs` - Monitors the status of each panel via the OPC-UA integration with the fault detection system, changing the status indicator material to orange if a fault is detected, or green if the solar panel string is functioning correctly.
- `HoverSystemTooltip.cs` - Enables tooltips for 3D objects, providing additional information upon hovering. For instance, hovering over a transformer presents detailed information about it.

Further details on the OPC-UA client and OpenWeather API communication are provided in the following.

OPC-UA Client Configuration To enable OPC-UA functionalities within Unity, first the OPC-UA .NET Standard library[4] provided by the OPC Foundation was added to the application's source code and the `Opc.Ua.Core.dll`, `Opc.Ua.Client.dll`, and `Opc.Ua.Configuration.dll` drivers were configured.

In the following, a C# script, using the OPC-UA drivers, was developed to handle the initialization and communication with the OPC-UA server. A session is created with the OPC-UA server, given the endpoint configured in Node-RED. In the following, the client subscribes to the desired nodes and reads their respective values, continuously monitoring them for any changes in data and ensuring real-time updates are received.

Lastly, after establishing communication with the necessary services and subscribing to the appropriate data points, the scripts parse the retrieved data into a format compatible with the application's components and `GameObjects`. The real-time synchronization

[4] Available at `https://github.com/OPCFoundation/UA-.NETStandard`

enabled by the OPC-UA client ensures that the metaverse's representation of the photovoltaic power plant remains current and responsive to changes in the actual environment. This way, the metaverse application can stay dynamically connected to the operational reality, whether monitoring equipment status, tracking energy production, or adapting to external factors.

In summary, while the SCADA and fault detection system write data on the OPC-UA server, the OPC-UA client configured in Unity continually reads the data, updating text, materials, and behavior of the appropriate `GameObjects`.

REST API Integration Besides subscribing to real-time data, this case study integrates with OpenWeather services through their REST API to demonstrate the application's ability to integrate with additional services. Implementing this solution involves securely integrating Unity with the OpenWeather API, parsing JSON to extract relevant weather data, and applying this data dynamically to update scene elements. The application was configured to make HTTP requests to the OpenWeather API, specifically targeting endpoints that provide weather data relevant to the case study's location. Moreover, a series of data models, including temperature, humidity, wind speed, and other relevant weather parameters, were created to map the JSON response to the desired parameters within Unity.

Chapter 5

Results and Analysis

This chapter presents the results obtained from the case study, evaluating the effectiveness of the proposed framework in the context of a solar power plant. In the following, the practical benefits, challenges, and limitations identified during the case study are discussed, offering insights into the real-world applicability and potential improvements of the framework.

5.1 User Interface

The visualization capabilities enabled by the Unity application were successfully implemented and enhanced the overall situational awareness. Users could navigate the 3D model, inspect components, and observe dynamic animations representing the operational state of the solar power plant. The video [1] depicts the application's functionality, illustrating both navigation within the virtual environment and real-time data update from the SCADA system.

Moreover, navigation within the application was facilitated through tooltips that appear when users hover over interactive elements, as presented in Fig. 5.1. These tooltips provide contextual information, guiding users through the power plant environment. Tooltips were added to elements such as the transformer, weather station, solar panels, and inverters.

Dynamic control of the sun's position through C# scripting further enhanced the visual realism of the scene by simulating real-world lighting conditions and time progression, as depicted in Fig. 5.2.

[1] Available at `https://youtu.be/p6e-o4nkpmA`.

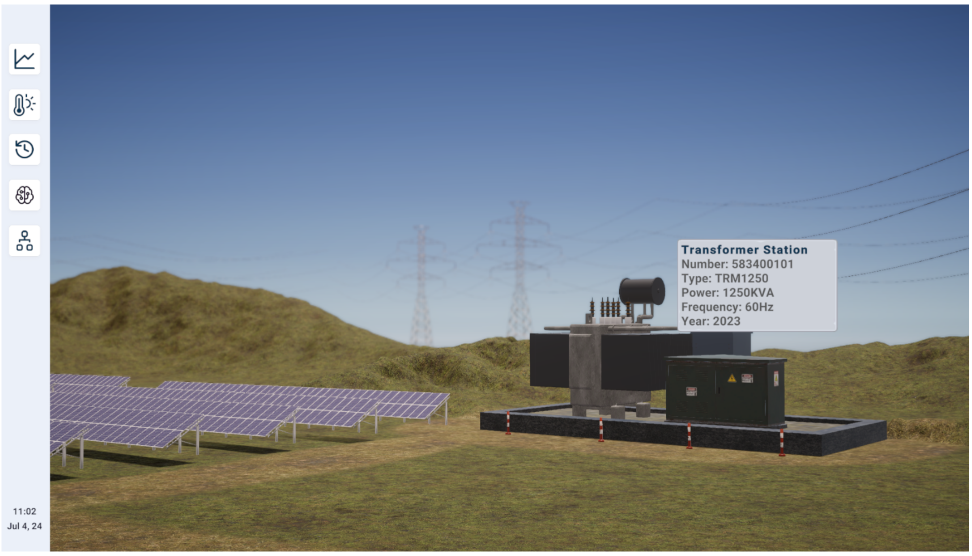


Figure 5.1: Metaverse navigation with tooltips being displayed to enhance situational awareness.

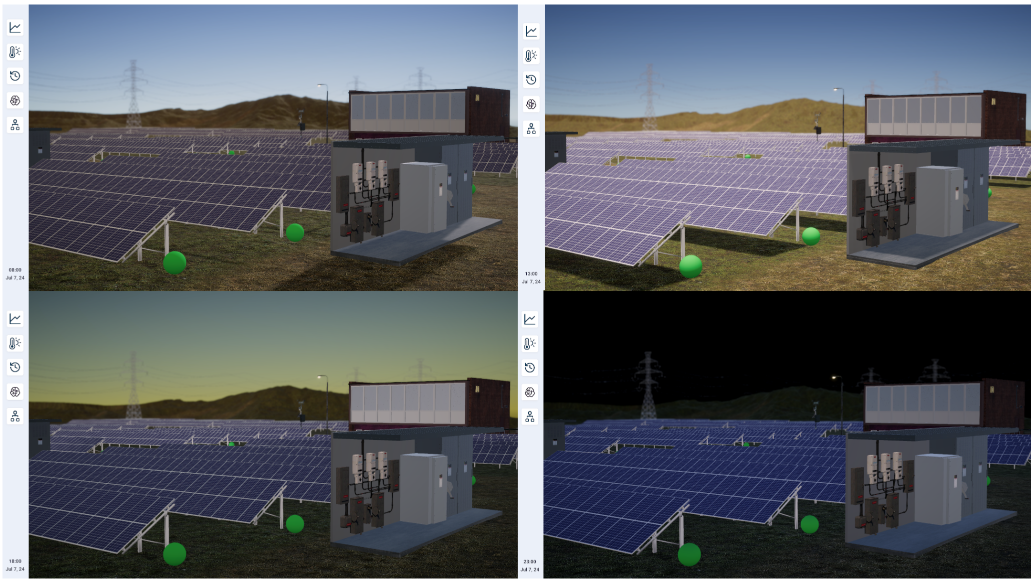


Figure 5.2: Dynamic lighting conditions based on the current time.

Concerning the administrative panel, interactions were also successfully implemented. Users could navigate between tabs and efficiently open and close the panel. The panel accurately displayed the current date and time, as well as real-time data from SCADA, fault statuses, and weather information. Additionally, it featured an alert icon that provided immediate notifications whenever a fault was detected, ensuring timely awareness and response to system issues.

5.2 Real-time Data Acquisition

The implementation of Node-RED as an OPC-UA server and gateway facilitated continuous updates and served as a centralized system for data collection, integrating data from both the SCADA and the fault detection systems.

The Unity OPC-UA client was successfully configured in the project, enabling communication with the OPC-UA server hosted in Node-RED. The integration was validated through successful read operations, depicted in Fig. 5.3, confirming that game engines, such as Unity, can be effectively used for this type of industrial application. This way, real-time data from the Elipse-based SCADA and fault detection system was effectively integrated, providing a continuous stream of information for analysis.

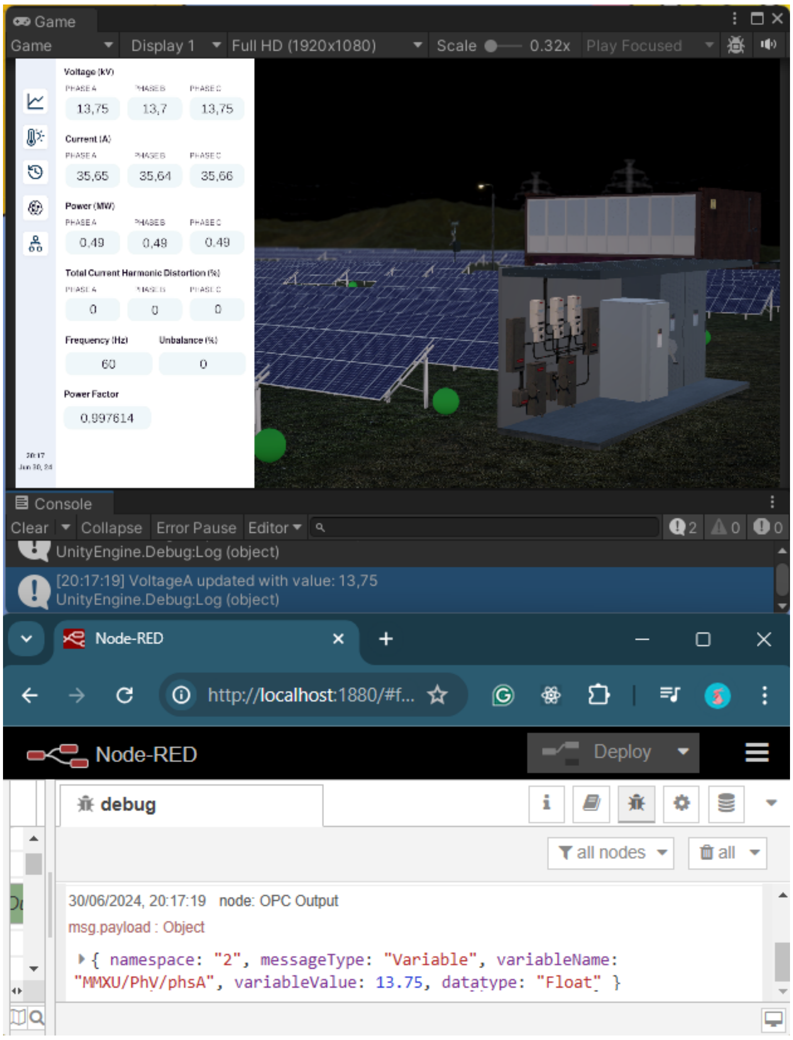


Figure 5.3: Metaverse interface presenting real-time data from the SCADA system, enabled by the OPC-UA communication layer.

5.3 SCADA

The SCADA system, operating under IEC 61850 standards, received power data injected by the Omicron Test Universe into the IED. These devices facilitated data transmission to the SCADA system, adhering to the IEC 61850 protocol specifications. Moreover, an OPC-UA driver, configured with appropriate associations to the IEC 61850 data model, interfaced with the OPC-UA server to relay this data.

Unity, functioning as an OPC-UA client, synchronized with the OPC-UA server to retrieve and display real-time operational data on the administrator panel. This integration successfully allowed the monitoring of critical power system metrics within the industrial metaverse application.

Moreover, latency measurements between OPC-UA and Unity were conducted to assess data transmission efficiency, revealing latency values ranging from 16 to 120 milliseconds, as presented in Fig. 5.4. These values reflect the time it took for data to travel from the server to the client, accounting for network transmission delays, processing times within the OPC-UA stack and Unity's internal processing overhead.

This analysis underscores the system's responsiveness in conveying real-time operational data from the SCADA system to the Unity application. The latency test involved recording timestamps at both the server and client sides to accurately determine the time delay in communication. The OPC-UA server is set to include timestamps with each value change notification. On the client side, a subscription is created for a monitored item, and when a notification is received, the timestamp from the server is extracted along with the current client timestamp.

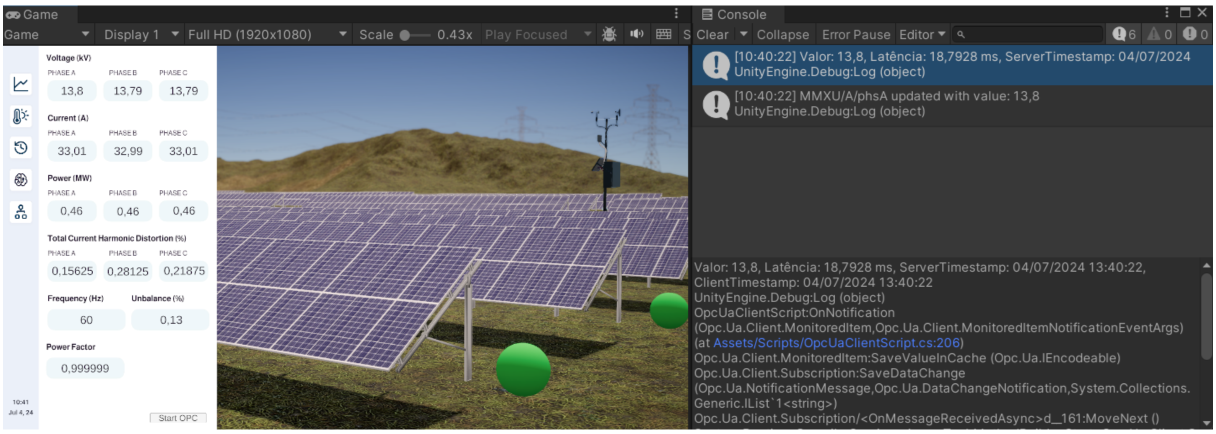


Figure 5.4: Latency logs, comparing the server and client timestamps.

5.4 Fault Detection System

The fault detection system, currently under development, utilizes a loop-based approach to periodically check the statuses of panel strings. The Python application updates the status of the panel strings at regular intervals and sends this data to the OPC-UA server, where Unity retrieves and processes it accordingly.

A latency analysis, depicted in Fig. 5.5, shows that data transmission between the Python application and Node-RED OPC-UA server averages between 2-5ms. This low latency ensures timely data updates and responsiveness within the fault detection system.

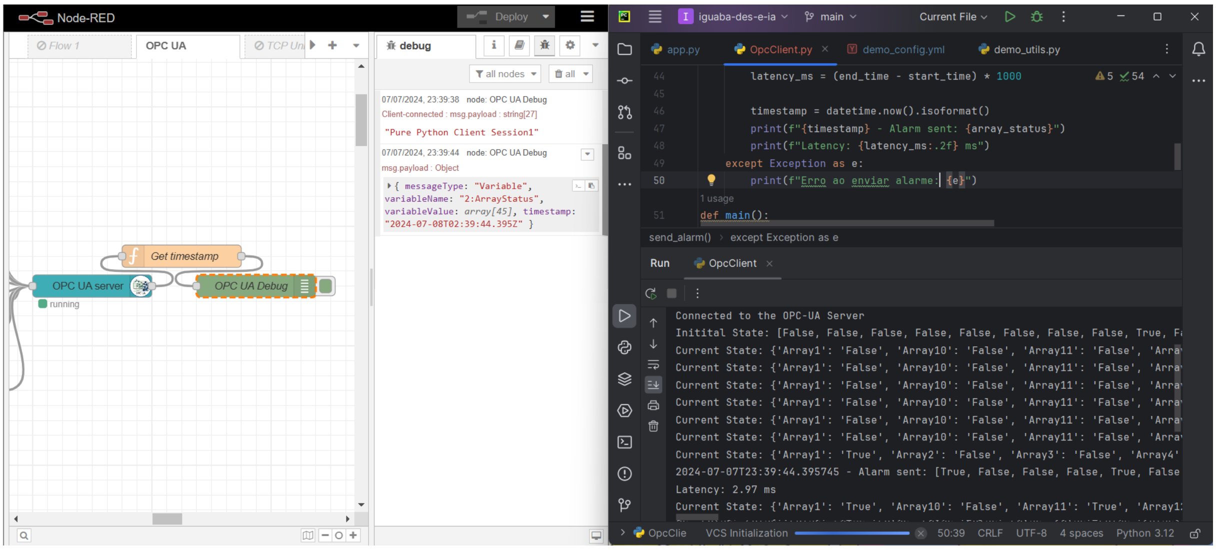


Figure 5.5: Latency analysis showing data transmission between the Python application and Node-RED OPC-UA server.

Upon detecting a fault state, the system promptly displays a warning icon and triggers a popup notification specifying which panel strings are experiencing issues, as presented in Fig. 5.6. In addition, the system dynamically updates indicators next to each panel string. When a fault is detected, the indicator changes color to orange, providing immediate visual feedback. Conversely, the indicator remains green when no faults are present, providing intuitive status indications throughout the application.

5.5 OpenWeather Data Integration

The integration with third-party HTTP APIs is exemplified through the utilization of the OpenWeather REST API, as presented in Fig. 5.7. This integration enables users to receive pertinent meteorological information specific to the solar power plant location.

Figure 5.6: Metaverse interface during a fault state. Animations are used to indicate the status of the solar panel strings.

Figure 5.7: Administrator panel within the metaverse application, displaying weather information obtained from the OpenWeather API.

Once the weather data is retrieved and parsed from the OpenWeather API, C# scripts dynamically update the administrator panel canvas to reflect current weather data.

It's important to note that this approach is tailored for discrete data exchanges rather than continuous streams. Unity applications using the OpenWeather API typically make periodic requests for updated weather information based on predefined intervals or specific events triggered within the simulation. This method ensures that the simulation remains responsive and aligned with real-time environmental changes without the overhead of continuous data streaming.

5.6 Discussions and Study Limitations

The presented case study provides a metaverse platform where users can enter and interact with a 3D representation of the power plant using VR devices. While it integrates real-time data and external backend modules and provides a 3D scene, the application currently lacks the actual DTs of the power power plant's components, such as the solar panels, inverters, and transformer. To address this, it is essential to develop detailed digital models of these components that can respond to external events such as environmental changes, system faults, and user inputs. Incorporating DTs within the metaverse application will facilitate bidirectional control for remote monitoring and operation, enabling real-time interactions and adjustments based on the current state and performance of the physical components.

Moreover, the application of the industrial metaverse framework in this work was successful, demonstrating the system's modularity and its capability to integrate with external services, such as OpenWeather's REST API, and real-time data from SCADA and fault detection systems. The services, encapsulated as independent modules, can be added or modified without disrupting the core functionality, making the framework adaptable to evolving requirements and technological advancements. This modularity is a significant strength, as it allows for future expansions and integrations with other data sources.

The use of OPC-UA and IEC 61850 standards in this application underscores their importance for interoperability and the continuous digitalization of the grid. These protocols facilitate communication and data exchange between different system components. Their inclusion in the industrial metaverse framework not only ensures compatibility with existing systems but also future-proofs the application against miscellaneous standards. Additionally, the ability to integrate with REST APIs like OpenWeather demonstrates the flexibility of the framework to leverage various external data sources and enhance the application's functionality with a comprehensive view of the system being simulated.

Nonetheless, for the proposed application to achieve greater fidelity and scalability, areas for improvement were identified. Tests were conducted using a controlled testbed and a local internet setup, which provided a stable environment for initial validation.

However, real-world deployment is necessary to fully understand the system's performance and scalability. For educational purposes within the university, the current setup may be sufficient, but broader application in actual power systems would require extensive field testing to ensure reliability and robustness under diverse and variable conditions.

Moreover, the 3D models used in this study were open-source assets, which, while functional, do not accurately represent the real-world power system components. Using 3D models based on actual physical counterparts would improve the realism and precision of the simulation, making the industrial metaverse more effective for both operational and educational purposes. Additionally, integrating real data with the 3D scene can also enhance the realism of the simulation. For example, detecting rainy weather through the OpenWeather API could trigger automatic updates to the scene within Unity. This could include visual effects like rain particles, changes in lighting conditions to reflect overcast skies, or adjustments to simulate wet surfaces.

Lastly, the implementation process itself proved to be complex and time-consuming, highlighting the need for a multidisciplinary approach. Developing an industrial metaverse for power systems involves expertise in various fields, including computer science, electrical engineering, and data analytics. Unity, the platform used for this development, is a powerful tool but comes with a steep learning curve. Moreover, the development required resource-intensive software and hardware configurations to handle the demands of 3D rendering and real-time data processing. This indicates the need for high investments in terms of time, expertise, and resources to achieve more advanced outcomes.

Chapter 6

Conclusions

This dissertation has explored the development and implementation of an industrial metaverse application in power systems, addressing several key gaps identified in the literature. The main contribution of this research lies in providing a specialized case study within the power systems domain, a field where industrial metaverse applications are relatively underexplored. Through a systematic literature review, it was evident that there is a significant need for detailed case studies that can serve as benchmarks for future research and development. This dissertation fills that gap by offering a comprehensive case study that not only demonstrates the practical application of industrial metaverses but also highlights the challenges and solutions encountered during the implementation process.

The case study detailed in this research involved integrating real-time data from a SCADA system, weather data via REST APIs, and implementing OPC-UA for interoperability. It provides a 3D virtual environment for users to interact with the solar power plant, including visual cues and dynamic lighting conditions based on real-time data. The administrator panel also provides users with real-time monitoring data, weather information, and fault notifications, demonstrating the application's practical utility. Moreover, tests conducted in a controlled testbed environment showed the system's robustness, though future real-world testing is recommended to further validate these findings.

Additionally, this research has introduced a modular approach and framework for developing industrial metaverse applications. This framework is designed to be flexible and scalable, allowing for easy integration with various external services and data sources. The modularity of the framework is a significant advancement, as it provides a structured methodology that can be adapted and extended for different use cases within the power systems sector. This aspect of the research addresses another critical gap in the literature, where comprehensive frameworks for industrial metaverse development are lacking.

Another noteworthy contribution of this study is its emphasis on interoperability. By integrating standards such as OPC-UA and IEC 61850, the industrial metaverse application ensures seamless communication and data exchange between different system components. This focus on interoperability is crucial for the continuous digitalization of the grid, as it enables the integration of diverse technologies and systems.

As a result, the presented framework and case study serve as a catalyst for collaboration among students and faculty from diverse academic backgrounds and open avenues for further research in the development of industrial metaverse and DTs applications for solar power plants.

6.1 Suggestions for Future Research

Future iterations of the case study presented in this work should focus on enhancing the industrial metaverse application to implement a multi-user and immersive experience. As a university-led initiative, this could provide a collaborative virtual environment for students and stakeholders to share knowledge and best practices, overcoming geographical barriers.

Moreover, integrating with other advanced capabilities, such as power forecasts and simulation capabilities, is also desirable. Lastly, addressing security concerns is paramount, necessitating improvements in cybersecurity measures. To this end, OPC-UA security policies should be further investigated.

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