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Digital Twins and Data Visualization in Cultural Heritage

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Digital Twins and Data Visualization in Cultural Heritage

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Abstract

Digital twins have become increasingly important in recent years due to advancements in technologies such as IoT, data analytics, AI and data visualization. These advancements have enabled the growth of digital twins in both the scientific community and the private sector, with significant investments being made in this technology. As a result, digital twins have become an essential tool for improving efficiency, optimizing processes, and making data-driven decisions in various industries. However, digital twins have to overcome certain challenges in various sectors such as data integration & management, performing informative and correct real-time updates, meet scalability and interoperability criteria, handle security and privacy concerns as well as respond to increasing costs to fully realize their potential. In this paper definitions such as digital model, digital shadow and digital twin are presented along with their use cases from within the industry and research projects. Additionally, enabling technologies for digital twins and semantic twins are discussed. More focus has been given to the Cultural Heritage field as this technology can help transform the field and elevate it to the next level. Finally, two cases studies of digital twins are presented.

Keywords: Digital Twins, Cultural Heritage, CFD, Simulations,

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1 Introduction

In 2002, Michael Grieves introduced the concept of Digital Twins (DTs) [1]. According to the original concept, DT models ensure a pairing between physical and virtual systems or objects, enabling data retrieval from either the physical or digital entity about any relevant information. DT is a bleeding edge technology which has elevated the industry to the next level by mirroring every aspect of product, process or service. In its maximum potential, it allows the replication of everything from the physical world in the virtual world and vice versa [2].

Today, DT technology is used throughout various industries to accurately represent objects, simulate and optimize operational processes. According to Gartner, 75 percent of Internet of Things (IoT) organizations already use or plan to use DT technology by 2020. Additionally, it is estimated that over 40 percent of worldwide companies will be using DTs in their day to day operations to maximize profits [3] as it enables companies to quickly detect and solve physical problems, perform faster design iterations and ultimately build better products [4].

These changes fall in line with the massive improvements introduced with the Industry 4.0 concept. Industry 4.0 is supposed to increase the level of digitilization, automation, augmentation and decentralization in several domains and fields. By leveraging numerous different technologies such as IoT, Artificial Intelligence (AI), Big Data Analytics, AR/VR/XR Technologies and Cloud Computing it is possible to achieve the highest degree of digitalization and data visualization [5].

Besides the industry's interest in DTs, researchers are also eager to explore this technology along with its applications. The authors in [6] analyzed the number of publications within the Scopus document database that included the phrase "digital twin" for the last few years. Figure 1 shows the substantial growth of interest as in the span of 3 years the number of articles containing the term "digital twin" has skyrocketed.

Since DTs incorporate a variety of different technologies and involve experts from several scientific fields, the cultural heritage field has the potential to transcend to its next level. Specifically, DTs may be used in designing virtual representations of cultural heritage sites, artifacts and buildings which in turn can be used to preserve them in any case of natural disasters or other forms of damage. Additionally, these DTs may be used to create virtual tours, allowing people to explore and experience them without having to physically move to the actual site. Moreover, by leveraging DTs it is possible to create accurate digital models of cultural heritage sites which can be used to plan and execute restoration and conservation projects. By simulating different scenarios, these models have the potential to test different scenarios, allowing for the best approach to be chosen and ultimately be an irreplaceable tool at the hands of expert conservators. Moreover, DTs could study and analyze digital models in a different manner compared to physical models. For instance, it is possible to program scenarios that study how light and shadow fall on a heritage site, how this affects the overall area or even analyze the materials and techniques used in a construction of a heritage site, potentially identifying issues before they even come up. Another use case of DTs which has started to gain ground on several museums is the creation of interactive and engaging educational resources, allowing people to be taught about cultural heritage. Finally, since DTs can simulate various scenarios, they may provide planning and management capabilities regarding visitors' comfort and management. Overall, DTs provide a powerul tool for preserving, studying, educating and managing cultural heritage sites which can potentially increase the understanding and appreciation of cultural heritage.

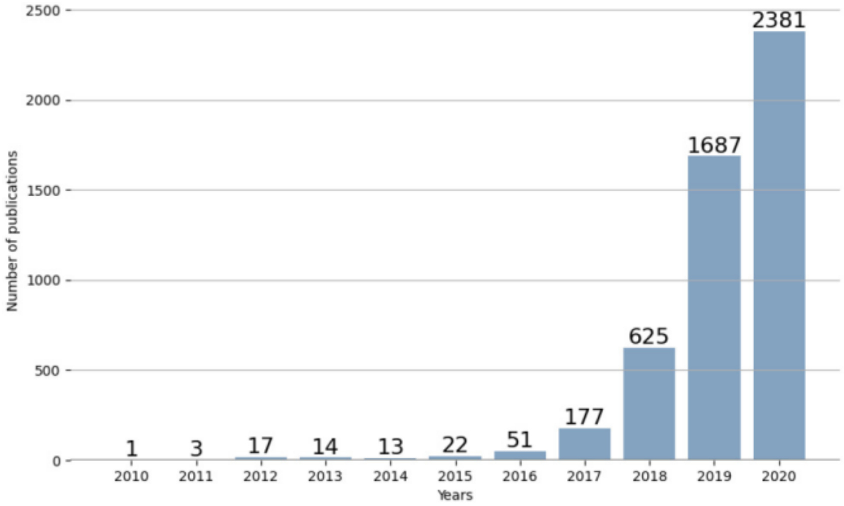

Figure 1: Number of articles in the Scopus database whose abstracts contain the phrase “digital twin” across the years.

1.1 Scope of the thesis

This thesis aims to study DTs in general and explore how they have been used throughout different scientific fields, highlighting their benefits. More focus has been given in the Cultural Heritage field, where various different use cases have been identified and discussed. Additionally, some DT use cases are presented, exploring their ties and potential contributions to the heritage field.

1.2 Structure of the thesis

The thesis starts off by providing various definitions that have been proposed throughout the years about Digital Twins, clarifying the terms digital model, digital shadow and digital twin. Then, it continues off by listing applications of DTs across smart cities, agriculture, manufacturing and in the industry. Moving on, a review of DTs in the Cultural Heritage is made and Semantic Digital Twins are discussed. In the next section, enabling technologies and their respective challenges are presented and discussed. Finally, in Section 3, two case studies about DT applications are presented.

2 Digital Twins

2.1 Definitions

Based on Grieve's definition, National Aeronautical Space Administration (NASA) published a paper in 2012 which defined Digital Twin as following: Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc.., to mirror the life of its corresponding flying twin" [7].

Following NASA's definition, Grieves expanded the concept twice. In 2014, Grieves mentions that a Digital Twin is consisted of three components, a physical product, a virtual representation of that product, and their bi-directional data connections that transfer data from the physical product to its virtual representation and vice versa. This flow is depicted as a cycle between the physical and virtual states (mirroring or twinning); of data from the physical to the virtual, and of information and processes from the virtual to the physical [8].

Following the previous definition, Grieves revisits the concept once again by introducing the terms Digital Twin Prototype (DTP), Digital Twin Instance (DTI) and Digital Twin Environment(DTE) to better distinguish the different manifestations of digital twins [1]. Both DTP and DTI are types of a digital twin, built for different purposes. Specifically, digital twin is redefined as a set of virtual data structures that fully resembles a possible or real physical object in all levels of manufacturing process that range from micro to macro geometrical levels. Therefore, all data can be gathered either from the physical object or the respective digital clone. Grieves and Vickers defined the Digital Twin Prototype (DTP) as a type of digital twin that describes the prototypical physical artifact. DTP contains the appropriate information to define and create a physical version of an asset that clones the virtual one. On the other hand, (DTI) was set as a kind of DT that defines the physical object, which is associated with a digital twin throughout its whole lifecycle [9].

Digital Twin is also defined as ”...a computerized model of a physical device or system that represents all functional features and links with the working elements” by Chen in 2017 [10].

In 2018, Liu, Meyendorf and Mrad [11] described DT as following: ”The digital twin is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data/information and can forecast the future of the corresponding physical counterpart.”

Vrabic et al. [12], described the DT as ”a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualized in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making”.

More recently, Cimino [13] defined DT as a virtual instance of a physical system which is continually updated with the latter’s performance, maintenance and health status data throughout the physical system’s life cycle.

According to [14], a DT should be the most realistic representation of a physical asset which incorporates all available information and models while also acquiring operational, organization and technical infromation while always beeing in sync with the physical asset. Additionally, it is noted that DT should be self-evolved.

Based on [15], different point of views and requirements for Digital Twins various different definitions were introduced. In any case, a DT is a digital counterpart of a physical object. Depending on the levels of data integration between these two entities the definitions of digital model, digital shadow and digital twin have been introduced to assist in classifying DTs based on the degree of dynamic information flow in real time [1].

2.1.1 Digital Model

Digital Model (DM) is a 3D representation of a real object or a prototype of an object under production that does not integrate any data flow between the real object and the digital. The DM may appear in various types of Level-of-Detail (LoD), allowing users to document, articulate and specify the 3D model according to their requirements. Without any automatic data streaming taking place between the real model and the digital one, the digital model can describe several different aspects and models which make up the physical model, such as simulations models of industrial plants or models of new products. If data exchange exists, it is done manually, thus a modification in the state of either entity does not automatically reflect to its counterpart automatically.

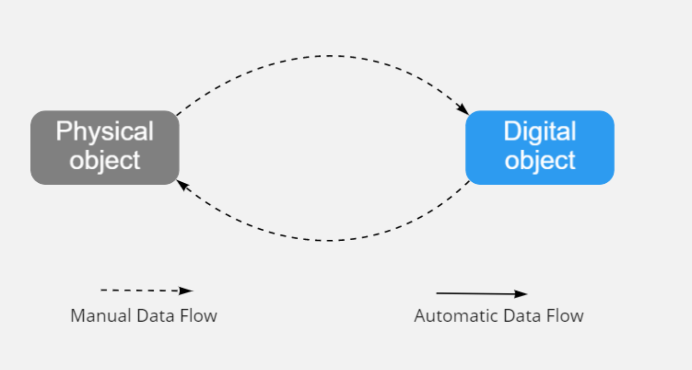

Figure 2: Data flow in a Digital Model

2.1.2 Digital Shadow

In case an automated data flow from the physical / real model to the digital object occurs, the concept of the Digital Shadow (DS) is introduced. In DSs the state and condition of the physical object defines the current status of the digital object and triggers any changes accordingly, but not the other way around. Figure 3 demonstrates the connection in a digital shadow.

2.1.3 Digital Twin

Going further from the concept of Digital Shadows, when a bi-directional data flow between the real physical object and its digital counterpart exists, we define a digital twin. In this case, the digital object may also trigger information and has impact on

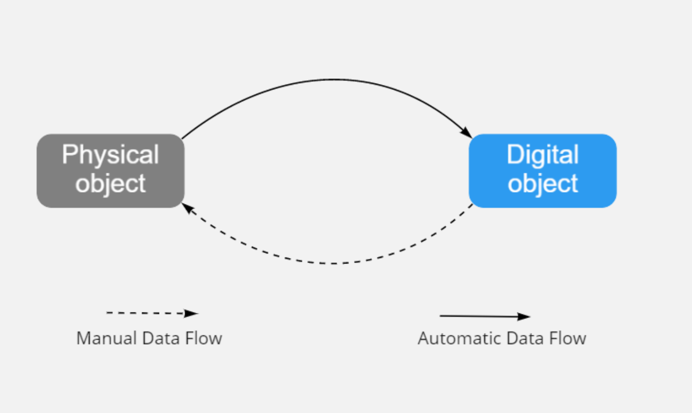

Figure 3: Data flow in a Digital

the physical one. This DT model may also be fully interconnected with other DTs (pairs of real and digital assets) that may stimulate changes of state between them.

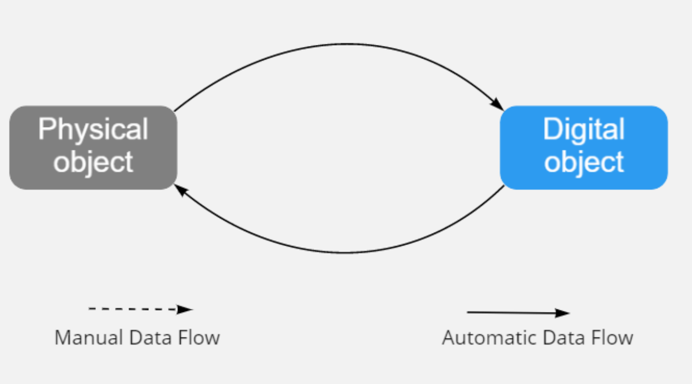

Figure 4: Data flow in a Digital Twin

2.2 Applications

With the technological advances taking place, Digital Twins applications have been constantly increasing across various sectors such as architecture, agriculture, engineering and manufacturing. In this section, some notable applications will be presented.

2.2.1 Digital Twins in Smart Cities

With the rapid growth of cities both in terms of size and population, significant challenges arise in the financial, economical and industrial future of the communities. Fueled by the ever increasing technical abilities of IoT sensors, a digital twin city can be updated in real time by the performance of its physical infrastructure, thus providing the ability to simulate possible challenges and required actions needed before these scenarios become a reality [16]. It is apparent, that Digital Twins can be leveraged to maximize the efficiency and adaptability of their physical counterparts in order to resolve problems that can be modelled and simulated [17].

In [18] an energy internet planning platform based on digital twin, named CloudIEPS, is introduced. By mapping energy related data, such as load and weather information and the topology of the system describing the system structure, the authors established a digital twin model. Once the model is established and the optimization algorithm is integrated in the system, the digital twin was able to provide optimal configurations for the system's usage to achieve better results overall plus reduce investment and maintenance costs.

Item	Original Configuration	Optimized Configuration
Gas generator capacity/kW	1023	750
Absorption chiller capacity/kW	800	2560
Boiler capacity/kW	1566	600

Table 2.1: Comparison of system operation before and after optimization of planning scheme.

Another distinct application of Digital Twin in the smart cities context is Virtual Singapore [19]. Considered among the more characteristic city-scale DTs it mostly focuses on urban planning. Even if the extent of the integrated real-world live data to the DT is not clear, there are thorough and detailed 3D mappings of the urban area which are used throughout the digital twin. Virtual Singapore is co-lead by the

Item	Original Configuration	Optimized Configuration
Equipment investment cost/10,000 yuan	1883.01	1552.96
Maintenance cost/10,000 yuan	123.56	87.23
Power generation (kWha)	202699	456232

Table 2.2: Comparison of system costs before and after optimization of planning scheme.

National Research Foundation, the Singapore Land Authority and the Government Technology Agency and it will be the country's authoritative platform, which will be used in simulations and virtual tests of new solutions to urban planning problems.

In [20] a digital twin prototype is developed and presented for the town of Herrenberg in Germany. Relying on collected data from citizens, it offers a wide range of applications mostly focused on mobility, transport and air quality. By enhancing the end-user interfaces and virtual reality options, decision-makers and urban planning professionals can cooperate and co-create scenarios into the project, enabling them to make smarter decisions. By validating and consolidating their project from a number of participants, the authors conclude that the digital twin allowed them to gain a better understanding of potential solutions for their use case.

2.2.2 Digital Twins in Agriculture

The union of data, modelling and simulation of what-if scenarios that Digital Twins offer, pave the way to overcome current limitations in decision making and automation across a diverse range of agricultural enterprises. Depending on the applications, use-cases in agriculture usually fall in one of the following categories [21]:

- Monitor and resource optimization and cultivation support for crops
- Monitor management and optimization for livestock
- Urban and controlled environment
- Environment and infrastructure
- Product design, smart services and machinery management and

Figure 5: Wind flow simulation for Herrenberg's use case

- Supply and value chain

Laryukhin et al. [22] presented a multi-agent approach for developing cyber-physical system to manage precise farms with digital twins of plants. In a combination with machine learning, the authors developed software agents working as digital twins of real plants. These agents can be used to reflect the current stage of plant growth and development at any point or for "what-if" scenarios to form the best possible options in plant cultivation. The authors conclude that by combining machine learning with digital twins, it is possible to extract hidden patterns and dependencies for predicting plant reactions in several different farmers actions or weather conditions.

Niswar [23] et al. proposed a low-cost water quality monitoring system for crab farming, based on IoT. By measuring the water temperature, salinity and pH of the water in the crab pond the system aims to assist the farmers in cultivating soft-shell crabs, thus contributing to increase the survival rate of crabs and achieve higher yield of soft shell crabs.

In an attempt to create resilient and adaptable automation for vertical farming structures, Monteiro et al. [24] discuss the development of Digital Twins, contributing to the agrofood lifecycle of planning, operation, monitoring and optimization. The authors conclude that Digital Twins clarify the interconnections between goals, tasks and resouces of IoT-enabled structrures for sustainable agriculture.

In [25] the WebGIS framework is introduced, which is a global Digital Twin. The framework leverages the spatial-dimension of agriculture, collecting data at the farm/producer level and aggregates it into regional and global views. The proposed Digital Twin could potentially assist policy making based on real-tile data open to all stakeholders.

Tsolakis [26] developed AgROS, a tool to address challenges that farmers encounter in the real world by providing a platform for emulating the functional capabilities and performance of real-world intelligent machinery in physical fields. AgROS provides several features to farmers allowing them to test a real robot's performance in quasi-real-world environment. Users are allowed to select their actual field from a map, add characteristics of the layout and select an agricultural robot from a list of commercial systems thus allowing them to assess a robot's real world performance.

Dolci [27] presented a digital twin of a Malthouse to increase accuracy in prediction of the effect of several changes of settings and schedules. Specifically, IoT sensors were placed around the building to collect data regarding physical variables. In a combination with a Bayesian Network Analysis [28], Multi-Variate analysis [29] and AI, the system was able to study the correlation of different inputs and outputs over time, thus improving the overall quality of various variables in a company with over 150 years of history of producing malt.

2.2.3 Digital Twins in Manufacturing

Another apparent use of Digital Twins lies in the Manufacturing sector as Grieves initially introduced the concept of DTs back in 2002 to create a Product Lifecycle Management Center. As production processes become more complex, the manufacturing industry is looking for ways to create smarter, faster and cost-efficient production pipelines to save time and increase profits [30]. Since product design and production units are based on modularity, DTs can be attached to every step along the whole process, starting from the design phase up until the distribution phase. For instance, a smart, autonomous production system can implemented with the ability to react to unforeseen events in an intelligent and efficient manner. With the help of IoT and by modelling each individual phase as separate DTs, professionals can leverage their technology to make smarter plans and make educated decisions to improve the overall performance and stability of the complete pipeline while also reducing overall costs [31]. Additionally, DTs empowered by Artificial Intelligence and Machine Learning can evaluate the impact of modifications in a production line and determine the system's state [32] by examing variables such as the machinery's current operating conditions, thus reducing risk of errors [33] that may occur in the future.

Semeraro [34] presented a real industrial case application of a digital twin for optimizing a manufacturing system. The case study of the paper revolves around die casting aluminium, which is the process in which molten metal is poured or forced into steel moulds to shape steel corners around doors and windows. The authors split down the whole process cycle into individual steps and then extracted patterns identified by the designed digital twin. The DT was able to predict problems regarding a specific pattern that was causing errors during the manufacturing process while also offering possible actions to the employees to either avoid possible failures, prevent quality scraps or alert operators through a system about abnormal behaviors.

Koulouris et al. [35] discuss about the potential benefits from using digital twins on food processes using a large-scale brewery as a case study. The authors proposed a system where the production process is made up by interconnected steps, containing the actual operations that consume the required resources for production. Ultimately, these representations can be leveraged to convert lab recipes to industrial production while also performing economic and environmental impact analysis as well as identifying and resolving bottlenecks in existing processes. The authors highlight that the interactivity of the system combined with real-time flow of information between the plant and the digital twin leads to an efficient production. The paper concludes that the digital twin can potentially assist in performing capacity analysis, estimate the certainty by which production goals can be met and rationalize production plans.

Xu et al. [33] present a two-phase Digital Twin assisted Fault Diagnosis method using Deep transfer learning (DFDD) in a car body-side production line. The authors established a digital shop floor, including the structure, characteristics, behaviors and rules of its physical counterpart. The two models are connected via programmable logic controllers (PLCs). The system is using a Process Visibility System (PVS), shown in Figure 6, by the Envision platform to collect data from both the physical and the digital model.

In the presented case study, the authors conduct three groups of experiments, DFDD and two Deep Neural Network (DNN) alternatives, namely DNNV and DNNP. The results suggest that the digital twin assisted method for fault diagnosis scores a staggering 97.96% while DNNV and DNNP scored approximately 74.74% and 97.96% respectively (Figure 7).

Finally, the authors conclude that through the dual fault diagnosis in virtual space and physical space, the risk of accidental breakdown is greatly reduced, making smart manufacturing sustainable, reliable, and efficient.

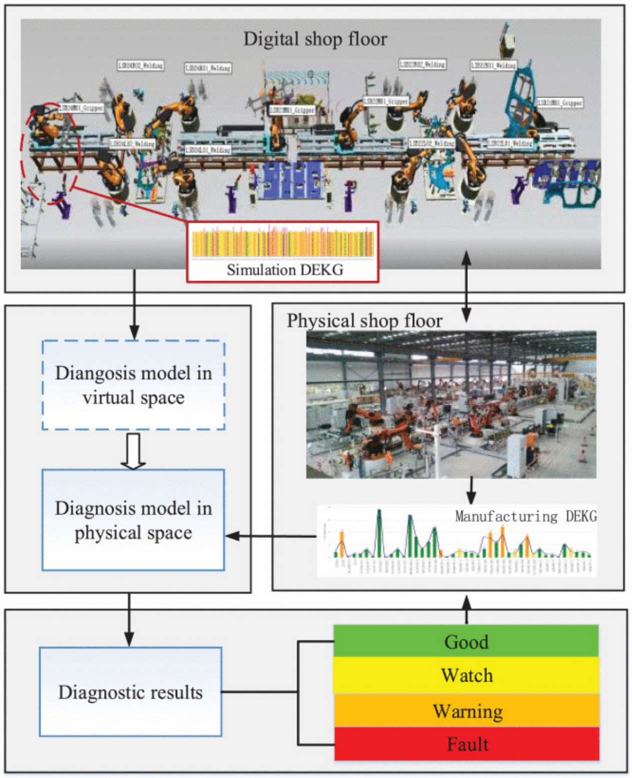

Figure 6: Architecture of PVS

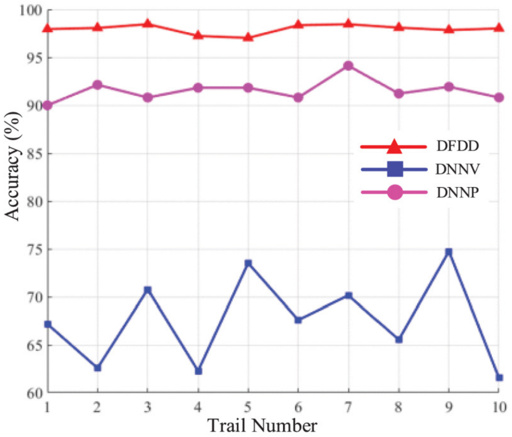

Figure 7: Comparison of accuracies between DFDD, DNNV, and DNNP.

2.2.4 Digital Twins in the Industrial Sector

The massive improvement of technology happening over the course of the last century has fueled rapid advancements in the industry kick starting the fourth industrial revolution, namely Industry 4.0. Industry 4.0 will provide the highest degree of digitalization and data visualization which are some of the key characteristics of digital twins [36]. With the widespread application of IoT sensors and the resulting data integration, the industry is evolving across all domains. Already as of 2014, "ThingWorx" and "Watson IoT" platforms are introduced to the public by PTC and IBM respectively. Both platforms are suitable for creating digital twins as they are focused on industrial IoT and multiple device management.

Specifically, "ThingWorx" incorporates a Product Lifecycle Management program while the platform itself is a collection of different components, each one equipped with different functionalities but all of them connected to the main component named ThingWorx Foundation, which acts as the central part of the system. These components include the ThingWorx Studio, ThingWorx Analytics, ThingWorx Utilities and ThingWorx Industrial Connectivity. The core component of the system (ThingWorx Foundation) connects to all different components with end-to-end security encryption, enabling operators and managers to link, build and develop industrial applications across the IoT platform [10].

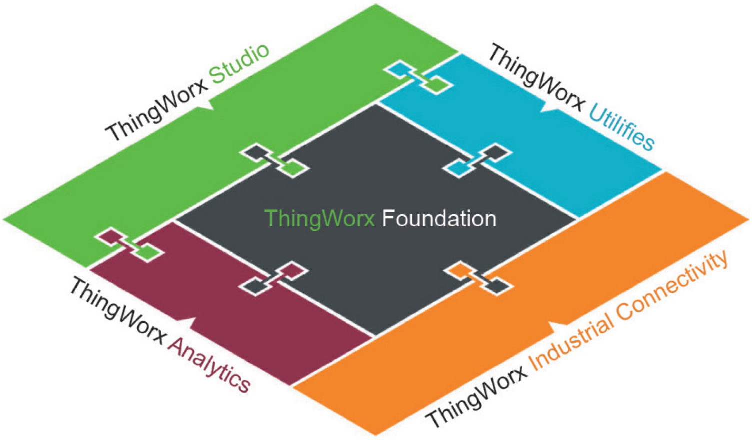

Figure 8: ThingWorx platform overview

On the other hand, the Watson IoT platform is a complete IoT data tool offered for commercial use. The platform's main selling point is the possibility of connecting to millions of IoT devices, enabling large-scale systems to be managed in real time. Users are able to connect their own sensors and devices to the platform and manage it from anywhere in the world, as long as both the devices and the users are connected on the platform. Kumar and Jasuja [37] verify this by building an air quality monitoring system using the platform and their own Raspberry Pi.

In 2016 General Electric (GE) introduced its patented industrial IoT (IIoT) edge-to-cloud platform called "Predix", which can be used to create digital twins [38]. Predix combines Amazon Web Services (AWS) with critical IoT functions to provide a common application foundation, shared user experience and rapid-time-to-value for customers by providing a secure and scalable IoT software infrastructure. The platform collects massive amounts of real-time data from sensors across its wide network and provides industry-specific intelligent analytic services to allow companies to make connected products, design and implement intelligent environments, create industrial analytics, monitor their asset performance and optimize their operations [10].

Similar to Predix, Siemens has developed an open, cloud-based operating system called MindSphere. MindSphere was primarily developed to monitor industrial assets for different industrial processes, connecting physical infrastructure and machines to digital twins. Additional software development is supported by Siemens own departments for their platform and on top of that the whole ecosystem supports third-party components that adopters can potentially develop.

Besides the readily available platforms for building Digital Twins, researchers have recently started using game engines as means to visualize their IoT data and eventually build their own DTs. Aside from the built in rendering tools that game engines offer, they also possess the power of realistic rendering by providing the user with a variety of points. Wang et al. [39] proposed a Digital Twin-Driven approach for Process Management and Traceability towards the Ship Industry, using Maya and Unity 3D, which is a game engine, for visualization purposes. Authors have built a ship's 3D model and assets into Autodesk Maya, which was then imported in Unity. Afterwards, a system was developed to allow Unity to consume and send data via an exposed Application Programming Interface (API) for the visualization to be completed.

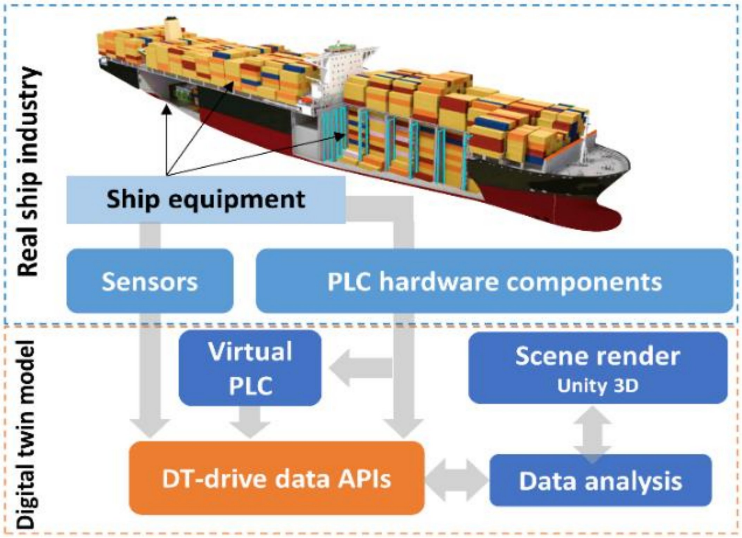

Figure 9: Data communication process between real and dt models

Once the digital twin was built, the authors applied a Bayesian Neural Network

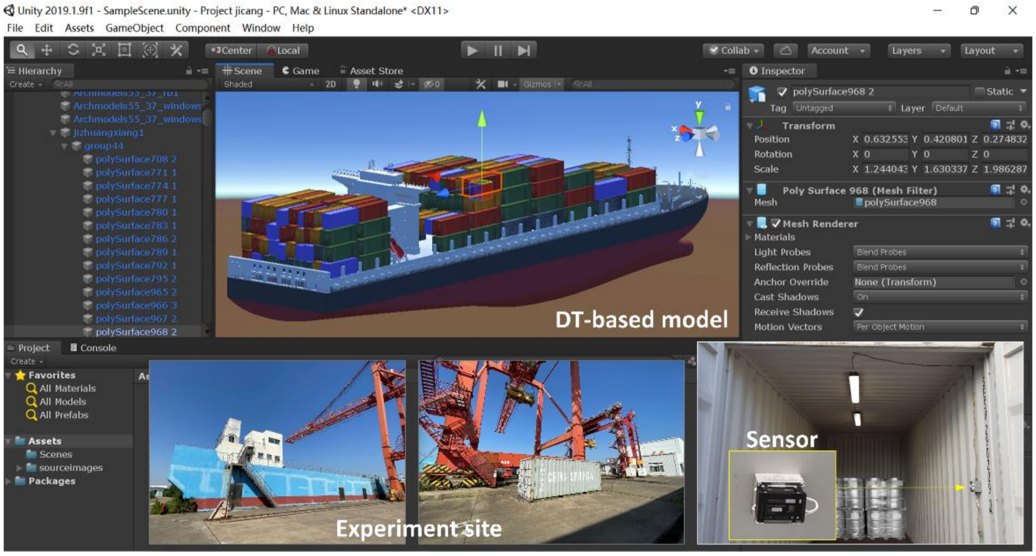

Figure 10: Ship and cargo containers in Unity

(BNN) algorithm to optimize the statistical values of critical parameters in the ship operation process to realize the dynamic prediction of failure and risk.

2.3 Review of DTs in Cultural Heritage

The digital twin technology is also gaining traction in the heritage field, where it can be used to provide prescriptive maintenance or predict damage from various sources in heritage sites, thus increasing the prospects of preserving and revitalizing them in new-found methods. DTs can be used as an assessment tool for conservators and specialized engineers working on preserving heritage sites since they can be used for simulating various phenomena or different environmental states to identify main causes of damage or tear [9].

Wang et al. [40] presented a pipeline to analyze the effect of wind erosion over the Yongling Mausoleum in China. The authors started by building an accurate digital 3d model of the whole Mausoleum, which was suitable for simulating computational fluid dynamics (CFD). After building the model and gathering hourly weather data over a two-year period it was possible to extract average, minimum and maximum wind speeds over the area of interest. By inserting the acquired data and the detailed 3d model into ANSYS workbench, which is a simulation software supporting CFD, it was possible to predict and calculate wind pressure values at each individual building in any of its surfaces, thus allowing the researchers to estimate the erosion caused by the wind without any in site measures. To help reduce high erosion in some building surfaces, a greening plan is proposed, suggesting planning of trees and shrubs in rows and windbreak green turfs. The authors were able to re-run their simulation with the updated geometry that included the greening plan which in turn verified that the proposed changes will have a positive impact in reducing the overall erosion caused in buildings. Figure 11 and 12 demonstrate the pressure distribution on buildings before and after the greening plans. This case study proves that DTs pose a great asset in mitigating issues in heritage sites by allowing researchers to find solutions without having to visit the actual site, thus reducing overall costs and time.

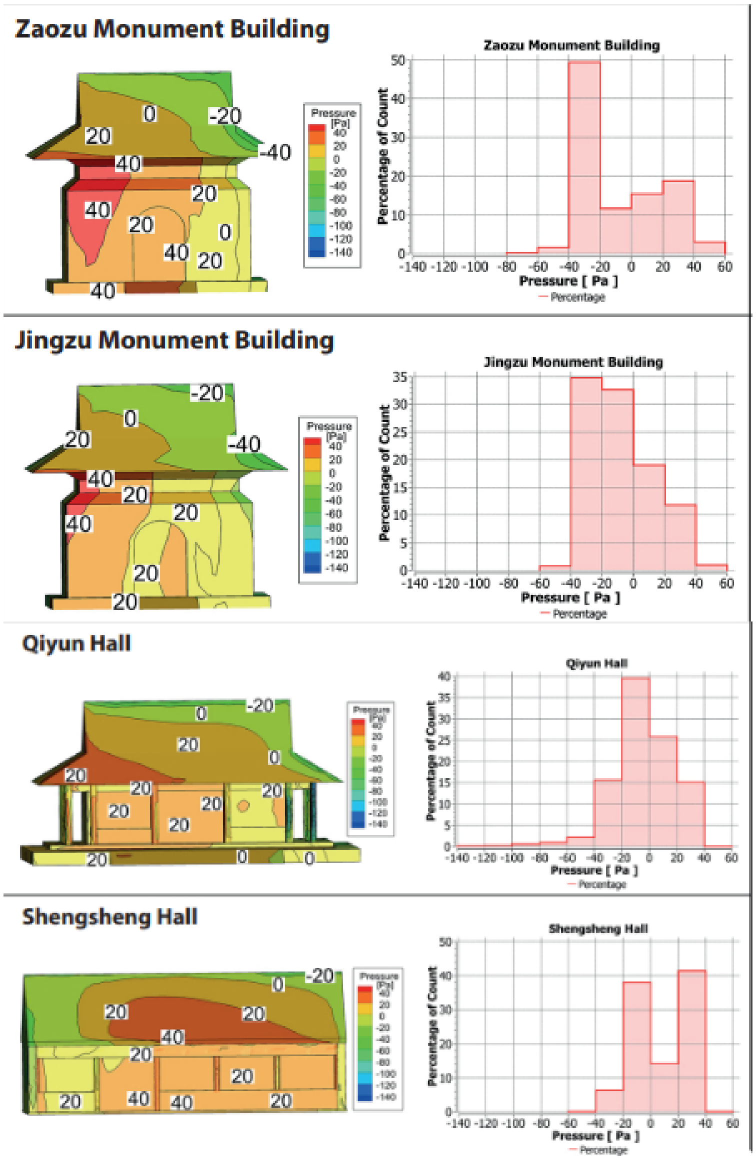

Figure 11: Yongling Mausoleum wind pressure before greening

A similar application of digital twin technology for heritage sites combined with CFD is the case study of Baelo Claudia in Spain where the authors analyzed the sand-loaded airflow erosion [41]. Pineda and Iranzo created a Digital Model of the "Cardo of the Columns" area, including the terrain's morphology. To run a successful and accurate CFD simulation, real environmental data were needed for the location. Instead of directly getting the data for the area of interest, the authors relied on wind rose data from [42] to get wind data of Valdevaqueros, which is close to the location

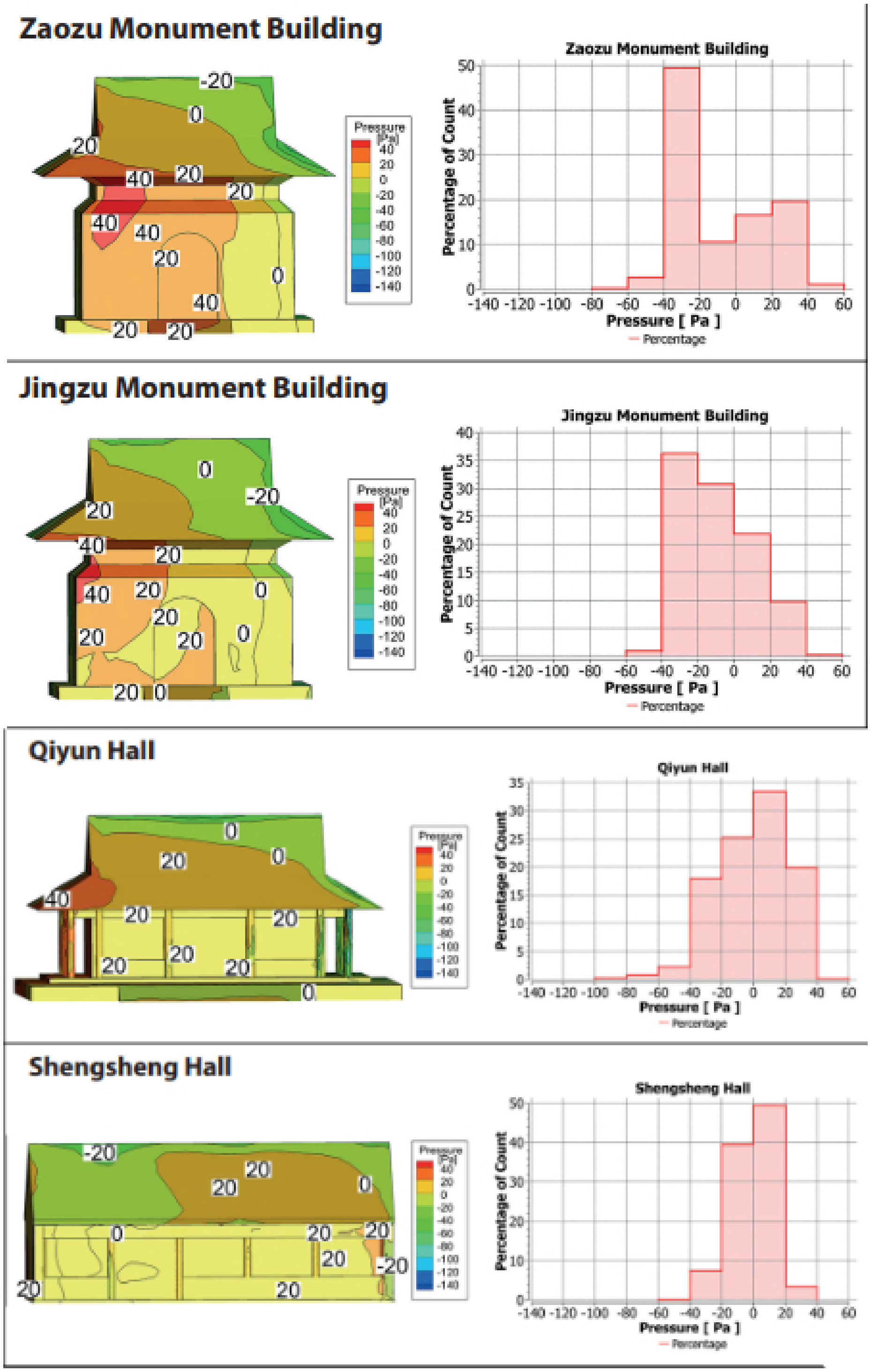

Figure 12: Yongling Mausoleum wind pressure after greening

of the heritage site. Unlike the Yongling Mausoleum, where the wind pressure was the main factor of erosion, the "Cardo of the Columns" is getting damaged from the erosion happening from the sand, which is carried by the wind. The authors mention that based on the retrieved wind data, four simulations needed to take place, in order to simulate the erosion from different wind trajectories.

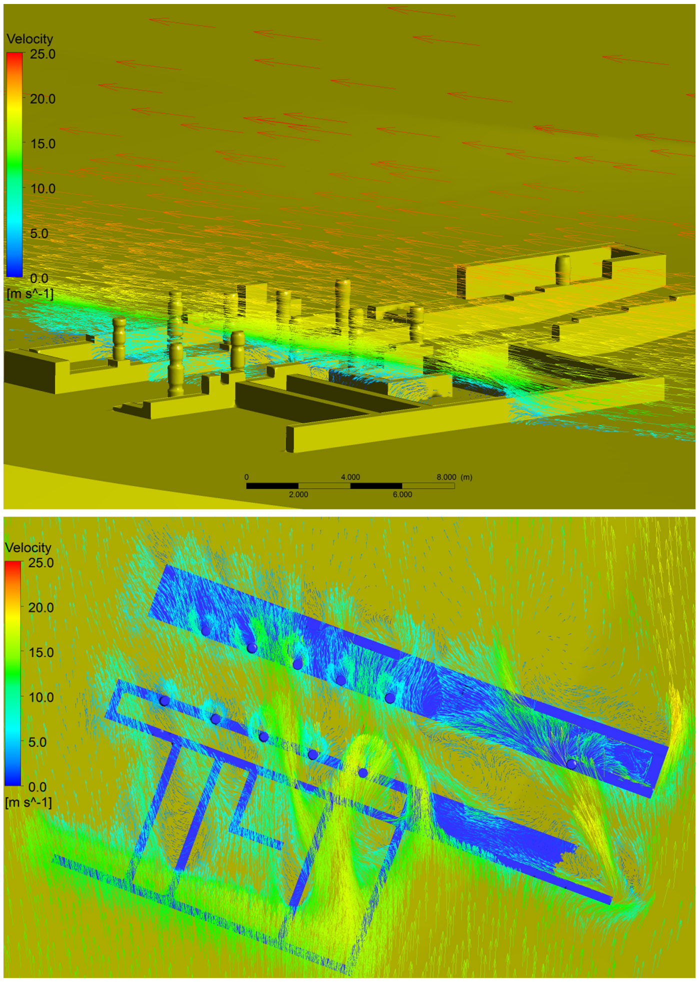

Figure 13: Velocity vectors from two different point of views over the area of interest.

Once the simulation took place and the impact of the erosion as well as the spots that were mostly affected were clarified, the authors proposed a few remedial measures such as transparent erosion-resistant coverings to be placed on the affected areas and a wind baffle installation at a particular location. The wind baffle should deflect the sand-loaded air flow preventing any sand particles from directly impacting the currently affected, a claim which the authors verified by re-executing their CFD simulation with the wind-baffle installed in the proposed place. Figure 14 displays the installed wind baffle and how it affected the overall wind flow to reduce the extent of the erosion.

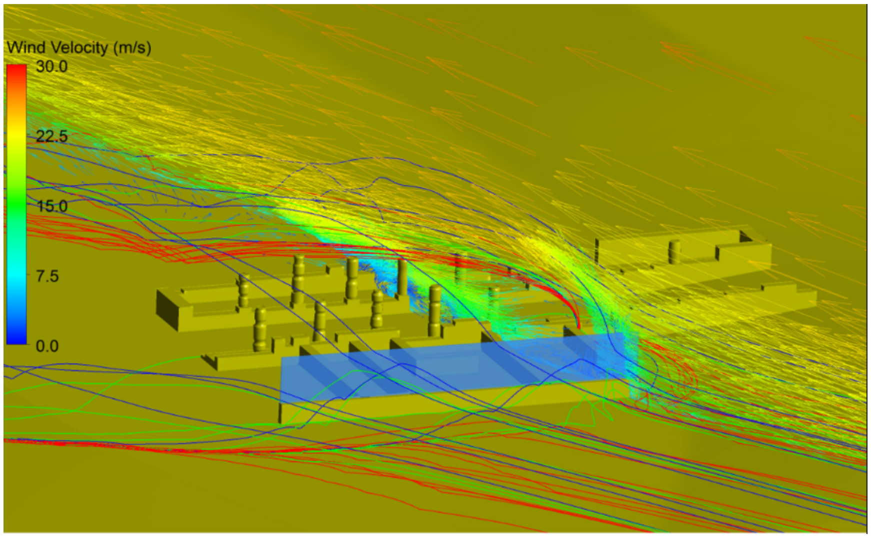

Figure 14: Wind streamlines with wind baffle installed

Contrary to both case studies in Yongling Mausoleum and Baelo Claudia, Yasa et al. [43] leveraged CFD simulations in the digital twin of the Slender Minared Madrasah in Konya to evaluate its microclimate, analyze its energy performance and determine the indoor comfort of people inside the site. While it is unclear how the 3D model was generated, the authors included numerous factors, such as the temperatures in the air and in the surface of the building, air fluctuation rate, relative humidity and illumination levels in their CFD simulations, which concluded that the Slender Minaret structure meets the criteria of thermal comfort. Additionally, the authors proposed that for buildings of traditional construction, the right balance between effective preservation of the building and appropriate measures to improve energy efficiency should be found, in order to avoid permanent damage to both the building itself and its structural material.

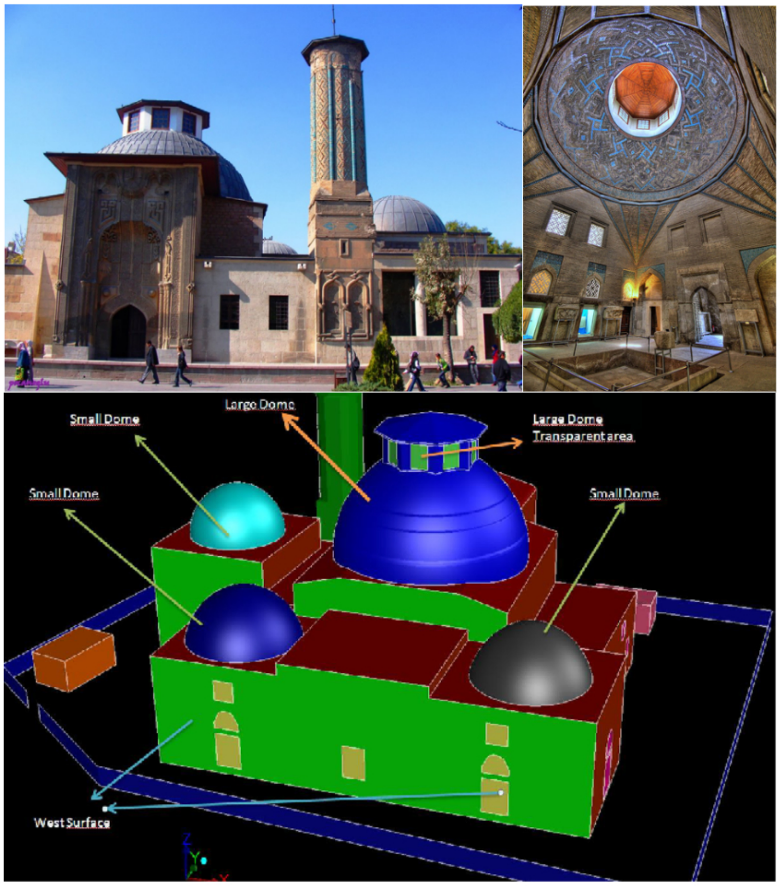

Figure 15: (Above) Exterior and interior view of the Slender Minaret Madrasah in Konya, (Below) the monument modeling in Ansys Gambit software

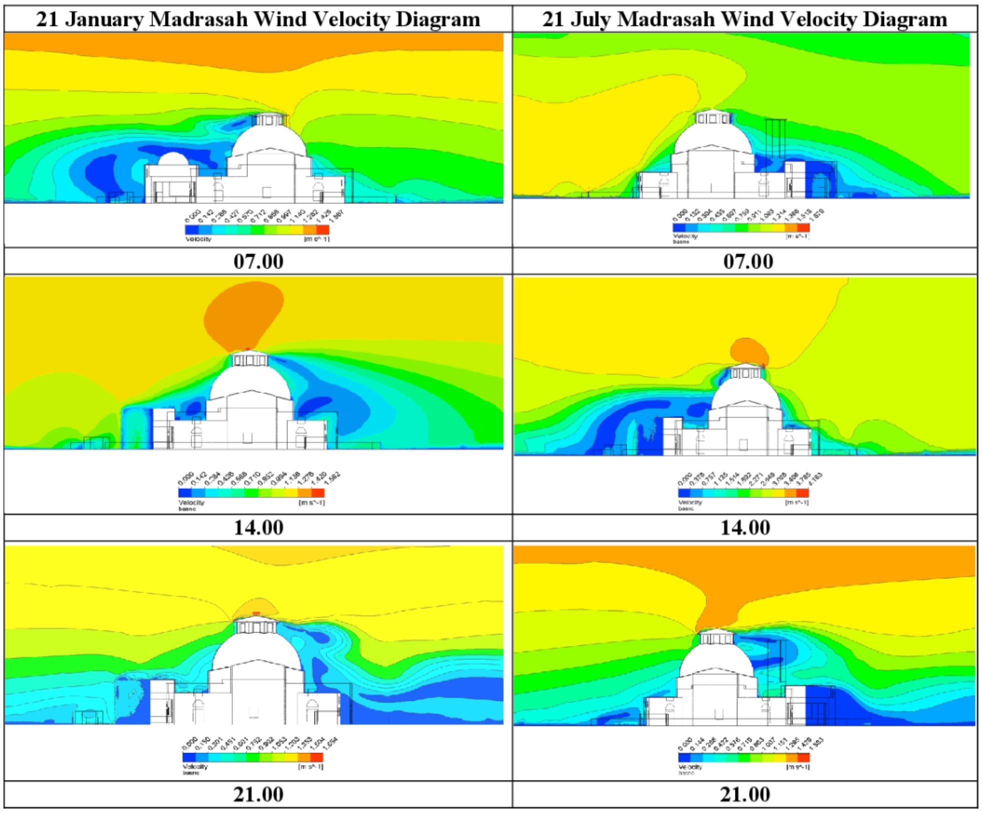

Figure 16: (Above) Exterior and interior view of the Slender Minaret Madrasah in Konya, (Below) the monument modeling in Ansys Gambit software

D'Agostino et al. [44] combined digital twins with CFD technology to observe the Crypt of the Cathedral of Lecce in Italy over the course of one year. The authors were able to develop a digital model which was used for a simulation of thermo-hygrometric parameters. Additionally, air flow patterns were applied in order to reproduce crystallization of salts and replicate deterioration of works of art. Initially, the current microclimate in the crypt was reproduced, which indicated inadequate storage conditions. After studying the environment closely, the researchers proposed a few changes, such as refraining from having all windows open simultaneously, triggering risky microclimatic conditions along the way and installing a double glass to help the Crypt's maintenance. Thanks to the CFD and DT simulations, they authors conclude that these changes will lead in a more suitable environment, which will help preserve the current state of the crypt. Figure 17 displays the improved effects of the crypt's state, after considering the authors' suggestions, while also comparing the initial state of the crypt without any changes. It is apparent that the temperature levels have been improved while the humidity level have dropped in every area of the crypt.

Extending the idea of Building Information Modelling (BIM), which is a digital representation of the physical and functional characteristics of a facility [45], Jouan

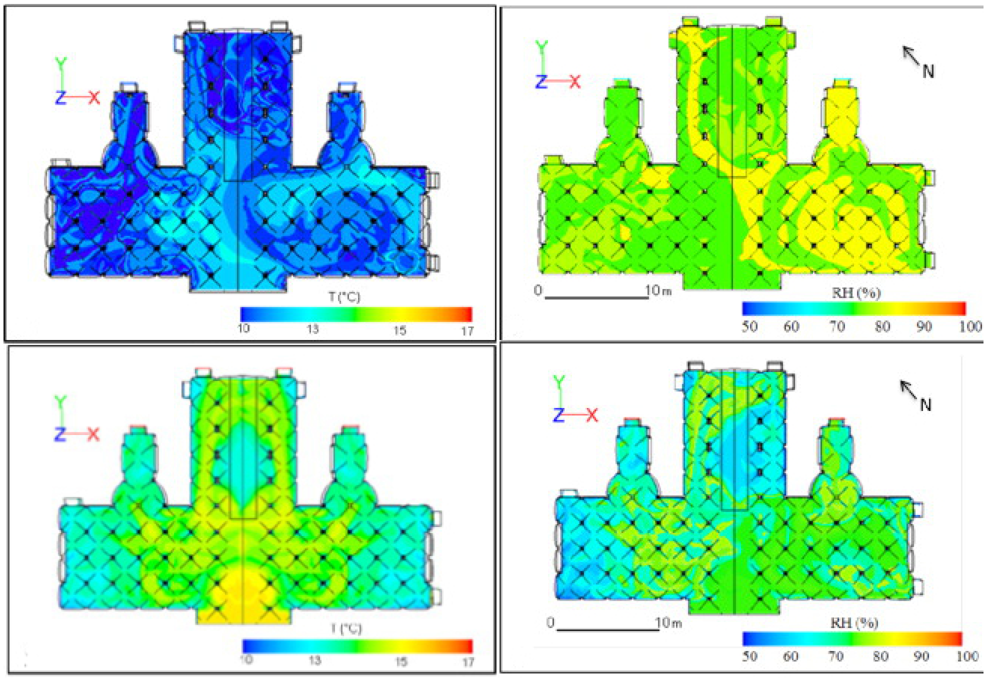

Figure 17: Comparison between initial and improved conditions. Upper left: initial temperature. Upper right: initial humidity. Lower left: improved temperature, lower right: improved humidity levels

and Hallot [46] suggest that a combination of Heritage Building Information Modeling (HBIM) and DTs lay the foundation of preventive conservation mechanisms for cultural heritage sites. By combining the DT technology with semantically enriching HBIM models with real-time information coming from on-site IoT sensors, the authors argue that the link between the physical and digital model is enhanced. The researches propose a framework that integrates the use of DTs in the management plan process for proactive safeguarding of heritage sites (Figure 18). Finally, Jouan and Hallot conclude that personalized information can be provided to non technical stakeholders engaged in the decision-making process for the administration of cultural heritage sites.

Eloisa et al. [47] leveraged the HBIM technology to propose a framework for AR visualization of the Ballroom and St. Francis of Assisi Church in the Pampulha Modern Ensemble in Brazil. The authors used terrestrial laser scanning (TSL) and an unmanned aerial vehicle (UAV) to collect spatial and documentary data. Then, they processed the data and created a surface model, which led to the creation of the HBIM model. To create the AR visualization application of the heritage sites, the Unity game engine was used, where the HBIM models were imported. The app retrieved various info about the heritage site and according to the authors, it enhances visitors'

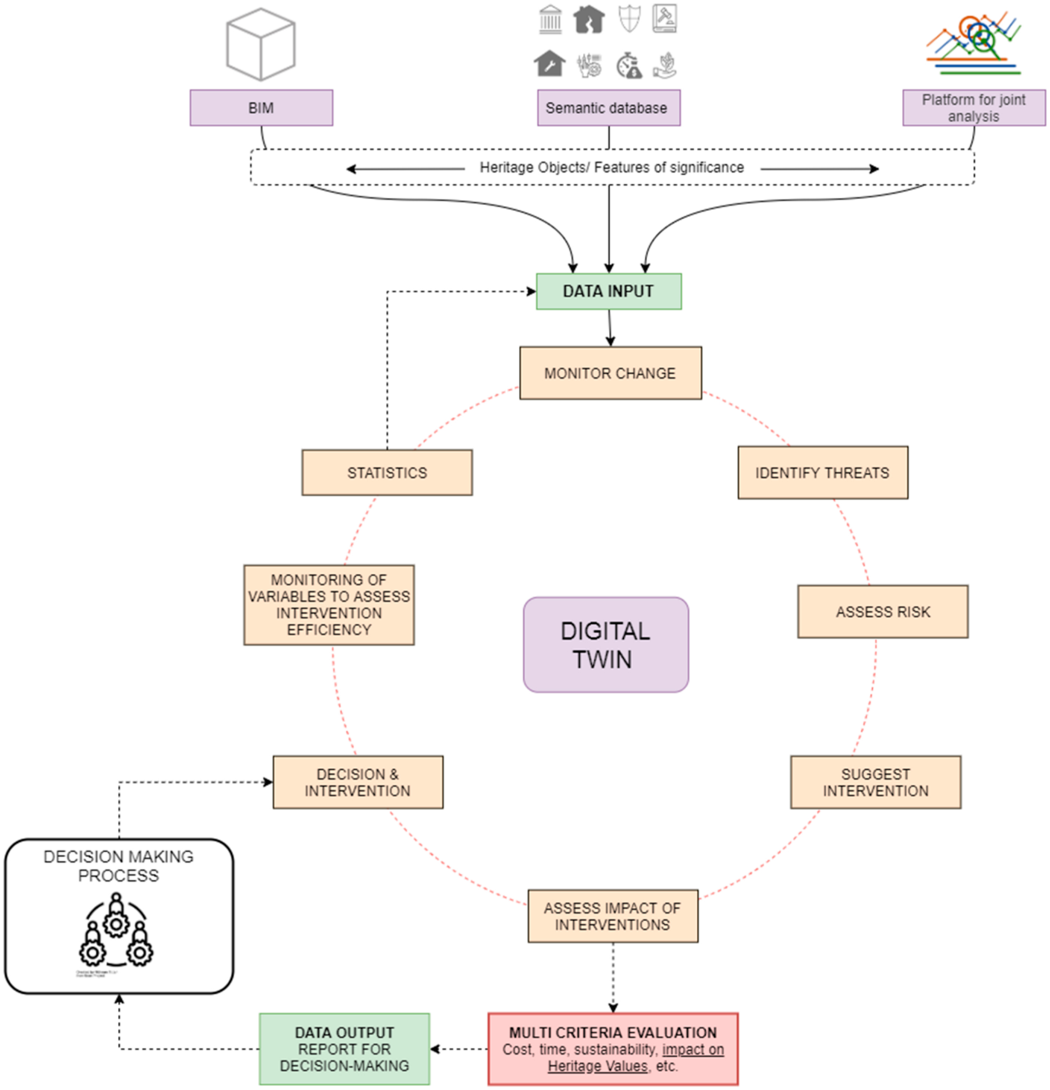

Figure 18: The digital twin process to include strategies for preventive conservation of heritage sites

engagement with the site as obtaining historical information is straight forward and can be done in an interactive way.

Shabani et al. [48] presented two similar workflows for developing 3D simulations models to create digital twins of heritage structures. Both workflows start by composing digital images from aerial and ground images as well as using laser scanners to generate point clouds for the structures of interest. Afterwards, the researchers performed a georeference on the collected to prevent any kind of deformations or noise. Then, the 3D dense point clouds are used in order to fill in any gaps, ultimately generating the final 3D point cloud. On the resulted point cloud, a triangulated irregular network (TIN) method is applied to generate the final 3D model. The authors note that a slightly different workflow, which is more efficient, is to use a CAD software based on the resulted point clouds which is then imported into the DIANA software. DIANA contains a set of tools for cleaning, simplifying and modifying the imported files which make it easier overall to prepare the models for digital twins. Figures 19 and 20 showcase each workflow respectively.

Figure 19: From left to right: 3D textured models, 3D model of the Nailac tower in Rhodes, Greece, cross section of the roman bridge in Rhodes, Greece

Another use case of digital twins combined with VR technologies in the Cultural Heritage field is demonstrated in [49]. The authors presented three different case studies demonstrating how VR methodologies, combined with digital twins can provide new knowledge on the world of architecture.

The first case study concerns the digital reconstructions of the provisional hall of the First Italian Parliament. The authors collaborated with multidisciplinary teams from the Department of Architecture and Design of the Politecnico di Torino and the Piedmont Regional Museums Department. The goals of the reconstruction process was to perform coherency checks of data from bibliographical, textual and iconographical documents, the verification of a hypotheses regarding the belonging to the building of wooden elements found in various places around the Parliament and the integration of the lacunae. The end result, displayed on Figure 21, was an immersive

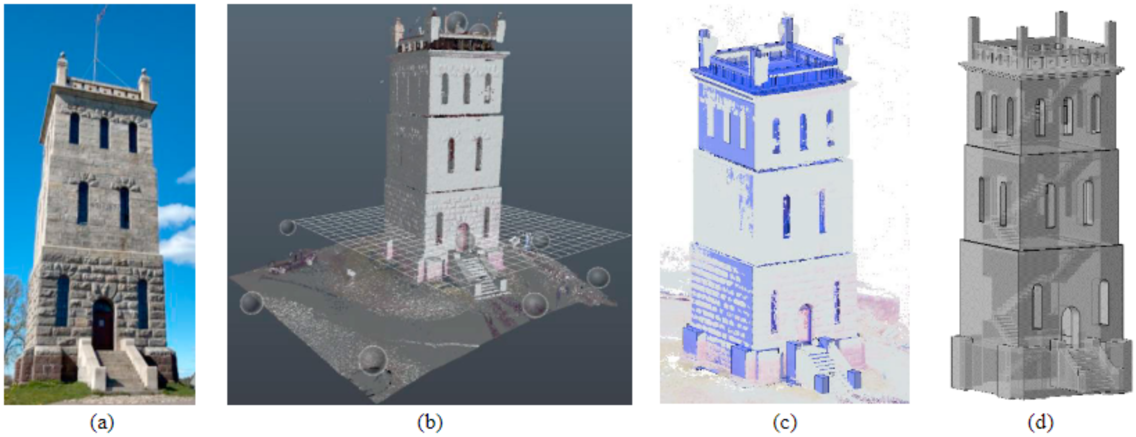

Figure 20: (a) The Slottsfjel tower in Tønsberg, Norway; (b) 3D dense point clouds in Recap software; (c) Imported 3D point cloud to Revit software; (d) Developed 3D model of the tower in Revit software.

VR experience which allowed the exploration of spaces that are no longer in existence.

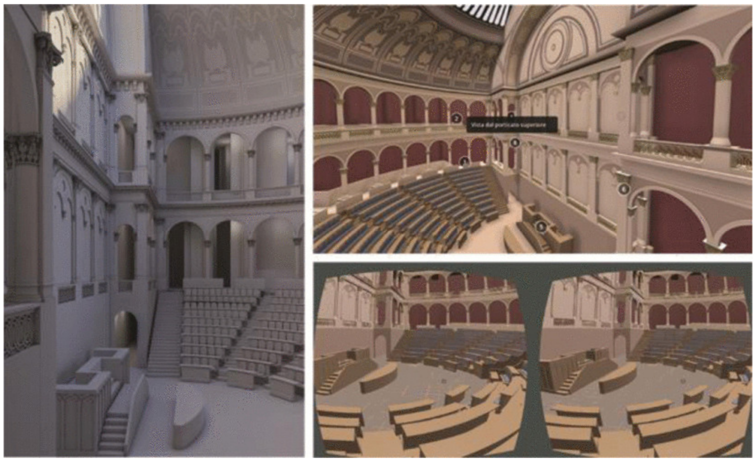

Figure 21: VR reconstruction of the First Italian Parliament hall

The main goal of the second case study is to enhance the experience of visitors to the National Museum of the Charterhouse of Pisa in Calci, located in Tuscany. Visitors are guided via audio-video prompts on tablets or smartphones around a path and are free to explore spaces such as the Chapel of St. Anthony and Cloister of the Chapter. Additionally, the authors created an introductory video which was projected at the entrance of the museum, showcasing the external view of different construction phases of the monastery.

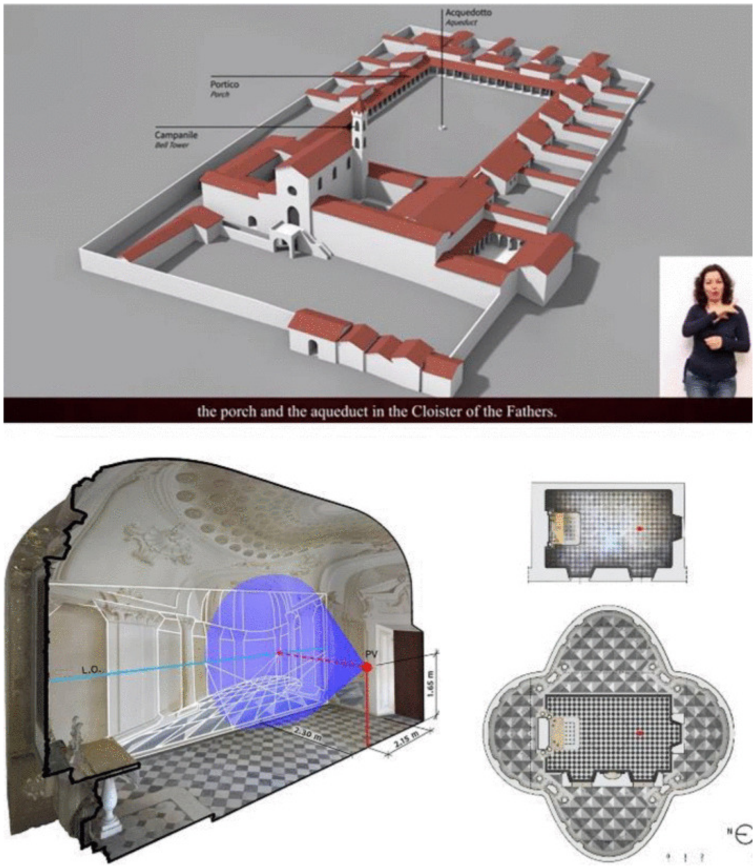

Figure 22: Top frame: Introductory video at the Charterhouse entrance. Bottom left: 3D model of the chapel of St Anthony. Bottom right comparison between the plans of the real and illusory spaces

The final case study of [49] is a digital reconstruction and AR projection of the cathedral by Baldassarre Peruzzi. A map of the church was printed in large scale and placed on the ground allowing visitors to frame it with a tablet in order to project a wooden model of the cathedral on their screens. The application (Figure 23) also contained information panels showcasing the reconstruction process of the virtual model.

The authors conclude that by creating digital twins of heritage sites in a combination with VR technologies, users can visualize and engage in interactive ways with the 3D models, which ultimately leads to valuable knowledge and understanding between the user and the built environment.

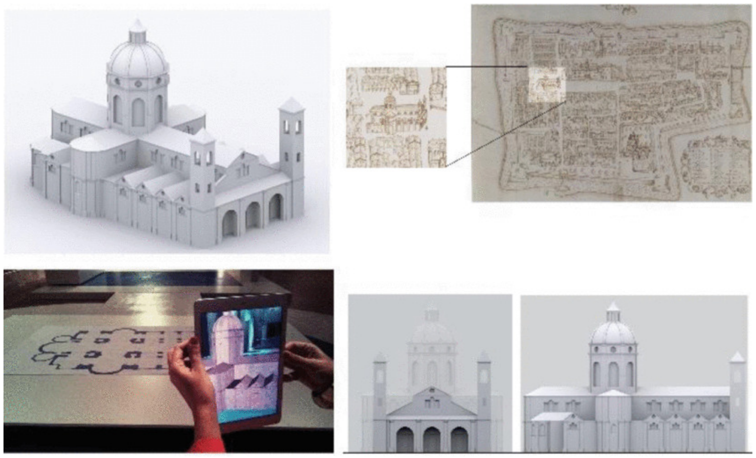

Figure 23: Virtual reconstruction and AR app of the church by Baldassare Peruzzi

2.4 Semantic Twins

The ”semantic” aspect in the semantic digital twins refers to the use of a common vocabulary or ontology to describe the object or system, which allows different digital twins to be connected and related to one another. This allows for more accurate and efficient data analysis, decision-making, and control of the physical object or system. Based on the listed applications from the previous sections, one can assume that digital twins will most likely continue to gain popularity among all different fields. This means that at some point a need of communication between different DTs will emerge, hence the need for Semantic Digital Twins. By default, applications of DTs are complex systems that usually consume and deal with big amounts of different types of data coming (usually) from IoT systems. [50] argues that IoT is a complex heterogeneous network platform which presents additional complexity between different types of devices across various communication technologies without any standardization. This means that to fully support integration and interoperability, standardized abstractions and architectures need to be presented [51]. Additionally, new frameworks, algorithms and methods are required to meet high reliability and security requirements for different cooperating components. Furthermore, the involved hardware and software on IoT need to be modular and reconfigurable for the whole ecosystem to work. All these challenges highlight the importance of designing Semantic Digital Twins (SDT) to reduce the overall complexity of DTs.

Already there have been attempts to include semantics in BIM tools. Specifically, the Industry Foundation Classes (IFC) standard was designed to solve the industry’s interoperability problem, including concepts across several well defined application domains [52]. IFC includes definitions that cover data related to buildings over their life cycle, however, it was not designed to be modified or used dynamically. Models such as Linked Data (LD) and Web Ontology Language (OWL)[1] have attempted to resolve these challenges [53]. The use of OWL models seems to better align multiple domains such as actors, sensors, management workflows and web resources. Additionally, an ontology approach is also considered more suited for future-proofing compared to old standard file formats.

On [54] the authors present a SDT, based on Industrial IoT Data Management and Knowledge Graphs (KG). According to Paulheim [55], ”A knowledge graph (i) mainly describes real world entities and their interrelations, organized in a graph, (ii) defines possible classes and relations of entities in a schema, (iii) allows for potentially interrelating arbitrary entities with each other and (iv) covers various topical domains”. In other words, knowledge graphs can effectively organize and represent knowledge so that it can be efficiently utilized in applications. Gómez-Berbís and Amescua-Seco [54], state that KGs were conceived to deal with the ever increasing data added constantly on the Web. Their aim is to add semantics to published data, so machines can interpret these data in a similar fashion as humans. For this to work, ontologies are deployed since they provide structured vocabularies that describe relationships between different terms, allowing computers to interpret their meaning in a flexible way.

In the SDT presented in [54] (Figure 24), the authors build their methodology around five steps:

1. Digital Twin Parameters (DTP)
2. Set of IIoT sensors responsible for capturing mentioned parameters
3. Knowledge Graph relating DTP data throught IIoT sensors
4. Algorithms that evaluate and analyze the DTP data
5. Provide feedback about the impact on the System

The SDT is made up from two DTs. The first one, named OPTYFY, focuses on operational efficiency of the production considering the variables Time, Rate and Flow. The workstations displayed on Figure 24 represent three different units, Kitting, Assembly and Testing Units. The IIoT sensors provide the data from Time, Rate and Flow for each workstation. On the next step, the authors use their designed KG to conceptualize the production line. On the last step, the algorithms which evaluate and analyze the data are applied. The algorithms notify the system whether any workstation is under-performing or following expected performance.

In [56] the authors leverage Docker containers to mimic IoT devices. Docker containers bundle up an application along with all its dependencies to create a single

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[1] https://www.w3.org/OWL/

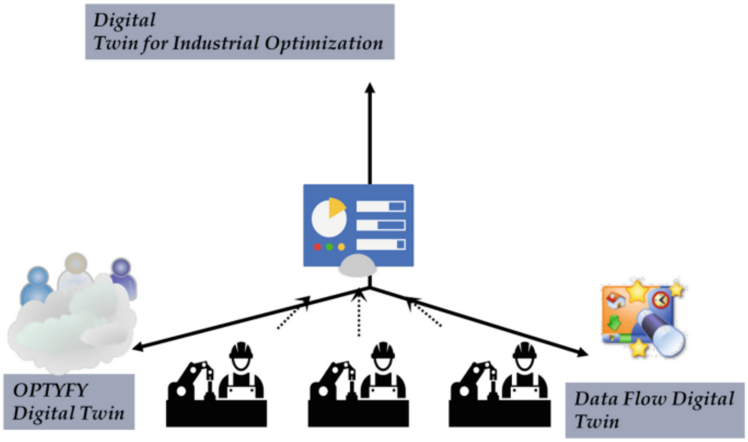

Figure 24: SDT for Industrial Optimization(S here)

package. W3C Web of Things (WoT) has proposed Things description (TD) which specifies a semantic way to map IoT devices to virtual things[2]. According to [57], TD can provide a semantic, structured description of the Thing's capabilities, interactions and data model. In the proposed SDT displayed in Figure 25 the semantic modeling is performed using the TD which expresses various info such as the address, location of the device as well as humidity, temperature and pollution levels. The TD implementation relies on a JSON-LD format. Furthermore, the authors note that the Kubernetes platform used in the proposed SDT allows better scaling and help locating issues, enhancing the reliability of large-scale IoT applications.

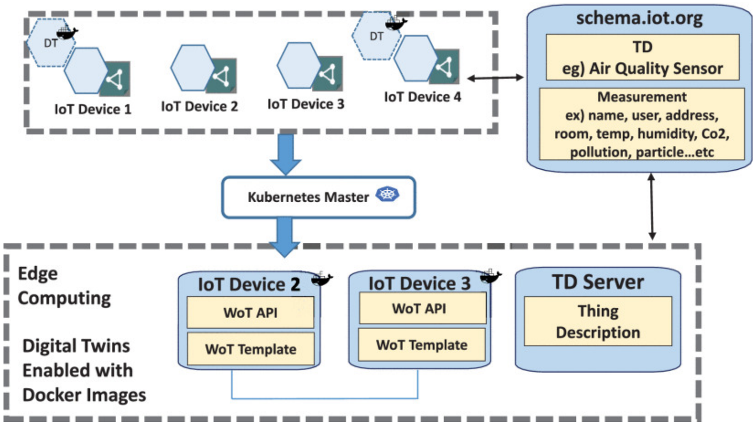

Figure 25: Proposed SDT model for IoT using Docker and Kubernetes

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[2] https://www.w3.org/TR/wot-thing-description/introduction

2.5 Enabling technologies and challenges

Since Digital Twins are complex systems, they rely on several different technologies and each technology is faced with different sets of challenges and problems that need to be resolved. The key technology behind Digital Twins is arguably the ”Internet of Things” (IoT). The term was introduced in 1999 by Kevin Ashton [58] and it describes a wide variety of objects with detectors and actuators that accumulate, analyze and distribute information with other systems, platforms and entities. Since DTs are by definition based on automatic communication of data between their physical and digital entities, IoT is a key ingredient for creating DT applications. However, dealing with a large number of sensors and physical systems, the IT infrastructure can become a challenge. To keep up-to-date hardware and software, companies tend to rely on on-demand GPUs through cloud services, like Amazon, Google and Microsoft [59]. This indicates that a scalable and well-designed IT infrastructure is crucial in guaranteeing that the designed DT model can fulfil its purpose.

Additionally, with the vast amount of transferred data, the science of Data Analytics can be listed as another key technology behind DTs. Data Analytics involves the integration of diverse data from different sources, which in turn assist in data-based decision making [60] and achieve better overall results, whether these are competitive performance in business decisions or better simulation results. Additionally, the term includes manipulating and calculating large volumes of data in order to identify patterns, correlations or any other useful information from the data itself [60]. Having access to large amounts of data means that another set of challenges that need to be addressed is the data manipulation, since they need to be sorted, be consistent and presented in an appropriate manner, so they can be used as inputs for the built tools and systems [61]. Moreover, depending on the data’s nature, privacy and security concerns may arise especially when dealing with sensitive data.

To combat challenges presented from both IT infrastructure and Data Analytics the technology of Cloud Computing has started to grow as well. Cloud Computing includes hosted services over the internet, whether this is storing and accessing data in servers or doing complex calculations in a remote machine [62]. Digital Twins with large volumes of data are able to store them into the cloud and effectively reduce computation time overall.

Besides IT infrastructure and Data Analytics, Artificial Intelligence (AI) along with other related technologies such as machine learning, Neural Networks and Deep Learning are key enablers in further developing the capabilities of built DTs [61]. By leveraging AI, DTs can be transformed to smart entities, which can assist users in making the right decisions for tasks at hand [9]. On top of that, AI can sometimes solve problems in seemingly unintuitive ways, compared to human solutions, which can greatly increase the efficiency of DTs, thus reducing additional costs caused by non-optimal solutions in the long run [63].

Extended Reality (XR) is another key technology used in DTs [64]. XR describes immersive technologies that fall in the Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR) scientific fields. These technologies play a pivotal role when it comes to merging physical and virtual worlds or extending the reality that users experience [65]. By using the tools provided in XR platforms, digital representations of objects are able to co-exist and interact in real-time with real world objects, allowing the creation of DTs that can reach their maximum potential.

Another significant technology for the creation of DTs is the Data Visualization field. One could argue that Data Visualization is the ultimate purpose that DTs need to fulfil as their scope (besides of having the options to control entities) is to showcase information from both the physical and their digital counterpart. This denotes that extra care should be given in terms of displaying both simple and complex data, to allow users to be in a position where they understand what is displayed, so they can take informed decisions that would otherwise be unable to do so.

Based on the aforementioned technologies, two additional challenges arise. First of all, even though digital twin technology has been advanced both by researchers and the industry, user expectations should be adjusted, discussed and evaluated continuously through the development process of DT systems. This is because depending on the context, the users background and point of view, a finalized production ready DT system may be entirely different compared to users expectations [9]. Last but not least, based on the literature review and the different use cases listed on the previous sections, it is apparent that currently there is no industry standard way of developing or designing a digital twin model. DTs can be built and used to solve completely different and unrelated problems belonging to entirely different scientific fields [66]. Therefore, a standard approach and pipeline from the initial to the final phase of DT is needed.

At this point, it is worth noting that the list of enabling technologies for DTs will be increased, in case one decides to include all the different tools, software and hardware that can be used to develop the modules and components that make up complex DTs. However, since this out of the scope of the thesis, no individual tools or specific hardware is listed as an enabling technology.

Even though DTs will continue to gain ground, an important factor that will likely slow their growth is the increasing costs. All of these different technologies, hardware and software that need to be managed and maintained, require significant investments. Furthermore, until a standard approach is established for various different scenarios, the creation of complex DTs will demand additional manpower, expertise and know-how in various fields to develop the required tools for the task.

3 Case studies

3.1 The fortress of Mytilene

In the first case study, a Computational Fluid Dynamics (CFD) and a 3D Visualization pipeline to simulate the wind flow over the fortress of Mytilene is presented. By building a Digital Model of the castle and performing an accurate simulation based on real environmental data, we conclude that an initial assessment of the effect of environmental parameters over any heritage site can be performed. Additionally, this work may form a basis for constructing a valuable assistive tool or workflow for conservators and engineers working on the preservation of heritage sites across the world.

3.1.1 History

The Fortress (or castle) of Mytilene in Lesvos Island is located around a hill between the city's northern and southern ports (Latitude 39° 1'1 N, Longitude 26°5'6 E). The monument construction is made up from three sections (Figure 26), consisting of the upper, middle and lower part of the castle. With the first construction phase being completed during the Byzantine period (5th century AC), it is considered as one of the largest and well-preserved castles of Greece that expands in an area of 200.000 sq. meters.

3.1.2 3D Geometry modeling and mesh generation

To create a valid Digital Model for the area of interest, the data had to be prepared accordingly. Specifically, in order to run an accurate CFD simulation, a watertight geometry including both the ground (terrain) and the castle itself had to be generated. To build the terrain, the Copernicus open access Digital Elevation Model (DEM) was used at a resolution of 20m height. While the retrieved data allowed the generation of heightmap texture for the area, the texture's resolution was relatively low, resulting in jagged edges and patches throughout the entirety of the mesh as displayed in Figure 27.

By deploying BigJPG AI image upscaler[3] and applying a gausian filter on the resulting mesh, the issue was mitigated in a large extent and a detailed model, which

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[3] https://bigjpg.com/

Figure 26: The Castle of Mytilene from a topdown view from Google Maps

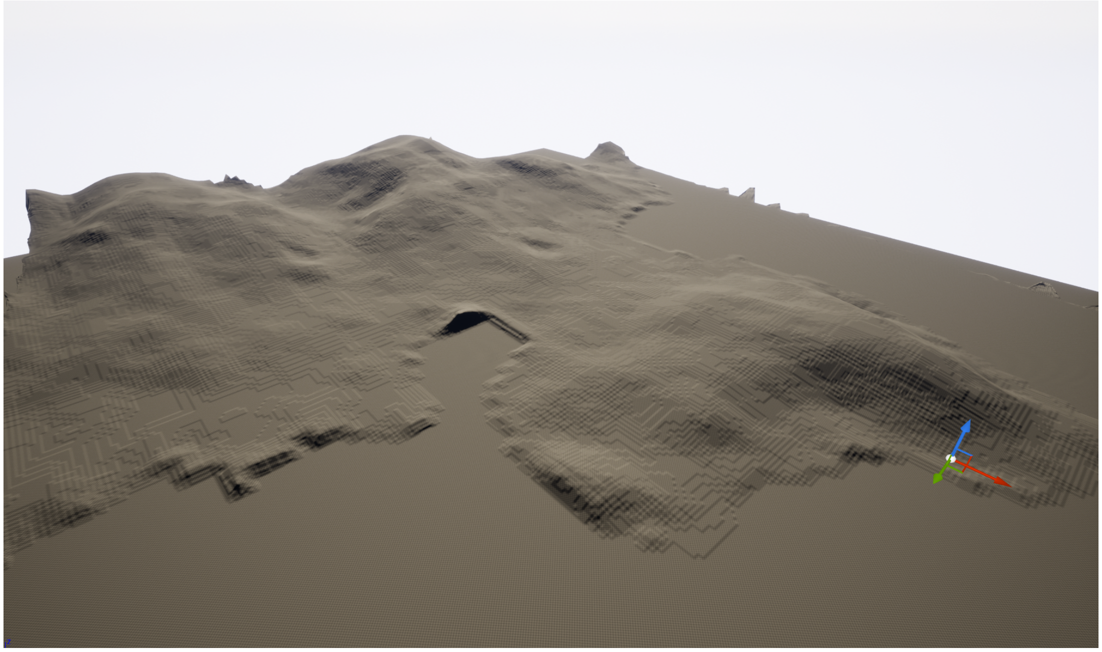

Figure 27: Patched ground from the original low resolution heightmap texture

was looked similar to real life, was generated (Figure 28).

To generate the castle's mesh, a topdown DEM view of all the sections of the castle was layered on top of the ground's heightmap. This resulted in a 2D mesh generation

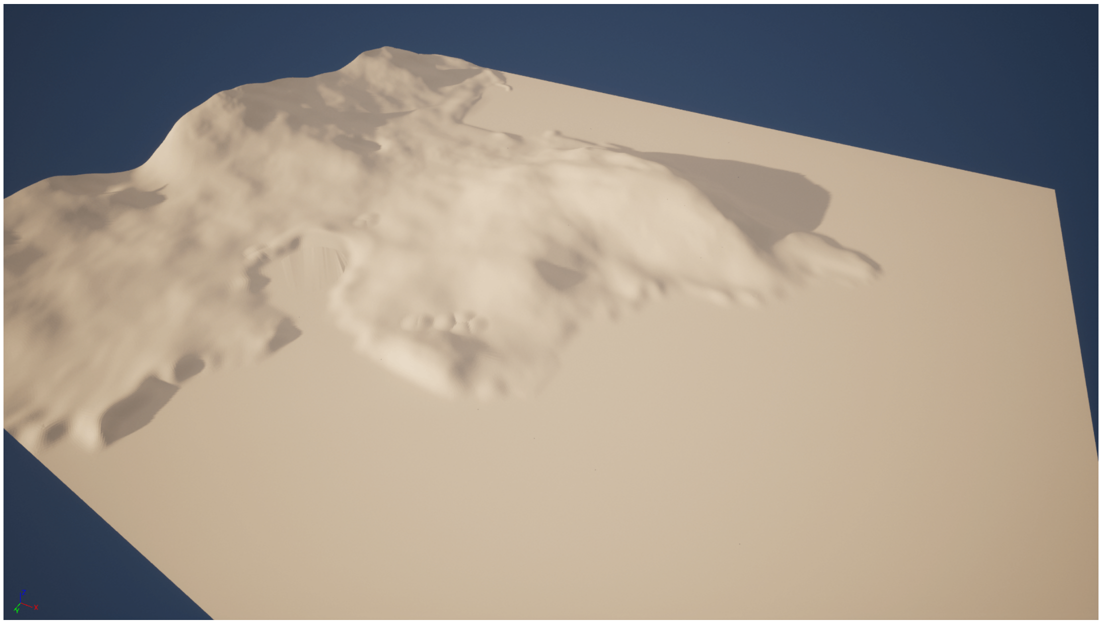

Figure 28: Ground generated from upscaled texture

that snapped along the edges of the topdown view of the castle. To match the real data coming from the DEM view, each wall segment of the 2D mesh was extruded to its correct height. Since the castle includes several windows, arches and some complex geometry, a 3D artist worked on adding some important details to create the final model (Figure 29) that was used in the simulation. Finally, by combining the two resulting geometries, a valid 3D digital model of the Fortress of Mytilene, which can be used effectively in CFD simulations was generated.

3.1.3 CFD Pipeline

The first step before setting up the CFD pipeline was acquiring real environmental data of the location of the fortress. Specifically, data from Open Weather Map[4] that included hourly values for wind direction and speed for each day over the span of 22 years, from January 1st 2000 until July 5 of 2022 were used. The measurements came from the town's airport METAR station with the sensors being located on top of a 10m pole from the ground. Both the indications and the sensors accurate location are required to achieve accurate initial conditions for the simulation. To effectively consume all the gathered data, a python script was built that parsed all values and concluded that the mean wind speed was about 3.42 m/s while the mean wind degrees was roughtly 155°corresponding to South East direction from a wind rose.

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[4] https://openweathermap.org/

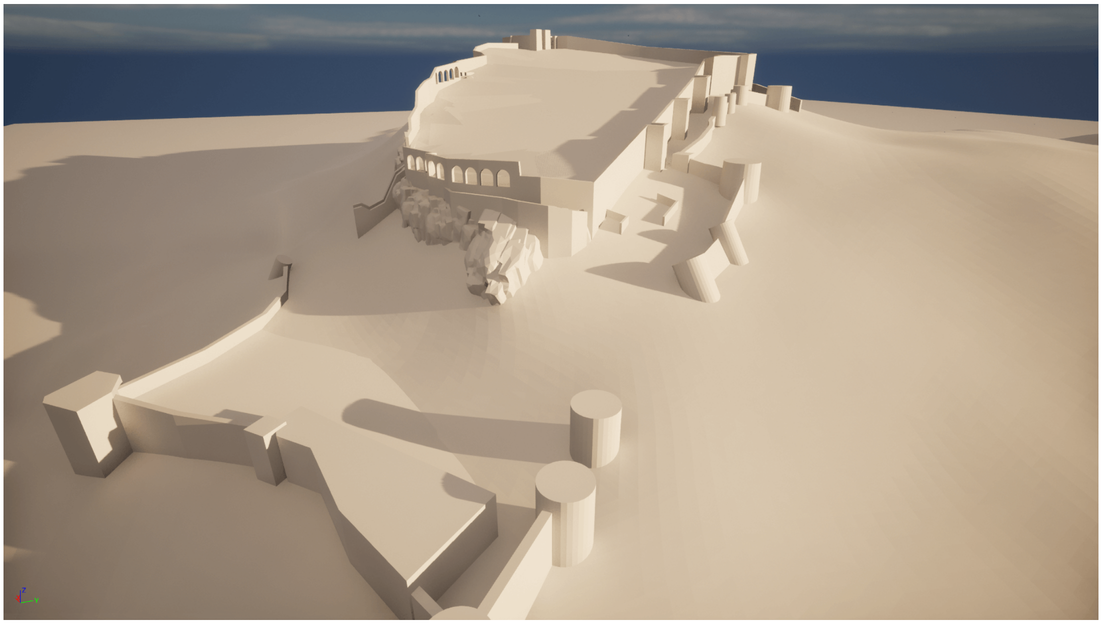

Figure 29: 3D Model of the castle of Mytilene

To perform an valid CFD simulation, the steady-state version of the in-house flow solver IBOFlow®(Immersed Boundary Octree Flow Solver [67]),developed at Fraunhofer-Chalmers Research Centre was used. The solver's procedure and settings are continuously being validated [68]. The solver assumes an incompressible, isothermal flow and integrates the Reynolds Averaged NavierStokes (RANS) equations:

$$\nabla \cdot \vec{u} = 0, \tag{1}$$

$$\frac{\partial \vec{u}}{\partial t} + \vec{u} \cdot \nabla \vec{u} = -\frac{\nabla p}{\rho} + \nabla \cdot ((\nu + \nu_t) \nabla \vec{u}), \tag{2}$$

along with the turbulent transport equations. Here $\vec{u}$ denotes the mean velocity of the fluid, ρ is the fluid density, p is the dynamic pressure, ν is the kinematic viscosity of the fluid and ν_t is the eddy viscosity. Further, the immersed boundary (IB) condition is solved,

$$\vec{u} = \vec{u^{ib}}, \tag{3}$$

which constrains the velocity of the fluid to the velocity at the immersed boundary, $\vec{u^{ib}}$. The Spalart-Allmaras (S-A) turbulence model is used. The eddy viscosity is given by:

$$\nu_t = \tilde{\nu} f_{\nu 1}, \qquad f_{\nu 1} = \frac{\chi^3}{\chi^3 + c_{\nu 1}^3}, \qquad \chi \equiv \frac{\tilde{\nu}}{\nu} \tag{4}$$

where $c_{\nu 1}$ is a model constant and $\tilde{\nu}$ is the Spalart–Allmaras (S-A) working variable and adheres to the following transport equation:

$$\frac{\partial \tilde{\nu}}{\partial t} + \vec{u} \cdot \nabla \tilde{\nu} = P - D + \frac{1}{\sigma} \left[\nabla \cdot ((\nu + \tilde{\nu}) \nabla \tilde{\nu}) + c_{b2} |\nabla \tilde{\nu}|^2 \right] \tag{5}$$

where P and D denote the production and destruction term respectively while c_{b2} is a model constant [69].

The dimensions of the computational domain were set as width × depth × height = 800m × 1170m × 400m based on the best practice guidelines (BPGs) provided by COST732 [70] and Architectural Institute of Japan (AIJ) [71]. Finally, a set of 70 points was selected around the castle and velocity was recorded at each point (Figure 30). The locations of the points were carefully chosen so that different parts of the flow can be captured and compared - upstream of the castle, its wake and around it.

Figure 30: Measurement points

3.1.4 Visualization Data Pipeline

To visualize the results of the simulations, the Unreal Engine 5 (UE5) game engine was used. UE5 provides a set of tools for games that can also be leveraged to display scientific results. By combining ready-to-use tools of the engine, such as Blueprints, Materials and the Niagara Particle System, the visualization of the air velocity on the castle's walls became possible. On top of that, a custom C++ plugin was developed for the visualization of the velocity streamlines.

The simulation results follow the Hierarchical Data Format 5 (HDF5), which is high-performance format used to achieve fast I/O processes and storage for big data. Since Unreal Engine doesn't support this format, an intermediate python layer was introduced, tasked with converting HDF5 data into comma separated values (csv). In this case, the csv format comes in handy since it is supported out of the box in UE5. With this workflow, it was possible to unpack the simulation's results inside the engine. The next step of the process, was feeding the data into the visualization systems that were developed. Figure 31 describes the complete process starting from the HDF5 format until the finalized data visualization.

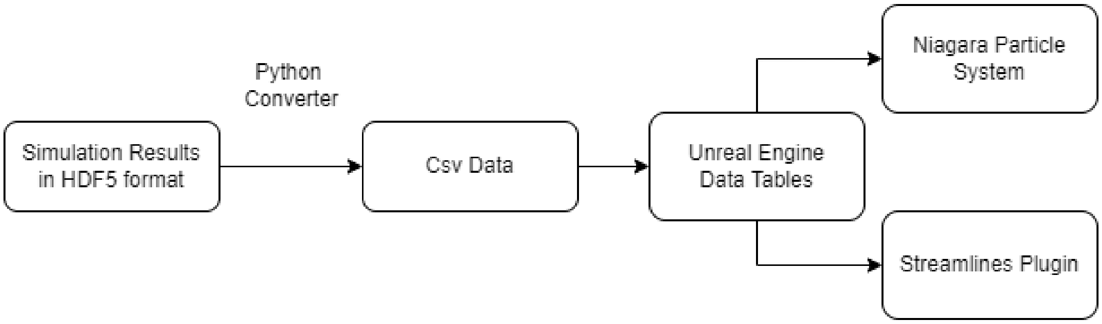

Figure 31: Data Preparation Flow for Unreal Engine

3.1.5 Niagara Particle System

To visualize the velocity on the castle's walls, Unreal Engine's Niagara Particle System was used. By running directly on the GPU, Niagara Particle System provides significant visualization performance. The system is a combination of modules and emitters, placed in a stack which are executed from top to bottom during the different stages of the particle's lifetime. Initially, the simulation data were packed into two different one-dimension arrays. Both arrays are a collection of 3D vectors and contained different information for the same points. The first array is required to store the world location of each point, while the latter one stores the velocity of the points along each axis. The arrays were filled following the same order, to achieve a mapping between their values.

The particle system is made up by two different emitters (Figure 32). The first emitter is expecting an array of locations and is responsible for spawning a single spherical mesh for each entry of the array. A custom material accepting a single 3D vector is built and assigned on each mesh. In reality, in the material's vector property the velocity for each axis is stored, allowing the mesh to store the velocity data directly on the shader. The second emitter was responsible for assigning the velocity values on the material code for each mesh. By passing the simulation data directly into the material code, a mapping system between values and colors can be built, allowing the usage of different colormaps to visualize the data. Finally, for the system to work, minimum and maximum velocity values had to be determined. By knowing the range of values, all data were normalized in that specific range and ultimately the normalized result is mapped to the colormap's texture UV coordinates to get the final color for each spherical mesh spawned by the particle system.

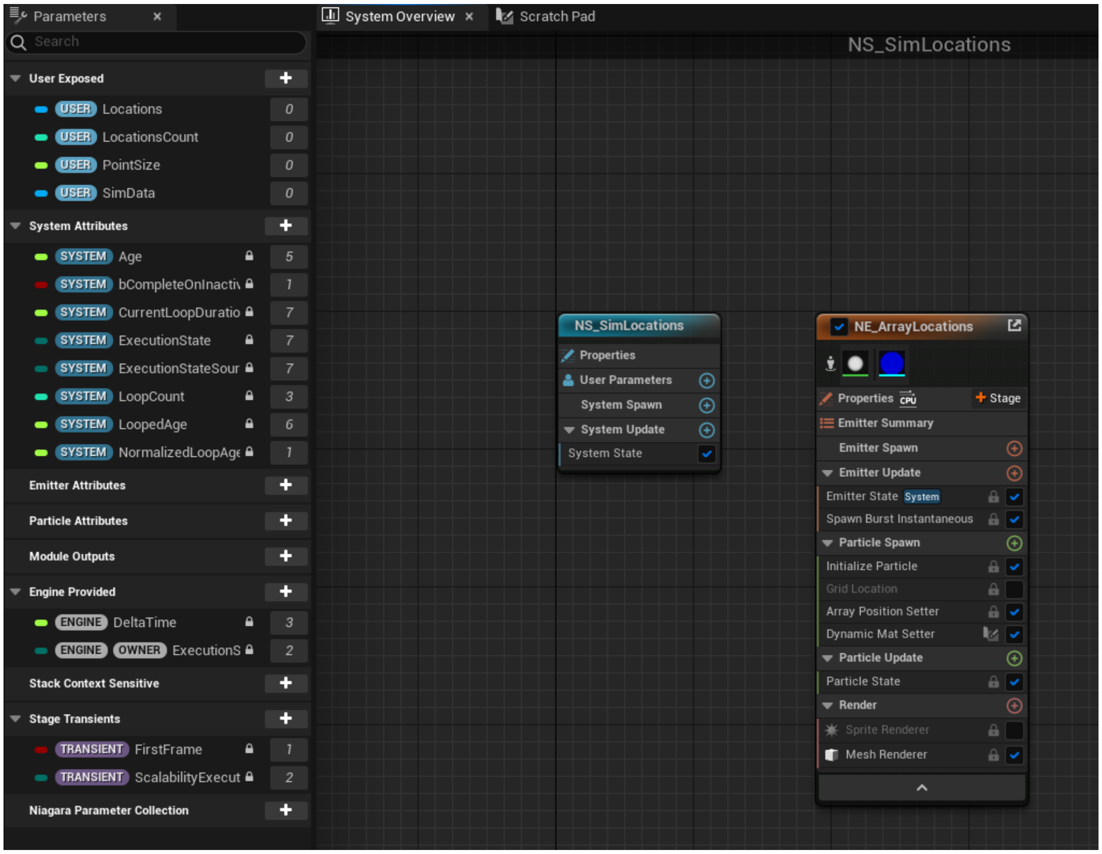

Figure 32: Niagara Visualization System for velocity visualization

When feeding all data into the Niagara system, the engine is able to render several thousand locations, which snap on the castle's walls as depicted in Figures 33 and 34.

3.1.6 Visualizing Velocity Streamlines

To visualize the velocity streamlines, a C++ plugin was developed for UE5. On a high level, the plugin expects a series of world locations along with their respective velocity values as inputs, in order to generate procedural meshes. The functionality of the plugin is split amongst two classes, the Streamline Generator and the Streamline

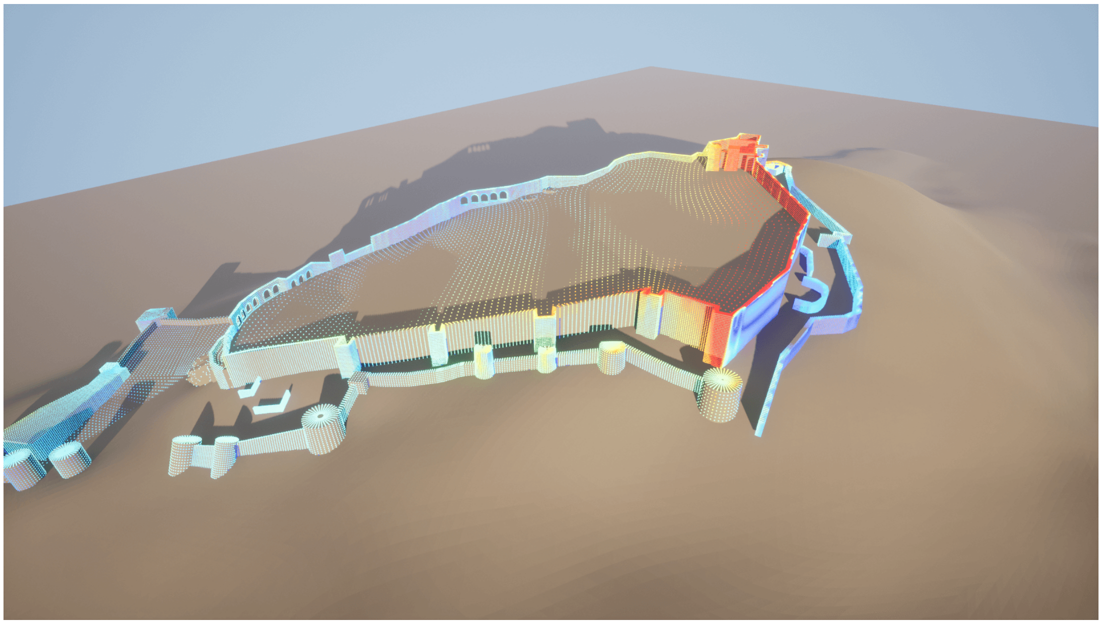

Figure 33: Velocity visualization on castle's walls

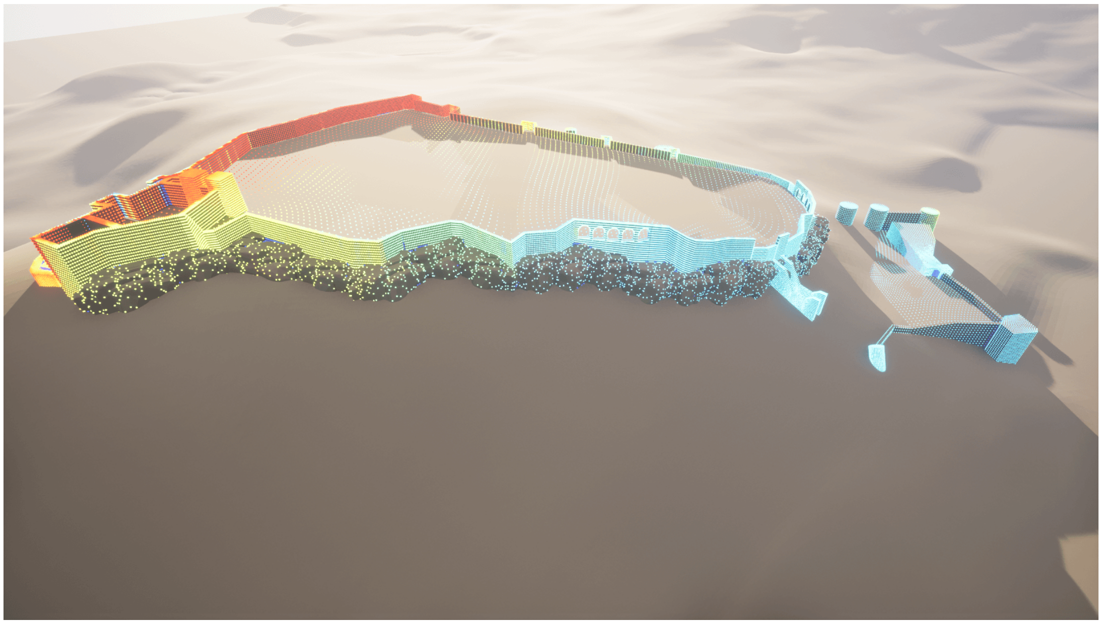

Figure 34: Velocity visualization on castle's walls (different perspective)

Actors. In UE5, an "Actor" is an object that exists in the virtual scene. In the plugin's case, the Streamline Actor is responsible for calculating and generating the geometry along the path of the provided wind flow. The Streamline Generator is responsible for spawning several Streamline Actors in the world, while also providing them with the original simulation data for each flow.

Even though the simulation data contain discrete points that form a curve, the procedural generated mesh is cylinder-like. The reason of using this representation is that it is easier, from a user's perspective, to comprehend the flow of the wind. To create cylinder-like meshes, the plugin generates additional vertices around the provided simulation data. The mesh generation algorithm of the Streamline Actor consists of the following steps:

1. Generate X number of vertices around the first added point on the streamline
2. Generate triangles connecting the created vertices with the first point on the streamline
3. For every additional point on the streamline:
    (a) Generate X number of vertices around the given point
    (b) Generate 2*X triangles, connecting the generated vertices of the previous point on the streamline with the generated vertices of the new point
4. On the last point: repeat previous step plus generate triangles connecting the created vertices with the point

Assuming X equals 12, Figures 35 and 36 visualize the process of each mentioned step from above.

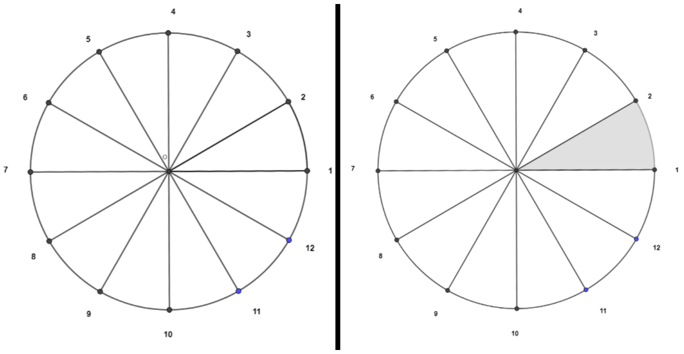

Figure 35: From left to right, step 1, additional vertex generation around starting point O (X=12). Step 2, triangle generation on additional vertices for starting point

On step 3b to generate the cylinder like mesh a counter-clockwise triangle generation is need. In this case, the triangles needed to be generated are displayed on Figure 37.

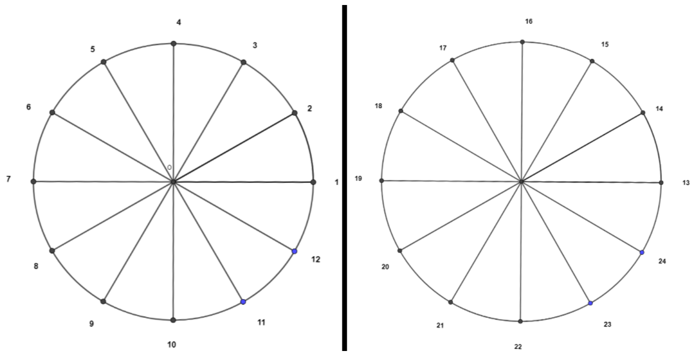

Figure 36: Visualization of additional vertices from first and second point that need to be connected to form the mesh

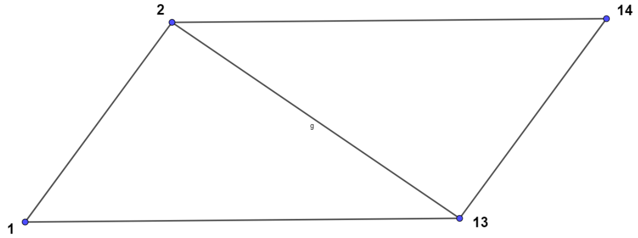

Figure 37: Connecting vertices in a counter clockwise fashion from first to second point. 2,13,1 and 2,14,13

Figure 38 displays the streamline visualization system on the 3D model. By comparing the color (meaning the velocity values) of the streamlines versus the Niagara Visualization system, it is noticeable that both systems display approximately the same values. The downside of the Streamline Visualization system is that it mostly relies on the CPU to render the meshes, therefore it does not scale up as well as the Niagara System. Additionally, it is noticeable that on figures where the Niagara Visualization is displayed, additional points are displayed. This is because if the Streamline system was to visualize every single streamline from the simulation data, the user would be unable to see the geometry underneath, which would result in a bad user experience overall.

3.2 Saving Energy with Comfort

In the second case study, a digital twin approach for smart buildings along with a first prototype implementation in the energy-saving domain is proposed. Building Energy

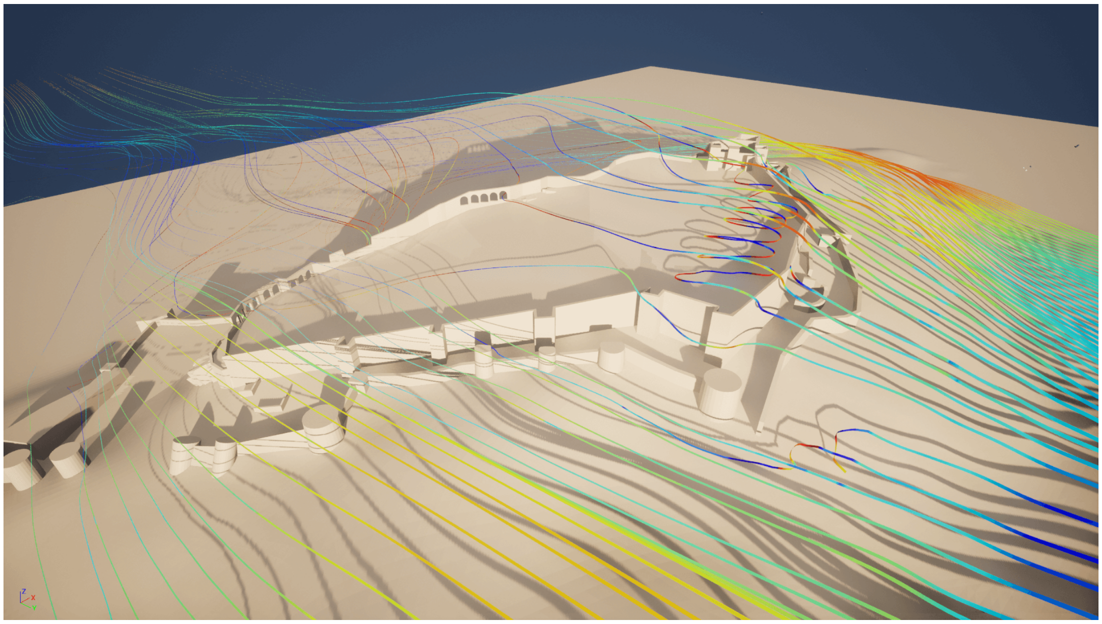

Figure 38: Streamline Visualization System

Management Systems (BEMS) are computer-based systems that monitor, control, and optimize the energy usage of a building. They typically include a network of sensors and controllers that collect data on the building's energy usage, as well as software that can analyze the data and make decisions about how to manage the building's energy usage. The sensors in a BEMS may include devices for measuring temperature, humidity, lighting levels, occupancy, and other factors that can affect energy usage. This data is then transmitted to a central control unit, which uses algorithms to analyze sent data and make decisions about how to optimize energy usage. BEMS also includes actuators, which are devices that can control various systems in the building such as Heating, Ventilation and Air Condition (HVAC), lighting, and shading systems. Additionally, it is capable of sending commands to these actuators to adjust the settings of the systems based on the decisions made by the system. Moreover, a BEMS can be connected to other BEMS or metering systems allowing better energy management and coordination with other systems [72].

The key objective of the system is to maintain ideal and comfortable conditions for the buildings' occupants, while also mitigating energy consumption [73]. However, without any visualization of the processes or the simulations, stakeholders struggle to understand the outcome of their actions [74]. Since BEMS enable interlinking, integration and communication between heterogeneous components [75], semantics should be deployed to ensure interoperability and enhance interconnections between different modules [76].

3.2.1 System Architecture

In this case study, a new model emphasizing on the representation of knowledge related to energy saving within a DT simulation environment is needed. Semantically integrated and visualized real-time sensor data within a digital asset is used to support real-time actuation of semantically annotated physical objects via the interaction with their semantically interlinked DTs.

Figure 39 displays a layered architecture, which reduces the dependency between its discrete layers, while also facilitating the portability and the flexibility. Additionally, all layers are connected with each other using semantics.

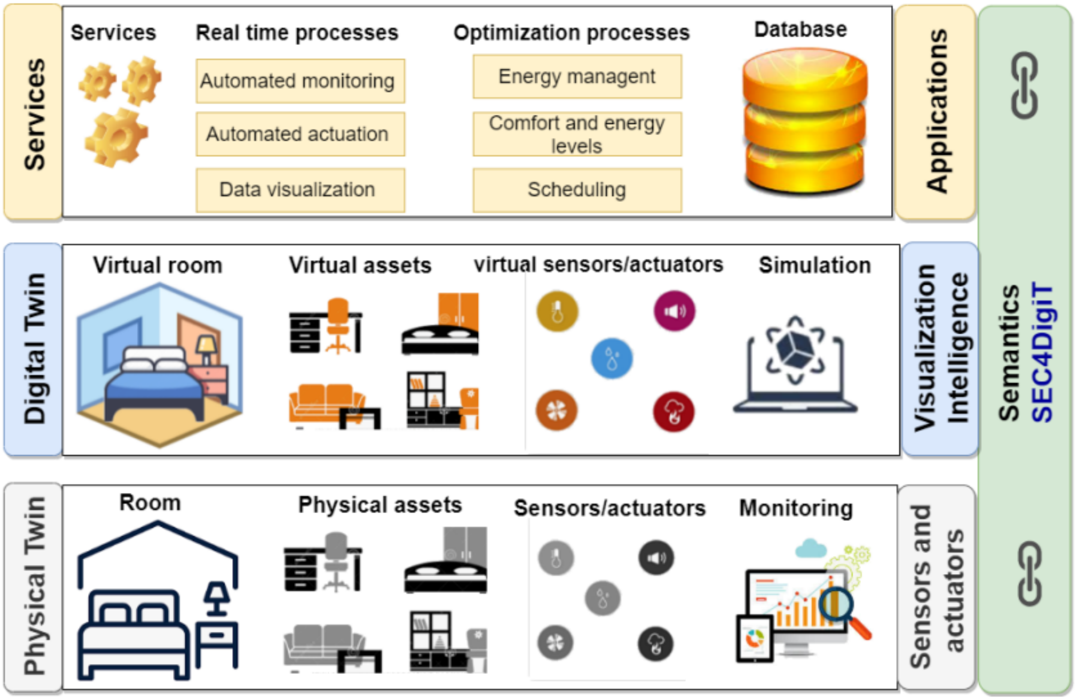

Figure 39: SEC4DigiT conceptual architecture

The Physical Twin layer contains the rooms and their corresponding physical assets along with all the smart devices, sensors and actuators which monitor indoor environmental conditions, energy consumption and generation. All the collected data from sensors are sent over to other layers via the Semantic Layers.

The Digital Twin layers consists of the virtual room, its assets and the virtual sensors. Like in all Digital Twins, the virtual room is a copy of the physical room and contains copies of all the physical assets from the Physical Layer. The digital sensors may visualize data streams from the real sensors however the actuators may also simulate digital data or even perform control actions to the real sensors via the data streams which are pushed to other layers via the semantic layer.

The Service layer consists of the processes and applications, which manage the physical room. Raw sensor data and actuation services are deployed as part of a BEMS. Additionally, in this layer all the optimization process about comfort and energy levels, along with energy optimizations such as scheduling processes, plan actions and interventions are taking place which ultimately get retrieved from the semantic layer.

All the aforementioned layers can communicate with each other via the Semantics layer. All data and information are semantically enriched, allowing end-users and building managers to query all available assets and devices in order to make strategic and more educated decisions about possible actions.

3.2.2 Ontology

Both the ontology and the respective DT application presented in this case study are available on GitHub[5]. The initial version is based on the SSN/SOSA and BOT(W3C) ontologies. Additionally, related knowledge from well-defined and evaluated ontologies were reused, such as EEPSA[6], which acts as a candidate knowledge that includes External Building Elemenent, Wall, Window, Door, External Wall/Door/Window, Observable quality, Comfort quality, Illuminance, Indoor temperature, Indoor humidity, Meteorological quality, Outdoor temperature, outdoor humidity and wind speed.

The developed model is composed of two main modules: the Digital Twin and the Comfort Observations module. Initially, the ontology didn't reflect this modularization and all the concepts of both modules were included in a single model. The developed ontology is utilized to connect and make sense of the data managed in the Digital Twin demo application. The populated version of the ontology includes examples of visual comfort observation data, which is implemented in the demo application.

Digital Twin module. The Digital Twin Module represents the Digital Twin concept, which is a subconcept of a Digital Asset, is distinct from the Physical Twin concept, a subconcept of Physical Asset. Both types of assets are defined as a FeatureOfInterest in the SOSA ontology and include different assets, such as Digital Lamps, Digital Thermostats, and Digital Rooms for Digital Twin, and Physical Lamps, Physical Thermostats, and Physical Rooms for Physical Twin. Smart assets like Smart

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[5] https://github.com/KotisK/SEC4DigiT

[6] https://iesnaola.github.io/eepsa/EEPSA/index-en.html

Lamps, Smart Thermostats, and Smart Rooms are considered subconcepts of the corresponding physical ones. For instance, a Smart Room is classified as a Physical Room and defined as an Element in the BOT ontology. It comprises various assets, such as a Smart Room Intelligent System, sensors and actuators, defined in the SOSA ontology. All physical, digital and smart assets in the ontology are defined as FeatureOfInterest in the SOSA ontology.

Comfort Observation module. The proposed conceptualizations for comfort observations in both digital and physical twin make use of the sosa:Observation and sosa:ObservableProperty concepts. A Digital Visual Comfort, for example, is a property of Visual Comfort and a subclass of both the Comfort and IEQ classes. Similarly, a Digital Visual Comfort Observation is a subclass of sosa:Observation and a type of Visual Comfort Observation.

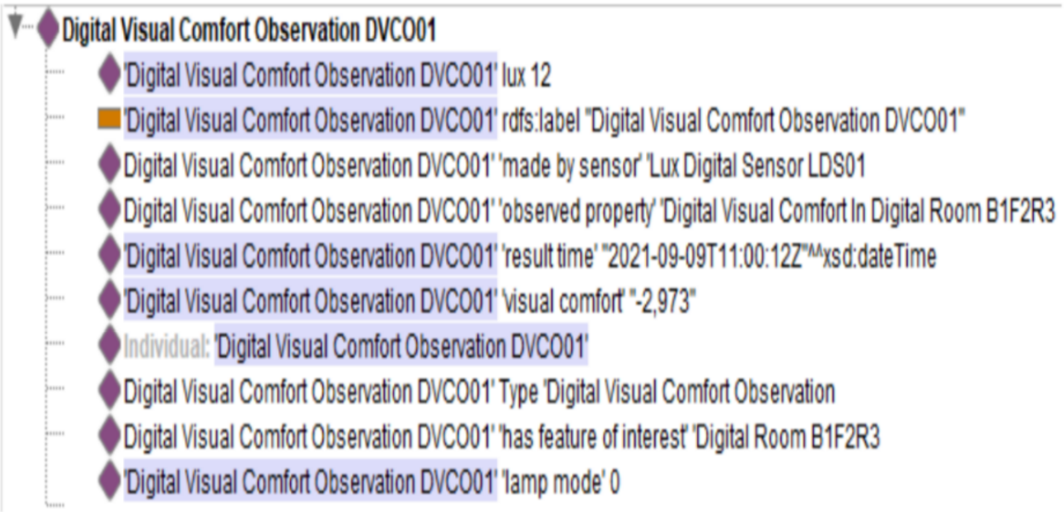
In Figure 40 some examples of linking properties are demonstrated. For instance, observations such as the ”Digital Visual Comfort Observation DCVO01” are linked with:

- **Observable properties** such as the ”Digital Visual Comfort in Digital Room B1F2R3”, via the sosa:observedProperty
- **Sensors** such as the ”Lix Digital Sensor LDS01” via the sosa:madeBySensor and
- **Features of interests** such as the ”Digital Room B1F2R3” via the hasFeatureOfInterest from the sosa ontology

Finally, properties such as ”lux”,”visual comfort”,”lamp mode”,”result time” are used. HCOME collaborative engineering methodology [77] in a combination with Protege 5.5 and Web Protégé were used to develop the ontology.

3.2.3 Application

Unreal Engine 4 (UE4) was used to generate Digital Twins of the spaces of interest. The Blueprint Visual Scripting system was used to visualize physical entities, such as the Physical Lamp and Thermostat. This system is a visual scripting tool, which relies on C++ reflected code and can be used as a fast prototype tool for object-oriented (OO) programming in the engine. Each physical entity was modeled by implementing a corresponding Blueprint (BP) class, which is used throughout the application. This means that two classes were initially generated, one for the Physical Lamp (BP Lamp) and one for the Physical Thermostat (BP Thermostat).



- Digital Visual Comfort Observation DVCO01
  - 'Digital Visual Comfort Observation DVCO01' lux 12
  - 'Digital Visual Comfort Observation DVCO01' rdfs:label "Digital Visual Comfort Observation DVCO01"
  - Digital Visual Comfort Observation DVCO01' 'made by sensor' 'Lux Digital Sensor LDS01
  - Digital Visual Comfort Observation DVCO01' 'observed property' 'Digital Visual Comfort In Digital Room B1F2R3
  - 'Digital Visual Comfort Observation DVCO01' 'result time' "2021-09-09T11:00:12Z"^^xsd:dateTime
  - 'Digital Visual Comfort Observation DVCO01' 'visual comfort' "-2,973"
  - Individual: 'Digital Visual Comfort Observation DVCO01'
  - Digital Visual Comfort Observation DVCO01' Type 'Digital Visual Comfort Observation
  - Digital Visual Comfort Observation DVCO01' 'has feature of interest' 'Digital Room B1F2R3
  - 'Digital Visual Comfort Observation DVCO01' 'lamp mode' 0

Figure 40: Example definition of a digital visual comfort observation from Protege 5.5

The visualization process in the engine consists of the following steps:

- Collecting data from IoT sensors, pre-processing them and sending them over to the engine
- Building a dynamic material shader that modifies the way objects look inside the game based on various parameters
- Inserting parsed data from the engine to the material shader

Data communication between IoT sensors and UE4 were handled by UE4Duino, an open-source plugin acting as a bridge between the engine and the sensors available on Arduino[7]. Sensor data stream from Arduino were retrieved through an automated process, which was sending console messages via a COM3 port on the Blueprint side. In case the user takes any action, the application sends a message to the Arduino's console, where the micro-controllers are able to interpret these messages and proceed in required actions. This workflow allows for a two-way communication between sensors and the digital world in UE4, and thus creates digital twins of physical entities.

In addition to the Blueprints that model physical entities, two additional BP classes, BP ThermalComfortVisualization and BP VisualComfortVisualization, were implemented to visualize the collected data in the Digital Twin. Once the data are parsed, these BPs process them in a fixed timestep and send them to a Material Parameter

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[7] https://www.arduino.cc/

Collection (MPC). The MPC is used by the material shader of each object in the scene, allowing for a uniform change in the overall appearance of the Digital Twin.

The material shader blends the default texture of each object with a solid color corresponding to a data value. To match data values with colors, the data range was remapped from [-3,3] to [0,1] and the final colors are retrieved from colormap textures.

The demonstration application used synthetic data for visual comfort observations, provided in CSV format.

Figure 41 showcases the visualization from the first application of the DT in an indoor environment, where the initial temperature and humidity values are monitored allowing the thermal comfort estimation. Indoor thermal perception is cold (blue color) (th.1), which leads to an optimization action that sets the thermostat to 22 degrees Celcius in order to raise the temperature in the room (th.2). After a while, the temperature rises, which leads to a change in the indoor conditions from cold to slightly hot (orange color) presented in instance th.3. An additional optimization follows, setting the thermostat level to 20 degrees Celcius (instance th.4), restoring the thermal comfort levels to neutral (green), while also ensuring energy savings.

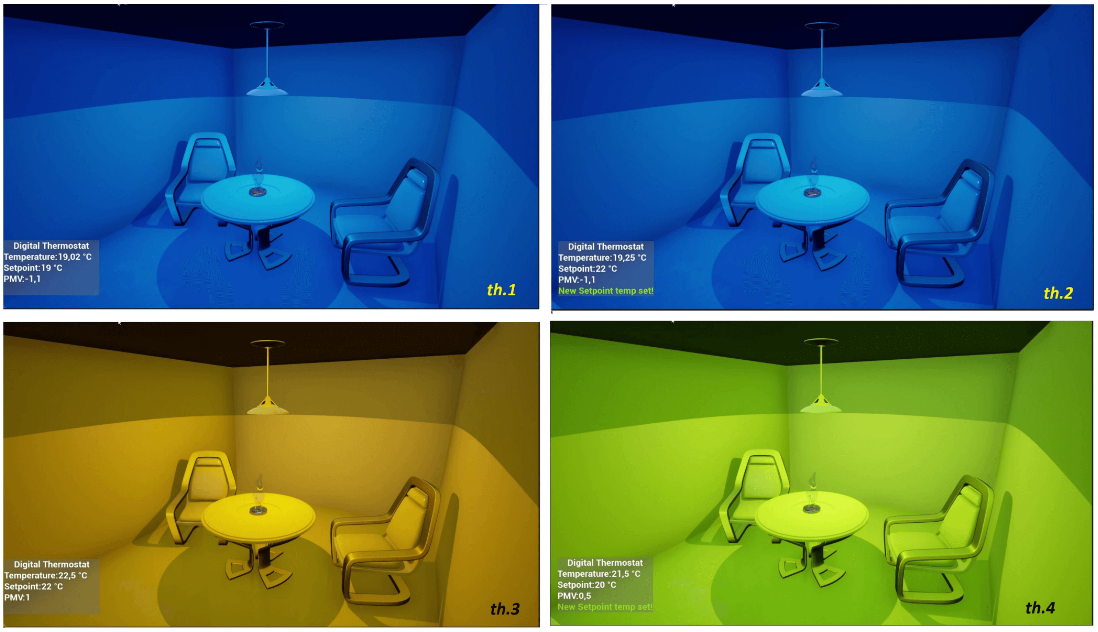

Figure 41: Thermal comfort instances

Additionally, Figure 42 depicts a DT of a smart room where luminance condition and Visual Comfort (VC) levels are monitored and visualized. Like the previous scenario presented above, the initial indoor visual comfort is estimated as dark (blue color in the visualization), since the sun start rising (vis.1). While the daylight is not sufficient and the indoor visual comfort is not neutral, the system proceeds on turning the light on (vis.2). This action leads to increased visual comfort levels initially. However, after a few hours, the provided daylight is sufficient, which leads to optimization from the system that turns the light off (vis.3). During the night the visual comfort is estimated (vis.4) and if motion is detected in the room, a control action is performed that turns the light back on (vis.5). With the optimized actions, the overall VC levels in the room are increased.

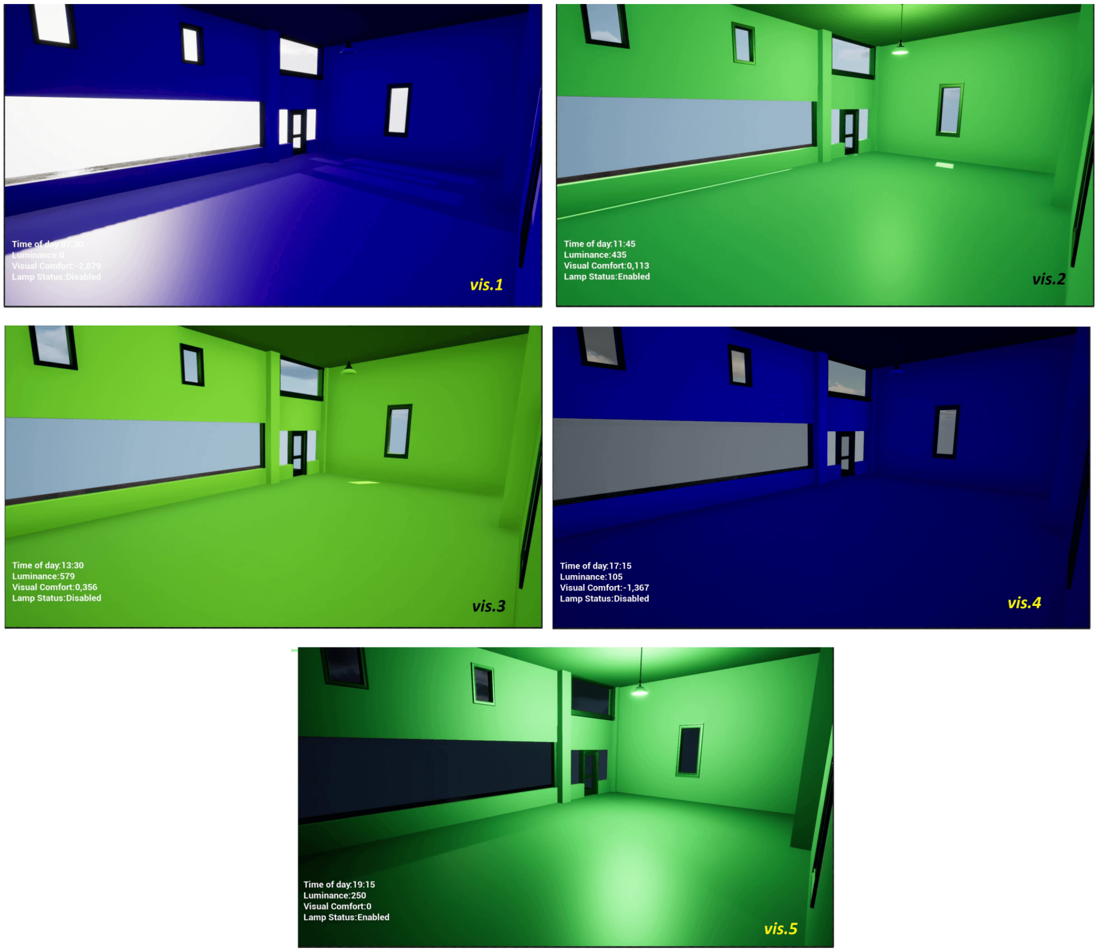

Figure 42: Visual comfort instances

3.2.4 Potential uses for smart cultural sites

The mentioned systems could potentially assist in converting regular cultural sites to smart heritage sites. For instance, in [44] the authors concluded that among other things, opening selected windows could potentially reduce the humidity levels for the Crypt of the Cathedral of Lecce in Italy. Therefore, in that particular case, a similar application to the proposed Saving Energy with Comfort could be developed. However, instead of turning lights off or on for visual comfort, windows could be connected with actuators, allowing them to be turned on or off depending on the humidity levels of the crypt. Additionally, the system can be deployed 'as is' in order to maintain consistent temperature levels, which in turn provide better indoor thermal comfort and also achieve better conditions for the crypt's preservation.

Another potential use for smart systems similar to Saving Energy with Comfort could be noted in [41]. The authors concluded that the damage of "Cardo of the Columns" area is happening because of sand-erosion. Researchers suggested two preventive measures, a) coating the area with sand-resistant materials and b) installing a wind baffle. While the authors verify that the second option can remedy the issue, it is apparent that the heritage site will not be original to its nature by having the wind baffle installed at all times. Alternatively, the government could harness the potential of IoT and by installing wind sensors near the area, they could potentially build a wind baffle that would only rise up when the wind direction is considered harmful to the site. By doing so, the wind baffle would only come up at specific times and only when needed, meaning that visitors could still enjoy the original area, as is, if the weather conditions permit it.

In [43] Yasa et al. suggested that appropriate measures have to be taken in order to improve the energy efficiency and avoid permanent damage to Slender Minared Madrasah in Konya. Since the thermal comfort criteria is met on the building, temperature sensors could be placed inside the building itself to make room for smart heating decisions based on a digital twin application similar to Saving Energy with Comfort. Even though the thermal comfort scenario dealt with synthetic data, the system is always adaptable to real data, which means that there is strong potential in effectively reducing the overall energy consumption, while also maintaining optimal comfort.

4 Conclusions - Future work

The use of digital twins is increasing rapidly due to advancements in technology such as IoT, Data Analytics, Big Data, AI and XR. These technologies are driving the growth of digital twins, both in the number of scientific papers published on the topic and in investments in actual applications from the private sector. However, the technology has still room to grow as long as standardization challenges still exist. The complexity and vast differences between different application of DTs, even in the same scientific field, pose a huge challenge that experts need to resolve. Hopefully, ontologies will pave the way in providing a standard way of developing DTs at least in specific scientific fields.

Even though DTs are complex in various sectors, it seems like all applications in the Cultural Heritage field fall in one of the following categories: a) Virtual/Digital Preservation, Restoration and Conservation, b) Simulation studies, c) Research Analysis, d) Education and Outreach and e) Planning and Management. Unlike other sectors where major differences exist in terms of the needed functionalities from the corresponding DTs, it seems like that in Cultural Heritage there are some applications that are constantly occuring. For instance, several papers were presented in this Thesis, where authors needed to create a CFD simulation to study the air dispersion in order to identify the areas of the digital model that was mostly affected. Additionally, several cases of virtual tours where presented as well. By identifying common functionalities along different DTs, it seems like there is a potential to create a unified platform that will offer users the options to create a DT for their own purpose or liking.

For instance, it is feasible to create a platform for museums, where stakeholders will be able to upload a 3D model of the museum along with its exhibits. Then, the platform could upload the data into a database. On the other end, a game engine implementing systems for first-person navigation around 3D spaces, could download the data dynamically and place the user inside the museum, allowing him/her to freely navigate to a procedurally created museum. In between these systems, an ontology could be implemented to allow dynamic changes in the tour if needed.

Another use case would be to create a streamlined process of modelling thermal and visual comfort levels for heritage sites. A platform could be deployed, where stakeholders once again will upload their 3D model and provide environmental data (or use IoT sensors for this purpose). Then, a game engine or any other visualization system could dynamically retrieve said data, perform a simulation for optimal comfort levels and showcase the results in the users.

Last but not least, based on the published papers that included CFD simulations for the air dispersion, it would be feasible to create a platform that accepts 3D meshes, specify the air's direction and other weather related data and let the system perform the simulation and the visualization of the results once completed. However, in this particular case, special care is necessary to verify that the physics simulation runs appropriately for each different use case.

To sum up, there is a huge potential for standardized DT applications, especially in the Cultural Heritage field. Even if all these proposed applications are feasible, a major factor that will come into play in implementing all of the aforementioned applications would be the final cost. Even if unified platforms that will allow users to create their own DTs come to life, the development and maintenance cost should be affordable to the public. Otherwise, this would endanger its sustainability from a financial point of view and therefore condemn these technologies to fail after a certain point.

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