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Digital Twin & Fleet Monitoring Dashboard

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# Glossary

AMQP - Advanced Message Queuing Protocol

API – Application Programming Interface

BDA – Big Data Analytics

BIM – Building Information Modelling

CAD – Computer-Aided Design

CM – Cloud Manufacturing

CoAP - Constrained Application Protocol

CPS – Cyber-Physical Systems

DIAMND – Diagnostics and Monitoring

ERP – Enterprise Resource Planning

FTP – File Transfer Protocol

HTTP – Hypertext Transfer Protocol

IMAP - Internet Message Access Protocol

IoT – Internet of Things

IQR – Interquartile Range

MAE – Mean Absolute Error

MSE – Mean Squared Error

OLE - Object Linking and Embedding

OPC-UA – OLE for Process Control Unified Architecture

PLC – Programmable Logic Controller

PLM – Product Lifecycle Management

POP3 - Post Office Protocol

ReLU - Rectified Linear Unit

RFID – Radio Frequency Identification

SMTP - Simple Mail Transfer Protocol

SQL – Structured Query Language

TCP/IP - Transmission Control Protocol/Internet Protocol

UDP - User Datagram Protocol

VR – Virtual Reality

XMPP - Extensible Messaging and Presence Protocol

# Abstract

Digital twinning presents a transformative opportunity in fleet monitoring, offering the potential to revolutionise the management of complex industrial systems. By leveraging digital twins as virtual replicas of physical assets and environments, coupled with intuitive dashboards, operators can make informed decisions, improve operational efficiency, and implement proactive maintenance strategies. Specifically, in the realm of crane testing environments, deploying digital twins enables comprehensive testing, prediction of potential failures, and optimisation of crane performance parameters, leading to increased safety, efficiency, and cost savings associated with crane operations. The partnership with Liebherr underscores the practical implications of this research, aiming to enhance the capabilities of Liebherr's existing fleet monitoring infrastructure. This collaboration strives to address operational challenges more effectively and elevate the overall efficiency and reliability of Liebherr's industrial assets.

The research aimed to investigate the efficacy of real-time digital twin implementation, coupled with a fleet monitoring dashboard, in enhancing visual clarity and operational efficiency in crane system monitoring. The approach involved a systematic progression through various phases, Unity project setup, interface design, and the integration of crucial crane data. By merging crane data into a 3D environment and designing a user-friendly interface, the project laid the foundation for effective monitoring and visualisation. Further efforts focused on integrating lift cycles, streamlining data processes through Azure Functions, and leveraging Power BI for visualisation and analysis. Additionally, neural network methodologies were explored to predict electrical consumption, aiming to optimise resource utilisation. The final phase hoped to merge the neural network model with the digital twin, enabling exploration and optimisation of electrical consumption efficiency across diverse operational contexts.

The integration of digital twin technology with a fleet monitoring dashboard demonstrated promising advancements in enhancing visual clarity and operational efficiency within crane operations. Significant improvements were observed in providing operators with detailed insights into crucial metrics and operational status through the comprehensive dashboard design and Power BI graphs. However, challenges persisted in validating real-time capabilities due to the absence of live data testing. Further work should focus on securing access to physical equipment for live data testing to validate real-time functionality and on refining modelling techniques to improve predictive accuracy. Collaboration with domain experts in crane engineering is essential to enhance the accuracy of digital twin simulations and address operational challenges effectively.

# Introduction

As the industrial landscape continues to advance, the need for precise and efficient monitoring systems is paramount. Digital twin technology, essentially a virtual representation of a physical system, has gained traction across various sectors, including industrial fleet management. This thesis situates digital twin technology within the sphere of crane operations, where the monitoring of intricate and dynamic activities is critical for safety and efficiency.

## Focus and Scope

This research narrows its focus on the specific application of digital twin technology in conjunction with a fleet monitoring dashboard for crane systems. By examining the implementation of this technology, the study targets enhancements in visual clarity and operational efficiency of crane monitoring processes, crucial for ensuring safe and streamlined industrial operations.

## Relevance of the Research

With an increasing emphasis on Industry 4.0 and smart technologies, this work fits into existing studies by bridging the gap between theoretical frameworks and practical applications of digital twins. It validates existing conceptual models against real-world scenarios and contributes to the literature on digital twin technology's impact on improving user experience and decision-making processes.

## Questions and Objectives

The central research question, "Does the real-time implementation of digital twin technology, combined with a fleet monitoring dashboard, contribute to enhancing visual clarity and efficiency in crane system monitoring?" aims to ascertain the practical benefits of digital twins in industrial settings. The objectives include evaluating user interface enhancements facilitated by the technology and measuring the efficiency gains in crane system operations.

## Overview of the Structure

The thesis is structured to address the research question methodically and is comprised of the following sections:

1. **Literature Review:** Outlines existing knowledge on digital twins, setting the conceptual foundation for their application in crane system monitoring.
2. **Methodology:** Describes the research design, data collection methods, and the approach taken to implement the digital twin technology.
3. **Implementation:** Details the practical steps taken to integrate digital twin technology with the fleet monitoring dashboard.
4. **Results:** Presents the findings of the study, focusing on the visual clarity and efficiency improvements ascertained from the implementation.
5. **Discussion:** Interprets the results, comparing them with existing literature and deriving meaningful insights.
6. **Conclusion:** Summarises the research findings, discusses their implications for industry practice, and suggests directions for future research.

Each section is crafted to cumulatively build upon the previous one, ensuring a cohesive and comprehensive exploration of the digital twin technology's capabilities within the realm of crane system monitoring.



# Literature Review



## Digital Twins



### Origin of Digital Twins.

The concept of the "Digital Twin," which has emerged as a pivotal framework in the realm of engineering and industrial applications, finds its origins in the early 2000s. Dr. Michael Grieves, a scholar at the University of Michigan, is credited with applying and pioneering the foundational ideas behind it (Sjarov et al., 2020). Initially referred to as the "Mirrored Spaces Model," later renamed by NASA’s John Vickers as “digital twin”, the Digital Twin comprises three fundamental components that collectively constitute its essence. These components, seen in Figure 1, consist of the "Real Space," representing the tangible, physical counterpart; the "Virtual Space," serving as the digital replica or simulation of the real-world entity; and the intricate web of connections that interlinks data and information, bridging the gap between the virtual and real products (D’Amico et al., 2019). This innovative framework has since evolved into a versatile and indispensable tool, offering profound insights into various domains, including crane fleet monitoring, where it enables the creation of highly accurate virtual representations of physical assets and facilitates the real-time tracking and analysis of their performance. The developmental trajectory of Digital Twins unfolds across three discernible phases. In its initial instantiation, the digital model lacks the mechanism for automated data exchange between physical and digital entities. Progressing to the second stage, identified as the digital shadow, a paradigm shift is observed with the introduction of automated unidirectional data flow from physical to digital objects. The third and most advanced stage, epitomised by the digital twin, witnesses the establishment of a bidirectional data flow facilitating seamless integration between physical and digital entities (Wang et al., 2020).

A diagram of a space shuttle

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*Figure 1 – Components of a Digital Twin (D’Amico et al., 2019).*

### How do Digital Twins Work?

1. On the physical side, we now collect more
2. and more information about the
3. characteristics of the physical product. We
4. can collect all types of physical
5. measurements from automated quality
6. control stations, such as Coordinate
7. Measuring Machines (CMMs). We can
8. collect the data from the machines that
9. perform operations on the physical part to
10. understand exactly what operations, at
11. what speeds and forces, were applied. For
12. For example, we can collect the torque
13. readings of every bolt that attaches a fuel
14. pump to an engine to ensure that
15. each engine/fuel pump attachment is
16. successfully performed.

Real-world machines are equipped with an assortment of sensors that record critical performance data. These sensors capture information on various aspects of the crane's operations, including parameters such as load capacity, movement, environmental conditions, and more (IBM, n.d.). In the realm of digital twinning for fleet monitoring, the convergence of physical and virtual elements assumes paramount significance. This integration is prominently illustrated through the acquisition of multifaceted physical measurements, derived from the Programmable Logic Controller (PLC) of cranes, which encompass variables such as spatial position and speed of the crane's spreader. These tangible data inputs form the foundation for the construction of a comprehensive digital twin. Furthermore, on the virtual side, the research underpins a substantial augmentation in the depth and breadth of available information. This augmentation is primarily achieved through the incorporation of an extensive array of behavioural characteristics. These attributes, inclusive of various performance parameters, not only facilitate the visual representation of the crane but also empower rigorous testing of its capabilities, ensuring a holistic understanding of its operational dynamics. Although the present investigation emphasises the capacity for virtual testing, it is pertinent to note that for certain applications, the focus may primarily be on generating lightweight virtual models to mirror physical counterparts, with the foremost aim being real-time visualisation of intricate systems, even in cases where comprehensive performance testing may not be feasible or necessary.

### Digital Twin: Use Case Models

The application of Digital Twin technology in crane monitoring and fleet management unveils a realm of profound utility, effectively harnessing the capabilities of conceptualisation, comparison, and collaboration as outlined by Grieves (2014). Conceptualisation, in the context of crane operations, enables a transformative approach to understanding the status and performance of these heavy machinery assets. Unlike conventional data processing, Digital Twins offer the unique advantage of real-time, visual representation, eliminating the need for manual translation of visual information into symbolic data. Through the Digital Twin, operators can simultaneously visualise the physical crane's condition and its virtual counterpart, allowing for a seamless comprehension of crucial data.

Moreover, comparison becomes an indispensable analytical tool in crane and fleet monitoring. The Digital Twin allows for the immediate evaluation of desired operational outcomes against actual results, eliminating the inefficiencies associated with manual data cross-referencing. By overlaying the ideal characteristics and tolerance corridors, the Digital Twin empowers users to swiftly assess whether the cranes and fleet are performing within acceptable parameters, with deviations colour-coded for instant recognition. These comparisons extend to various measurements, including tensile strength, torque readings, and other critical performance metrics, enhancing real-time decision-making.

Collaboration in crane and fleet management takes on a new dimension with the Digital Twin. Traditionally, operational assessments and troubleshooting were confined to a local context. However, the Digital Twin enables a shared conceptualisation that can be accessed and visualised by teams worldwide, transcending geographical boundaries. This global perspective allows stakeholders from various locations to monitor their fleet and compare their performance with fleets across the globe. In the event of an issue in one fleet, the solution can be promptly identified and shared with other fleets, fostering collaborative innovation on a global scale (Grieves, 2014).

In summary, the application of Digital Twins in crane monitoring and fleet management aligns seamlessly with the conceptualisation, comparison, and collaboration framework proposed by Michael Grieves. This technological advancement not only streamlines crane operations but also empowers global teams to collaborate in real-time, driving innovation and efficiency across the fleet management landscape.

### Choosing Unity 3D for Visualisation of Digital Twins

Unity3D serves as the linchpin in the landscape of digital twin development, offering an array of potent features and capabilities meticulously tuned to cater to the specific demands of digital twin applications. At its core, Unity3D excels in data ingestion and optimisation. This powerful technology seamlessly imports data from diverse formats, including BIM (Building Information Modelling) and CAD (Computer-Aided Design). It integrates data from various systems such as PLM (Product Lifecycle Management), ERP (Enterprise Resource Planning), and IoT (Internet of Things). Unity's data preparation tools are nothing short of impressive, facilitating the import and optimisation of over 70 formats. This results in the creation of a unified, real-time representation of physical assets that forms the bedrock of digital twins (Unity, n.d.).

When it comes to flexible and efficient creation tools for digital twins, Unity3D stands out as a global leader. Renowned as the foremost real-time 3D platform worldwide, Unity is further enhanced by a suite of complementary products that expedite the creation, editing, and real-time iteration of interactive 3D content. This accelerates the development process, enabling rapid deployment of digital twins.

Unity3D also shines in the domain of dynamic visualisation, supporting an extensive range of devices and platforms. With compatibility for over 20 platforms, including HoloLens, Quest, Windows, Mac, iOS, Android, and more, Unity3D emerges as a versatile choice for digital twin applications. It's not just versatility; Unity is a leading platform for crafting content for AR and VR applications, underpinning a substantial portion of head-worn AR experiences (Unity, n.d.)

To streamline digital twin development, Unity3D provides advanced simulation services. These services encompass sensor and robotics emulation, performance-optimised simulation testing, and training, among others. Collectively, these features expedite decision-making processes. Unity3D's hallmark features, including versatility, real-time capabilities, and extensive support for diverse devices and platforms, establish it as an indispensable platform for the visualisation and deployment of digital twins (Unity, n.d.).

The decision to adopt Unity as the foundational platform for the digital twin application is grounded in a solid foundation of reasons. Spatial rendering, especially for spatial-oriented data, presents a complex challenge that has long been the focus of the game industry. This challenge has led to the development of specialised software, often called game engines, which offer comprehensive toolsets and reusable components finely tuned for 3D rendering. In this landscape of options, Unity emerged as the optimal choice for the project, bolstered by familiarity with the platform, rooted in a background as a game development student (Leskovsky et al., 2020).

Unity earns favour for several compelling reasons. It provides extensive support for all essential aspects of the planned development, both directly and indirectly. Unity's user-friendliness ensures ease of learning, and its cost-effective pricing conditions are noteworthy. Moreover, Unity boasts comprehensive documentation and is distinguished for its rapid growth, continuously introducing new functionalities.

By choosing Unity, the potential of this versatile 3D engine is unlocked. It empowers the crafting of three-dimensional objects within a virtual space, offering dynamic manipulation, movement, and rotation. It also allows for the seamless integration of data from IoT devices. In the case of the crane, equipped with a multitude of IoT sensors, Unity's prowess in gathering and processing data from these sensors is invaluable. In the context of digital twin development, reliance on Figure 2, a schematic diagram illustrating the integration of Digital Twins within Unity3D serves as a valuable reference for the project (Gao et al., 2023). These capabilities lay the foundation for the immersive environment that the digital twin requires.

A diagram of a cloud server

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*Figure 2 – A schematic diagram of using Digital Twins in Unity3D (Gao et al., 2023).*

The camera, a pivotal component in 3D applications, plays a central role in shaping the user's viewpoint and impacting application control and display. Our application offers a spectrum of camera view modes, catering to diverse user needs, from PC desktop viewing to immersive VR experiences with headsets like Oculus. Unity's cross-platform compatibility is a standout advantage, allowing us to develop a unified application seamlessly running across platforms, spanning PCs, mobile phones, and the web. Unity further equips us with robust VR and AR tools that intuitively adapt the camera and interface to accommodate users and their equipment, whether involving a joystick, headsets, or other devices (Gao et al., 2023).

This combined section emphasises Unity3D's pivotal role in digital twin development and offers a comprehensive perspective on the reasons for choosing Unity as the foundational platform for our digital twin application.

## Case Study



### Importance of Case Studies

In the realm of technological advancements and systems improvement, case studies play a pivotal role in showcasing the significance of innovation. The case of DIAMND (Diagnostics and Monitoring), a Crane Management System, serves as a compelling example of how such studies shed light on the transformation of existing systems. It highlights the importance of critically examining and addressing the challenges posed by legacy technologies, especially when it comes to aesthetics and functionality. The importance of this case study lies in its potential to inspire others to explore new, more efficient solutions and improve the user experience, as well as to create visually appealing interfaces for data management systems.

### DIAMND: An Overview

In this case study, the goal is to address the limitations of the DIAMND system and propose a more effective solution. According to Dr David McMahon from Liebherr (2023), the existing DIAMND system used for crane management faces various challenges, particularly in terms of appearance and functionality.

Throughout this project, active engagement with members of the sales and engineering teams at Liebherr has been crucial in gathering insights and requirements for the improved system. These inputs have played a significant role in shaping the approach. This case study highlights the potential of modern technology and data-driven solutions in not only overcoming the limitations of legacy systems like DIAMND but also in improving the overall user experience and aesthetics of crane management operations.



#### Addressing The Challenges

In this section, the existing DIAMND system is examined, highlighting the imperative need for its transformation. DIAMND serves as the primary approach to crane management, but it presents a series of challenges, particularly in terms of aesthetics and functionality. These challenges stem from its reliance on data acquisition from various sources, including direct connections to a crane's PLC through SignalR and OPC-UA, hourly trace files containing approximately 35,000 signals, and feedback arrays within the PLCs, which are used to populate job and load statistics tables in SQL.

One of the significant challenges is the complexity of data management. The DIAMND system grapples with data acquisition, storage, and presentation intricacies. Diverse data sources not only make data management convoluted but also introduce noise and irrelevant information into the system. This noise can obscure critical data, contributing to inefficiencies and suboptimal data aesthetics.

Another issue is the outdated user interface. As highlighted in Figure 3 and Figure 4 below, the user interface of the DIAMND system is visually unappealing and does not align with modern design principles. This not only impacts the user experience but also underscores the pressing need for a modern and visually pleasing solution. It's worth noting that the current interface appears thrown together, lacking proper labels, and missing the company's distinctive touch, including its logo.

*A screenshot of a computer

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*Figure 3 – A view of the main spreader information displayed in DIAMND (Liebherr, 2023).*

A screenshot of a computer

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*Figure 4 – A view of some spreader information displayed in DIAMND (Liebherr, 2023).*

#### Proposed Solutions

To address these formidable challenges, a comprehensive transformation of the DIAMND system is proposed to streamline data management and enhance the user experience. Firstly, the utilisation of an API (Application Programming Interface) is recommended to seamlessly query data from an OPC-UA Server, connected to PLC, for certain variables and send it to an Azure database. This streamlined approach simplifies data acquisition, ensuring that relevant information is obtained swiftly and accurately. Secondly, data will be securely stored in an Azure database, offering enhanced data management capabilities. The Azure platform provides scalability, reliability, and accessibility, facilitating efficient data storage and retrieval. Lastly, to improve data aesthetics and user-friendliness, the implementation of Power BI for data visualisation is proposed. This powerful tool enables the creation of clear and visually appealing data presentations, making it easier for users to derive insights from the information.

The proposed solutions promise to mitigate the challenges faced by the existing DIAMND system, offering a path toward more efficient, user-friendly, and visually appealing crane management, in alignment with contemporary standards and user expectations.

### Lessons from Previous Implementations

Drawing on lessons from previous implementations, the DIAMND case study provides valuable insights for future projects. By examining the challenges and successes of this transformation, lessons can be extracted that extend beyond crane management. The key takeaway is the importance of aligning technology with user expectations and needs. Learning from this case study can guide future implementations, ensuring they are more efficient, user-friendly, and aesthetically pleasing.

## Internet of Things (IoT)



### Fundamentals of IoT

The IoT represents a transformative concept introduced by Kelvin Ashton in 1999, facilitating the connection of physical objects through the Internet to establish a platform for various activities (Gamil et al., 2020). The IoT framework encompasses a network of physical objects embedded with sensors, software, and other technologies, enabling data exchange with other devices and systems over the Internet. The current IoT landscape boasts around 14.76 billion connected devices (Howarth, 2023), with Oracle (n.d.) projecting a surge to over 22 billion by 2025.

The IoT framework is theoretically organised into four distinct layers, seen in Figure 5, that collectively contribute to its functionality. The application layer serves as a hub for various applications and services, ranging from smart cities and homes to transportation, utilities, and healthcare. In this layer, IoT manifests its diverse applications, becoming an integral part of modern living. The perception layer introduces sensory technologies like temperature, vibration, pressure sensors, and RFID (Radio Frequency Identification) sensors, allowing devices to gain awareness of their surroundings. This layer is pivotal in facilitating the acquisition of real-world data by IoT devices. The network layer is the communication backbone, encompassing both software and physical components that enable data transmission between devices and receivers. Its role is fundamental in ensuring seamless connectivity and interaction within the IoT ecosystem. Finally, the physical layer constitutes the basic hardware elements, including physical components, smart appliances, and power supplies, forming the infrastructure that supports the networking of smart objects. Each layer plays a crucial role in shaping the intricate fabric of the IoT (Kumar et al., 2016).

A diagram of a network layer

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*Figure 5 – The four layers that make up the IoT (Kumar et al., 2016).*

### IoT and Industry 4.0

Industry 4.0 represents an important paradigm shift in the manufacturing sector and involves the integration of information and communication technologies into industrial processes. Formed in Germany, Industry 4.0 represents the fourth industrial revolution, after the era of mechanical energy (Industry 1.0), mass production (Industry 2.0), and the digital revolution (Industry 3.0). At its core, Industry 4.0 relies on the fusion of CPS (Cyber-Physical Systems), CM (Cloud Manufacturing), and the IoT. CPSs comprise machines, storage systems, and production facilities capable of autonomously exchanging information, triggering actions, and monitoring one another. These systems combine virtual and physical elements of production by integrating analogue and digital devices. The Internet of Things is the key technology of Industry 4.0, providing the platform to connect CPSs through a network of sensors, actuators, and devices. CM, a concept born from Industry 4.0, harnesses the capabilities of cloud computing in external data centres to optimise production processes. This harmonious integration of technologies underpins the Industry 4.0 revolution, fostering a new era of smart manufacturing characterised by efficiency, connectivity, and data-driven decision-making (Ben-Daya et al., 2017).

### IoT Integration and Digital Twinning Integration

After elucidating the fundamentals of IoT and its crucial role in Industry 4.0, attention now turns to the transformative amalgamation with Digital Twinning, unveiling its practical application in refining construction processes. The convergence of IoT with Digital Twinning heralds a groundbreaking advancement in technological capabilities. The seamless connectivity facilitated by IoT aligns seamlessly with Digital Twinning's virtual replication of physical entities. Within this integrated framework, IoT sensors and devices continually gather real-time data from the physical environment, ensuring a constant update of corresponding digital twins. This dynamic interconnection significantly enhances comprehension of the physical system's behaviour, performance, and potential issues (Gamil et al., 2020).

In the context of the overarching Digital Twinning in Cranes project, the synergy between IoT and Digital Twinning goes beyond mere connectivity. It enables the creation of virtual replicas of cranes that are continuously updated in real-time. This functionality not only facilitates advanced monitoring but also empowers predictive maintenance capabilities. This harmonious integration becomes a catalyst for optimising crane operations, resulting in reduced downtime and an overall enhancement of efficiency in construction processes (Gamil et al., 2020).

Moreover, the significance of real-time monitoring is underscored by its application in construction project management. Observations derived from websites and sensor-based information prove pivotal in advancing critical stages of construction projects (BIM Engineering, 2018). These insights, by minimising delays and fostering efficient operational strategies, play an invaluable role. IoT solutions complement this by providing real-time alerts to supervisors concerning resource shortages or operational issues, highlighting real-time monitoring as a top-tier application of IoT. This proactive approach effectively mitigates downtime caused by stockouts or employee performance issues. The amalgamation of IoT-driven real-time observations and Digital Twinning's virtual replication establishes a comprehensive framework for elevating construction project management and operational efficiency.

## Big Data and Visualisation



### An Overview

In the contemporary business landscape, success is intricately tied to the effective utilisation of data. The evolution of technology and the internet has led to an unprecedented proliferation of information, making data a cornerstone of every successful enterprise.

Big Data refers to extensive datasets characterised by complex structures that present challenges in storage, analysis, and visualisation. With the continuous growth in data generation from various sources such as online transactions, social interactions, and IoT devices, businesses and organisations are compelled to explore innovative approaches for managing and extracting value from these vast datasets (Allaymoun et al., 2022).

Big data encompasses vast and exponentially growing quantities of information. Traditional data analytics tools face challenges in analysing such massive datasets, with examples including the daily generation of over 1 TB of data by the New York Stock Exchange and 400 TB+ daily data by social media platforms like Facebook (Rana et al., 2023).

### Classifying Big Data

Delving into the taxonomy of big data, Rana et al. (2023) provide valuable insights into its various types, namely structured, unstructured, and semi-structured data. Each category brings its own set of characteristics, highlighting the multifaceted nature of data in contemporary analytics.

Structured data is represented in a well-defined manner, often in the form of rows and columns. It is easily amenable to data models, facilitating relationships, updates, deletions, and modifications. The security features of structured big data are also relatively straightforward.

In contrast, unstructured data lacks a definite structure and cannot be easily fit into data models. This type of data is often portable and scalable, presenting challenges in storage due to the absence of a proper schema.

Semi-structured data possesses some structure but does not conform to a rigid data model. It includes metadata for grouping and describing data, offering flexibility and portability. While queries on structured big data are more efficient, semi-structured data accommodates diverse properties and sizes within the same group.

A diagram of a big data

Description automatically generated

*Figure 6 – Big Data Types (Rana et al., 2023).*

### Benefits and Challenges of Big Data Analysis

The analysis of large datasets offers substantial benefits, including the development of efficient techniques for predicting future observations and gaining insights into the relationships between different variables. Big data analytics, with its focus on exploring heterogeneity and commonality across subpopulations, provides a unique opportunity to uncover hidden structures and extract essential common traits.

The landscape of big data analytics is evolving rapidly, driven by technological innovations such as big data and cloud computing. Cloud-based delivery models, exemplified by platforms like Amazon’s Big Data Analytics and SAP Big Data Analytics, offer scalable and accessible solutions for organisations seeking to harness the power of big data (Allaymoun et al., 2022).

Despite the advancements, challenges persist in efficiently pricing and distributing data in big data services. To address this, an auction-based big data market model is proposed, incorporating considerations of data size and analytics performance. The integration of machine learning algorithms and Bayesian profit maximisation auctions aims to provide a rational and computationally efficient mechanism for optimising service pricing and data distribution (Allaymoun et al., 2022).

### Data Visualisation in the Era of Big Data

Data visualisation, the graphical representation of information, has long been a valuable tool for conveying complex concepts quickly and effectively. Traditionally, data visualisation has been instrumental in detecting patterns in data; however, with the exponential growth of data, traditional approaches are becoming obsolete (Allaymoun et al., 2022). Now, more than ever, the importance of data visualisation is huge: it helps people see, interact with, and better understand data. Whether simple or complex, the right visualisation can bring everyone on the same page, regardless of their level of expertise.

In the realm of IoT, Data visualisation emerges as a state-of-the-art technology. The continuous stream of information from IoT devices gains exponential value through meaningful insights derived from visualisation techniques. Visualisation serves as a bridge between raw data streams and actionable insights, enhancing users' understanding of data patterns and trends (Allaymoun et al., 2022).

The intersection of Big Data and the IoT is a critical juncture in the technological landscape. IoT focused on assigning IP addresses to every object and enabling their interconnectedness, generates massive volumes of data. Big Data analytics becomes indispensable in extracting meaningful conclusions from the raw data churned out by trillions of interconnected devices (Allaymoun et al., 2022).

The characteristics of IoT data align with the defining features of Big Data, encompassing volume, variety, velocity, veracity, and value. The sheer volume of data generated by IoT devices, its diverse forms, real-time streaming, reliability, and the practical value it provides contribute to categorising IoT data as Big Data.

A diagram of a big data flow

Description automatically generated

*Figure 7 – Big Data and IoT relationship (Mukherjee et al., 2022).*

The symbiotic relationship between Big Data and IoT is evident in their mutual benefits. While Big Data enables real-time analysis of IoT-generated data, the growth in IoT technologies prompts a demand for greater Big Data capacities. This reciprocal interaction drives technological advancements in both fields.

### Data Visualisation in the IoT Landscape

Data analytics in IoT involves analysing datasets to extract fundamental conclusions and valuable insights. Effective data analytics is crucial for advancing IoT applications and ventures, providing the necessary tools for making informed decisions based on the analysed data.

The transformative potential of insights derived from IoT data hinges on robust reporting and visualisation tools. Key factors influencing effective data visualisation in IoT include identifying pertinent information, selecting an appropriate reporting style, simplifying reports, considering enterprise data integrations, and establishing best practices for streamlined reporting (Il-Agure & Dempere, 2022).

IoT visualisation systems incorporate custom dashboard interfaces to aid users in analysing raw metrics. These dashboards provide real-time updates, interactive elements, and clarity, enhancing operators' confidence in AI models. Various visualisation models, including Tableau, Thingsboard, IBM Watson, Grafana, and Kibana Platform, offer diverse approaches to presenting and simulating IoT metrics.

### Data Visualisation and Unity

The integration of Unity, a robust game development engine, with Adobe Photoshop, introduces a dynamic synergy that transcends traditional boundaries in data visualisation, especially considering the limited availability of dedicated visualisation tools compatible with Unity. While Unity provides a powerful platform for creating immersive and interactive environments, the existing tools for intricate data visualisation within Unity are scarce. This scarcity highlights the significance of incorporating external software, such as Adobe Photoshop, to meet the advanced visualisation needs. By combining Unity's game development prowess with Photoshop's sophisticated visualisation capabilities, creators can unlock a new dimension in visual storytelling, addressing the challenges posed by the absence of dedicated data visualisation tools tailored for Unity. The result is a harmonious blend of Unity's interactive potential and Photoshop's graphic finesse, offering a unique solution to the limitations of conventional data visualisation tools within the Unity framework.

In addition to leveraging Adobe Photoshop for advanced visualisations in Unity, another viable option is the integration of Power BI, a robust business analytics tool, seamlessly embedded within the Unity environment. This integration not only expands the visualisation capabilities within Unity but also provides a user-friendly interface for dynamic data exploration. By embedding Power BI into Unity, developers and designers can harness its rich features for data analysis, reporting, and interactive dashboards, seamlessly merging the functionalities of both platforms. The combination of Unity, Adobe Photoshop, and Power BI offers a comprehensive solution to the challenges posed by the lack of dedicated visualisation tools, allowing creators to craft visually engaging and data-driven experiences within a unified development environment.

In the context of handling substantial datasets, opting for a business intelligence (BI) tool like Microsoft Power BI, as advocated by Rana et al. (2023), proves advantageous compared to conventional tools like Excel. One notable advantage lies in the superior processing speed of Power BI, outpacing Excel's capabilities when dealing with extensive data volumes. The visualisations crafted within Power BI are not only faster but also more aesthetically appealing, enhancing the overall user experience. The utility of Power Queries further facilitates the manipulation of vast datasets with ease, providing a streamlined approach to data management. In contrast, Excel encounters limitations, capping at 1.4 million rows and 16.38 thousand columns, rendering it inadequate for handling big data scenarios. Relying on Power BI, as recommended by Rana et al. (2023), addresses these shortcomings, offering a robust solution for efficient data processing, visually compelling representations, and seamless data manipulation in the realm of extensive datasets.

### Data Acquisition in Industry 4.0

Data acquisition in Industry 4.0 big data analytics systems involves collecting data from field devices for storage, visualisation, and analytics. Common data communication protocols such as OPC-UA and Modbus enable real-time or batch-oriented data collection. IoT gateways play a crucial role in data gathering, providing services like protocol translation, encryption, data processing, and wireless networking (Kahveci et al., 2022).

The accessibility and affordability of sensors allow industrial devices to generate massive amounts of data. IoT-enabled cloud platforms, exemplified by solutions like GE’s Predix, ABB’s Ability, and Microsoft Azure, offer capabilities for analysing raw production data. However, these platforms introduce dependencies on external connectivity, proprietary technologies, and custom implementation (Kahveci et al., 2022).

## Communication Protocols



### An Overview.

Communication protocols play a crucial role in enabling the seamless exchange of data and information across networks. These protocols are sets of formal rules that define how data should be transmitted or exchanged, especially in the context of real-time monitoring and the IoT. Various standardised communication protocols facilitate the availability of data through different channels, such as web servers using HTTP (Hypertext Transfer Protocol), file servers through FTP (File Transfer Protocol), or well-documented APIs. In addition, other examples include TCP/IP (Transmission Control Protocol/Internet Protocol), UDP (User Datagram Protocol), POP3 (Post Office Protocol), CoAP (Constrained Application Protocol), XMPP (Extensible Messaging and Presence Protocol), AMQP (Advanced Message Queuing Protocol), IMAP (Internet Message Access Protocol), and SMTP (Simple Mail Transfer Protocol) (Rouse, 2023).

A diagram of a cloud computing system

Description automatically generated

*Figure 8 – Types of Communication Protocols (Bayılmış et al., 2022).*

One notable protocol that has evolved beyond its original purpose is HTTP, which, through APIs, allows computer applications to efficiently share and access machine-readable data across the internet. APIs, or Application Programming Interfaces, act as messengers facilitating the interaction between software applications, systems, or platforms for data exchange (Airfocus, n.d.). MQTT also stands out as one of the most used, with HTTP leading the way in terms of widespread adoption. HTTP, originally designed for transmitting web pages, has evolved into a versatile protocol, particularly favoured for its simplicity, flexibility, and ease of integration. Its dominance is evident in its ranking as the most used protocol, as reflected in the 2020 data where it slightly outpaces MQTT. This preference for HTTP underscores its ubiquitous role in facilitating data transfer in web-centric applications and real-time projects. Meanwhile, MQTT, known for its efficiency in resource-constrained environments, continues to be a formidable choice, particularly in scenarios where low-cost reliability and asynchronous communication are critical. The dynamic between HTTP and MQTT exemplifies the nuanced decision-making involved in selecting communication protocols and aligning with project requirements and priorities. (Bayılmış et al., 2022).

A graph of different colored lines

Description automatically generated with medium confidence

*Figure 9 – Most used IoT Communication Protocols (Bayılmış et al., 2022).*

In the realm of real-time monitoring and IoT, communication protocols are vital for capturing and transmitting data efficiently. For instance, in fleet management, real-time data collection through vehicle fleet management software utilises communication protocols to monitor factors such as reckless driving or driver impairment, optimising fleet utilisation (Barney, 2023). In industrial scenarios, communication protocols like Modbus TCP/IP are employed to connect digital dashboards with Human-Machine Interfaces (HMI) and databases, ensuring real-time and reliable data exchange (Khan et al., 2020). Additionally, MQTT is a messaging transport protocol with a publish-subscribe architecture widely used in IoT applications, providing a reliable and efficient means of communication between devices (Bayılmış et al., 2022). The open OPC UA protocol is utilised to break communication barriers between virtual and real environments, enabling seamless data interaction in monitoring systems (Zhou et al., 2022).

### MQTT

MQTT stands out as a robust communication protocol, particularly well-suited for resource-constrained environments and scenarios where low-cost, open-source reliability and simplicity are paramount (Bayılmış et al., 2022). Developed with a publish-subscribe architecture, MQTT facilitates efficient messaging between clients and brokers. In this model, clients can take on the roles of either publishers or subscribers, and communication is achieved through topics assigned by the broker. MQTT's ability to handle different levels of QoS (Quality of Service) and its support for TCP/IP and TLS/SSL (Transport Layer Security/Secure Sockets Layer) make it a versatile choice for IoT applications (Bayılmış et al., 2022). With a focus on minimising data size, MQTT is designed to provide real-time communication for devices with limited resources, making it an excellent option for scenarios demanding lightweight and reliable messaging. (Bayılmış et al., 2022).

### REST

On the other hand, REST operates on an architectural style for networked systems, primarily using the HTTP protocol. Widely adopted for its simplicity, flexibility, and ease of integration, REST is a preferred choice for web-based applications (Barney, 2023). RESTful services adhere to a stateless client-server model, with data transfer accomplished through standard HTTP methods such as GET, POST, PUT, and DELETE. The REST architecture treats each component as a resource, accessible through a Uniform Resource Identifier (URI). This simplicity, coupled with the ability to use various data formats like JSON or XML, makes REST well-suited for real-time projects where a straightforward communication model and web-centric interactions are crucial (Barney, 2023). The stateless nature of REST simplifies implementation and ensures seamless integration, making it an attractive option for applications emphasising ease of use and standardised communication.

### APIs

APIs serve as essential tools in software development, facilitating interaction between different software applications, systems, or platforms by defining a set of rules and protocols for communication. An API acts as a messenger that enables the exchange of data between diverse software components. It allows developers to access the functionality of an application or service without delving into its internal workings. APIs play a pivotal role in enhancing interoperability, scalability, and efficiency in software development. They enable the seamless integration of various services and functionalities, promoting a modular and collaborative approach to building software systems. APIs can be used in a myriad of scenarios, from enabling social media logins and processing payment transactions to implementing price comparison features for vacations. Their versatility makes them a fundamental component of modern software architecture. APIs should be employed when there is a need for different software components to communicate and share data in a standardised and efficient manner. They provide a means for developers to harness the capabilities of existing services, fostering innovation, and streamlining the development process (Barney, 2023).

### Real-Time Monitoring

Real-time monitoring, as defined by Barney (2023), is the continuous delivery of updated data pertaining to systems, processes, or events with minimal latency between data collection and analysis. This approach involves the meticulous collection and storage of performance metrics as data traverses a network, utilising polling and streaming mechanisms from infrastructure devices. The significance of real-time monitoring lies in its ability to bridge the critical gap between the time a problem occurs and the time it is addressed. This is particularly crucial as delays in reporting and subsequent action can result in substantial financial costs. Real-time monitoring addresses this challenge by providing instantaneous data, alerts, and notifications. By offering a constant stream of information, organisations can promptly identify and respond to issues, ensuring that proactive measures are taken swiftly. This not only aids in preventing potential disruptions but also enhances overall system efficiency and reliability, making real-time monitoring an indispensable component in contemporary operational frameworks.

## Cloud Computing

Cloud computing, a transformative paradigm, provides users with internet-based access to diverse computing services, eliminating the need for on-site infrastructure. This model, featuring on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service, allows flexible resource management and cost-effectiveness. With three service models—Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS)—cloud computing supports various applications, from basic storage to advanced data analytics. In the context of the IoT, cloud technologies are crucial for managing the exponential growth of data. Cloud service models, including private, public, and hybrid options, offer versatile solutions for IoT integration. While financial considerations impact deployment choices, cloud computing remains a vital enabler for scalable and efficient IoT operations, aligning with industry trends (Khan et al., 2020).



# Methodology



## Research Undertaken

This project's research primarily focuses on digital twins, data visualisation, and real-time monitoring. Digital twins are explored for their potential to enhance ergonomic assessments by creating virtual replicas of physical processes. The study investigates real-time monitoring methodologies, including sensors and IoT, to establish a robust monitoring infrastructure. Additionally, the research emphasises the importance of data visualisation techniques, such as dashboards and 3D visualisations, to present complex spatial data in a comprehensible manner.

## Research Question

The central focus of this project is to investigate the impact of implementing Digital Twin technology alongside a fleet monitoring dashboard. The primary research question guiding this study is:

"Does the real-time implementation of digital twin technology, combined with a fleet monitoring dashboard, contribute to enhancing visual clarity and efficiency in crane system monitoring?"

## Proposed Implementation

The project's primary goal is to develop a comprehensive solution for crane system monitoring by integrating a Unity-based digital twin and a Photoshop-designed dashboard. The Unity digital twin will be instrumental in replicating and visualising historical data received from crane operations, providing a dynamic representation of the crane systems. Concurrently, a user-friendly dashboard will be created in Photoshop to seamlessly interface with the Unity digital twin, offering an accessible platform for users to monitor and interpret key spatial and operational data. The Unity digital twin will leverage real-life historical crane data to accurately mimic and simulate crane operations within a virtual environment.

## Functional Design

### Risk Analysis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Description** | **Likelihood** | **Impact** | **Mitigation Activity** | **Plan of Action** |
| Data cannot be acquired | Low | High | Look for an alternative dataset on Kaggle | Be in frequent contact with the company and ensure data delivery |
| Not enough data is available | Low | High | Reach out promptly to explore and acquire additional data. | Frequent communication with the company to obtain requirements on time |
| Data requires pre-processing | Medium | Low | Use the KDD process to pre-process the data | Use the KDD process to pre-process the data |
| Uncertainty in Physics and Forces Data | High | Medium | Use the best available data to create the most accurate digital twin. | Implement a continuous improvement process to update the model when updates are available |

*Table 1 – Risk Analysis Table.*

### Functional Specifications

The MoSCoW method is a prioritisation technique used in project management to categorise requirements into four priority groups: Must-haves, Should-haves, Could-haves, and Won't-haves. Here's a bit more detail on each category (Brush, 2023).

|  |  |  |  |
| --- | --- | --- | --- |
| **Must Have** | **Should Have** | **Could Have** | **Won’t have** |
| Digital Twin Integration | Real-Time Data Integration | AR/VR Integration | Mobile Application |
| Monitoring Dashboard | Data Storage and Retrieval | Interactive Dashboard | Predictive Analysis |
| Using Data sets from Real World Cranes |  | Customisable Dashboard | Alerting System |

*Table 2 – MoSCoW Method.*

## Data Collection and Analysis

Data is collected via a Crane’s PLC in the form of .trc files. These files encompass an extensive dataset, comprising over 30,000 variables that encapsulate the nuanced details of the STS crane's operation at specific timestamps. Employing Liebherr's trace tool program proves instrumental in navigating this wealth of variables, facilitating the extraction of those most pertinent to the project's objectives. This tool streamlines the process of organising and extracting the selected variables, which are subsequently exported into a CSV file. The initial dataset used for prototype one was provided by our team; however, for future iterations, the plan is to autonomously handle the data collection process. Additionally, before deployment, thorough cleaning and validation processes will be implemented to ensure the integrity and reliability of the data before its incorporation into the project.

## Prototype

In the initial phase of developing Prototype 1 for the digital twin in Unity, the focus was on implementing basic functionality, starting with the movement of the trolley. The foundation was laid by coding an incremental loop that enabled manual control of the trolley's position within the virtual environment. Once this fundamental movement was successfully established, the next step involved introducing a more dynamic and realistic element. Values representing the trolley's position were then read from a CSV file, a process integral to mirroring real-life crane movements. This approach allowed for a more nuanced and data-driven simulation, aligning the digital twin's behaviour closely with the operational data collected from the physical crane.

A computer screen shot of a bridge

Description automatically generated

*Figure 10 – Unity Scene for Prototype 1.*

# Implementation



## Sprint One (Jan 18th – Feb 1st)

During the initial sprint, tasks encompassed data manipulation using a trace tool, setting up a Unity project, establishing a scene for the digital twin, integrating crane data into a 3D environment, and designing a user interface in Photoshop.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Manipulate data via Trace Tool | Complete |
| 2 | Set up a project in Unity | Complete |
| 3 | Set up a scene for the Digital Twin | Complete |
| 4 | Integrate data from task one with Digital Twin | Complete |
| 5 | Design the first draft of the UI in Photoshop | Complete |

*Table 3 – Sprint one tasks.*

### Task 1

In the preliminary project phase, the utilisation of Liebherr’s trace tool facilitated a comprehensive exploration of raw data. The tool's functionality enabled effective manipulation and analysis, leading to the extraction of valuable insights. The result was the creation of a meticulously structured .csv file, containing pertinent information for subsequent integration into the Unity environment.

A screenshot of a computer

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*Figure 11 – Liebherr Trace Tool.*

### Task 2

The initiation of the development process involved the creation of a new Unity project. This encompassed the configuration of project settings, the establishment of a clear project structure, and alignment with the digital twin initiative's requirements. The setup in Unity laid a sturdy foundation for ensuing tasks, streamlining the overall development workflow.

### Task 3

A basic scene was set up with the crane model, as illustrated in Figure 10 above. This involved the incorporation of the crane model into the Unity environment, establishing a preliminary spatial layout for the digital twin. This foundational step set the stage for subsequent tasks related to crane data integration.

### Task 4

Leveraging the prepared .csv file, the successful integration of manipulated data into the Unity 3D environment was achieved. This encompassed mapping crane data to corresponding elements within the scene, generating a dynamic representation of real-world crane operations. The integration process facilitated seamless data visualisation in a 3D space. Two key classes, namely ReadData and CraneMovement, played crucial roles in achieving this goal.

The ReadData class handles asynchronous reading of crane data from a CSV file. It utilises a coroutine to continuously read and update trolley and hoist positions based on the CSV data. The class ensures proper error handling and provides flexibility with a configurable delay between data reads.

private IEnumerator readCSV()

{

string fullPath = Path.Combine(Application.dataPath, csvFilePath);

if (!File.Exists(fullPath))

{

Debug.LogError("CSV file not found: " + fullPath);

}

string csvFileText = File.ReadAllText(fullPath);

StringReader reader = new StringReader(csvFileText);

string headerLine = reader.ReadLine();

string[] headers = headerLine.Split(',');

while (reader.Peek() != -1)

{

string line = reader.ReadLine();

string[] rowData = line.Split(',');

trolleyPosString = rowData[Array.IndexOf(headers, "Trolley\_Position")];

hoistPosString = rowData[Array.IndexOf(headers, "Hoist\_Position")];

string dateTime = rowData[Array.IndexOf(headers, "Timestamp")];

modeInt = int.Parse(rowData[Array.IndexOf(headers, "Mode")]);

string windSpeedString = rowData[Array.IndexOf(headers, "Wind\_Speed")];

string totalLoadString = rowData[Array.IndexOf(headers, "Hoist\_TotalLoad")];

int isLockLocked = int.Parse(rowData[Array.IndexOf(headers, "TwistLockAreLocked")]);

int isLockUnlocked = int.Parse(rowData[Array.IndexOf(headers, "TwistLockedAreUnlocked")]);

int isSpreaderLanded = int.Parse(rowData[Array.IndexOf(headers, "SpreaderIsLanded")]);

startInt = int.Parse(rowData[Array.IndexOf(headers, "IsStartTime")]);

endInt = int.Parse(rowData[Array.IndexOf(headers, "IsEndTime")]);

if (!hasContainer && isLockLocked > 0)

{

if (!initialConditionMet)

{

initialConditionMet = true;

containersCarried++;

}

hasContainer = true;

}

else if (isLockLocked < 1 && isSpreaderLanded < 1)

{

initialConditionMet = false;

hasContainer = false;

}

date = DateTime.Parse(dateTime);

timeOfDay = date.TimeOfDay;

trolleyPos = float.Parse(trolleyPosString);

hoistPos = float.Parse(hoistPosString);

windSpeed = float.Parse(windSpeedString);

totalLoad = float.Parse(totalLoadString);

isLocked = isLockLocked == 1 ? true : false;

isUnlocked = isLockUnlocked == 1 ? true : false;

isLanded = isSpreaderLanded == 1 ? true : false;

modeChar = checkMode();

checkMove();

yield return new WaitForSeconds(LOOP\_DELAY);

}

}

private void checkMove()

{

if(startInt == 1)

{

moveStarted = true;

activeMove = true;

}

else

{

moveStarted = false;

}

if (endInt == 1)

{

moveFinished = true;

activeMove = false;

}

else

{

moveFinished = false;

}

}

private char checkMode()

{

if (modeInt == 0)

{

return 'M';

}

return 'A';

}

*Code Snippet 1 – ReadData.cs script*

The CraneMovement class orchestrates the real-time visualisation of crane components in the Unity scene. It relies on the positions obtained from the ReadData class to dynamically update the positions of the trolley and hoist game objects. The continuous Update method ensures synchronised movement in the Unity environment, offering a visually representative digital twin of the crane operations.

### Task 5

In the pursuit of enhancing user interaction and data presentation, Photoshop was utilised to craft an intuitive and visually appealing user interface (UI). The UI design prioritised clarity and conciseness in displaying crane data, ensuring users could readily interpret and interact with information within the digital twin environment. This step aimed to enhance the overall user experience and facilitate efficient data analysis.

A screenshot of a computer

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*Figure 12 – First draft of UI*

### Results

The sprint concludes with the successful creation of a basic digital twin prototype, emulating historical crane movements. Additionally, a preliminary UI draft has been developed, setting the stage for further integration and refinement in subsequent phases.

## Sprint Two (Feb 1st – Feb 15th)

Sprint two focused on expanding the Unity project by integrating additional important data such as wind speed and weight. A redesigned user interface for a spreader view was implemented and seamlessly integrated into the Unity project. A useful feature introduced was a dynamic switch for users to effortlessly toggle between different views, enhancing flexibility and user engagement.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Add more key data points to the Unity project | Complete |
| 2 | Design new UI for Spreader analysis | Complete |
| 3 | Integrate UI and Unity project | Complete |
| 4 | Add a feature to allow a spreader view or full crane view | Complete |

*Table 4 – Sprint two tasks.*

### Task One

Task one in sprint two involved the retrieval of additional crucial data using the trace tool. This data, converted to CSV format, was seamlessly read by the Unity script, expanding the range of information integrated into the digital twin. By broadening the spectrum of data sources, the digital twin became enriched with additional parameters, such as wind speed and weight, elevating the overall accuracy and realism of the simulation.

### Task Two

The second task delved into the refinement of the user interface, specifically tailored for the spreader view. Building upon the initial UI draft, significant improvements were made to enhance clarity and usability. Notable enhancements included the incorporation of twist lock states and the transition from radial to linear gauges, offering users a more precise visual interpretation of data. Additionally, the introduction of labels in the top row provided explicit insights into the meaning of each reading, fostering a more intuitive understanding for users interacting with the spreader view.

A screenshot of a computer

Description automatically generated

*Figure 13 – Update UI for Spreader Analysis.*

### Task Three

Task three seamlessly integrated the redesigned UI into the Unity project using the canvas element. Leveraging the expanded dataset from task one, the UI effectively displayed a comprehensive set of information, contributing to an enriched user experience within the digital twin environment.

A screenshot of a computer

Description automatically generated

*Figure 14 – Unity & Spreader UI (Fig.13) integrated.*

### Task Four

The fourth task introduced a pivotal feature to enhance user interaction – a dynamic switch between different views. Through the implementation of a toggle and a snippet of C# code, users gained the capability to effortlessly navigate and toggle between various perspectives within the 3D environment. This not only added a layer of flexibility but also elevated user engagement, allowing for a more personalised and dynamic exploration of the digital twin's features and functionalities.

A screenshot of a computer

Description automatically generated

*Figure 15 – Spreader Cam toggle on.*

### Results

The outcomes of sprint two yielded a digital twin that significantly advanced in both functionality and user experience. The expanded integration of trace tool data, including wind speed and weight, enriched the simulation's realism and accuracy. Users now benefit from a more comprehensive and nuanced understanding of the crane's behaviour within the 3D environment. The refined spreader view UI, with its improved clarity and precise gauge representations, ensures a more user-friendly interaction, facilitating a more intuitive grasp of critical information. The successful integration of this enhanced UI into the Unity project further solidifies the cohesion of the digital twin, providing users with a seamlessly integrated platform for comprehensive data analysis. The introduction of the dynamic switch feature adds an extra layer of versatility, empowering users to effortlessly switch between different views and tailor their exploration based on specific needs, contributing to heightened engagement and usability. Overall, sprint two delivered a more sophisticated and user-centric digital twin, well-equipped to meet the evolving demands of the project.

## Sprint Three (Feb 15th – Feb 29th)

Sprint three marks the lift cycles being incorporated into the Unity project, providing a comprehensive representation of the crane's operational patterns. Concurrently, in task two, Azure Functions are developed to streamline and automate processes. In task three, the Unity project leverages these functions to store lift cycles in an Azure database, fostering efficient data management. The integration of the Azure database sets the stage for task four, where lift cycle data is seamlessly implemented into Power BI for comprehensive visualisation and analysis. Sprint Three not only expands the digital twin's functionality by incorporating lift cycles but also establishes a robust data pipeline, utilising Azure services to enhance storage, retrieval, and visualisation processes, thereby advancing the overall sophistication and utility of the digital twin.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Add lift cycles & display them in the Unity Project | Complete |
| 2 | Create Azure Functions | Complete |
| 3 | Use Function in Task 2 to store lift cycles in the Azure database | Complete |
| 4 | Using the Azure database implement the lift cycles into Power BI | Complete |

*Table 5 – Sprint three tasks.*

### Task One

In addressing the first task of sprint three, the focus was on integrating lift cycles into the Unity project, enhancing the digital twin's ability to accurately reflect the crane's operational patterns. The LineRendererManager.cs script stands at the core of this implementation.

public class LineRendererManager : MonoBehaviour

{

[SerializeField] internal ReadData data;

private LineRenderer lineRenderer;

private Line line;

private GameObject lineObject;

private int positionCount;

private int cycle = 0;

private float SecondTimer = 0;

private const float Second = 1f;

private DateTime startTime;

private DateTime endTime;

private double totalTime;

private string arcPath = "Assets/Data/ArcValues.csv";

private string liftCyclePath = "Assets/Data/LiftCycles.csv";

private const float MILLISECONDS = 1000f;

void Update()

{

SecondTimer += Time.deltaTime;

if (SecondTimer >= Second)

{

if(lineRenderer != null)

{

lineRenderer.positionCount = positionCount + 1;

lineRenderer.SetPosition(positionCount, transform.position);

line.AddPoint(data.trolleyPos, data.hoistPos, data.date, data.modeChar);

positionCount++;

SecondTimer = 0;

}

}

if (data.activeMove)

{

if (data.moveStarted)

{

cycle++;

CreateNewLineRenderer();

}

}

if (data.moveFinished)

{

GetPoints(line);

if (lineObject != null)

{

Destroy(lineObject);

}

}

}

private void CreateNewLineRenderer()

{

lineObject = new GameObject("Line " + cycle);

lineRenderer = lineObject.AddComponent<LineRenderer>();

positionCount = 0;

lineRenderer.material.color = Color.yellow;

line = new Line();

}

private async void GetPoints(Line line)

{

if (line.points.Count == 0)

{

Debug.Log("Line is empty.");

return;

}

for (int i = 0; i < line.points.Count; i++)

{

Line.Point point = line.points[i];

await SendToArcValues(cycle, i, point.Trolley\_Position, point.Hoist\_Position, point.DateTime, point.Mode);

startTime = line.points[0].DateTime;

endTime = line.points[line.points.Count - 1].DateTime;

TimeSpan duration = endTime - startTime;

totalTime = duration.TotalMilliseconds / MILLISECONDS;

}

await SendToLiftCycles(cycle, startTime, endTime, totalTime);

}

*Code Snippet 2 – LineRendererManager.cs script.*

Through the utilisation of Unity's Line Renderer component, the script efficiently tracks the crane's movements over time, creating a visual representation of lift cycles. The script employs timers to control the frequency of point updates, ensuring a dynamic and detailed depiction of the crane's trajectory. Additionally, it distinguishes between various operational modes, dynamically adjusting the colour of the automation line to provide clear visual cues. The creation of new line renderers for each lift cycle contributes to an organised and comprehensive visualisation of the crane's historical performance. This task sets the stage for subsequent tasks, establishing a foundation for efficient data management and external interactions in the ongoing development of the project.

### Task Two

The implementation of Azure Functions in sprint three represents a pivotal step towards achieving efficient data processing and storage within the digital twin project. The FunctionApp\_\_\_Database script encompasses two distinct functions: SendToArcValues and SendToLiftCycles, each responsible for handling specific data entries.

In the 'SendToArcValues' function, HTTP-triggered requests are processed, extracting essential data such as cycle ID, point, position coordinates, timestamp, and mode from the request body. Leveraging a secure SQL Server connection string, the function establishes a connection to the Azure SQL database and executes parameterized queries to insert the acquired data into the 'ArcValues' table. This seamless integration ensures the real-time storage of critical crane operational data.

[FunctionName("SendToArcValues")]

public static async Task<IActionResult> SendToArcValues(

[HttpTrigger(AuthorizationLevel.Function, "post", Route = null)] HttpRequest req,

ILogger log)

{

string connectionString = "Server=tcp:dwspocliebherr.database.windows.net,1433;Initial Catalog=ArcValues;Persist Security Info=False;User ID=dws1234;Password=dws\*1234;MultipleActiveResultSets=False;Encrypt=True;TrustServerCertificate=False;Connection Timeout=30;";

string requestBody = await new StreamReader(req.Body).ReadToEndAsync();

var data = HttpUtility.ParseQueryString(requestBody);

Console.WriteLine(data);

int cycleID = int.Parse(data["Cycle\_ID"]);

int point = int.Parse(data["Point"]);

float trolleyPos = float.Parse(data["Trolley\_Position"]);

float hoistPos = float.Parse(data["Hoist\_Position"]);

DateTime dateTime = DateTime.Parse(data["DateTime"]);

char mode = char.Parse(data["Mode"]);

try

{

using (SqlConnection connection = new SqlConnection(connectionString))

{

await connection.OpenAsync();

string insertQuery = "INSERT INTO ArcValues (Cycle\_ID, Point, Trolley\_Position, Hoist\_Position, DateTime, Mode) " +

"VALUES (@Cycle\_ID, @Point, @Trolley\_Position, @Hoist\_Position, @DateTime, @Mode)";

using (SqlCommand command = new SqlCommand(insertQuery, connection))

{

command.Parameters.AddWithValue("@Cycle\_ID", cycleID);

command.Parameters.AddWithValue("@Point", point);

command.Parameters.AddWithValue("@Trolley\_Position", trolleyPos);

command.Parameters.AddWithValue("@Hoist\_Position", hoistPos);

command.Parameters.AddWithValue("@DateTime", dateTime);

command.Parameters.AddWithValue("@Mode", mode);

await command.ExecuteNonQueryAsync();

}

}

log.LogInformation("Data saved to ArcValues successfully.");

return new OkResult();

}

catch (Exception ex)

{

log.LogError(ex, "An error occurred while saving data to Azure SQL.");

return new StatusCodeResult(StatusCodes.Status500InternalServerError);

}

}

*Code Snippet 3 – SendToArcValues function.*

Similarly, the 'SendToLiftCycles' function processes HTTP-triggered requests, extracting data related to lift cycle information, including cycle ID, start and end times, and total time. Mirroring the approach in the previous function, this data is securely inserted into the 'LiftCycles' table within the Azure SQL database. This function contributes to the holistic representation of crane performance, storing pertinent information on lift cycles for comprehensive analysis.

[FunctionName("SendToLiftCycles")]

public static async Task<IActionResult> SendToLiftCycles(

[HttpTrigger(AuthorizationLevel.Function, "post", Route = null)] HttpRequest req,

ILogger log)

{

string connectionString = "Server=tcp:dwspocliebherr.database.windows.net,1433;Initial Catalog=ArcValues;Persist Security Info=False;User ID=dws1234;Password=dws\*1234;MultipleActiveResultSets=False;Encrypt=True;TrustServerCertificate=False;Connection Timeout=30;";

string requestBody = await new StreamReader(req.Body).ReadToEndAsync();

var data = HttpUtility.ParseQueryString(requestBody);

int cycleId = int.Parse(data["Cycle\_ID"]);

DateTime startTime = DateTime.Parse(data["Start\_Time"]);

DateTime endTime = DateTime.Parse(data["End\_Time"]);

float totalTime = float.Parse(data["Total\_Time"]);

try

{

using (SqlConnection connection = new SqlConnection(connectionString))

{

await connection.OpenAsync();

string insertQuery = "INSERT INTO LiftCycles (Cycle\_ID, Start\_Time, End\_Time, Total\_Time) " +

"VALUES (@CycleID, @StartTime, @EndTime, @TotalTime)";

using (SqlCommand command = new SqlCommand(insertQuery, connection))

{

command.Parameters.AddWithValue("@CycleID", cycleId);

command.Parameters.AddWithValue("@StartTime", startTime);

command.Parameters.AddWithValue("@EndTime", endTime);

command.Parameters.AddWithValue("@TotalTime", totalTime);

await command.ExecuteNonQueryAsync();

}

}

log.LogInformation("Data saved to LiftCycles successfully.");

return new OkResult();

}

catch (Exception ex)

{

log.LogError(ex, "An error occurred while saving data to Azure SQL.");

return new StatusCodeResult(StatusCodes.Status500InternalServerError);

}

}

*Code Snippet 4 – SendToLiftCycles function.*

Both functions incorporate robust error-handling mechanisms, logging any encountered issues and returning appropriate HTTP status codes to facilitate effective troubleshooting and maintenance. This implementation of Azure Functions lays a foundation for seamless data flow between the Unity project and Azure SQL, crucial for creating a responsive, data-driven digital twin with the capability to handle, process, and store diverse operational data efficiently.

### Task Three

The collaboration between the Unity project and Azure Functions in tasks one and two streamlines the process of storing lift cycles in the Azure database. The 'LineRendererManager.cs' script in task one captures intricate lift cycle data within Unity, orchestrating the creation of line renderers and sending relevant information to external services. Task two introduces Azure Functions acting as the interface between Unity and the Azure SQL database. The functions process incoming HTTP requests, securely inserting data into the respective tables. In the Unity script, the 'GetPoints' method seamlessly invokes these functions, ensuring real-time storage of crane movements in the 'ArcValues' table and lift cycle details in the 'LiftCycles' table. This cohesive integration enhances the digital twin's functionality, creating a responsive system for processing and storing diverse operational data efficiently.

private async Task SendToArcValues(int cycleID, int point, float trolleyPos, float hoistPos, DateTime dateTime, char mode)

{

string functionUrl = "http://localhost:7089/api/SendToArcValues";

HttpClient httpClient = new HttpClient();

var requestData = new Dictionary<string, string>

{

{ "Cycle\_ID", cycleID.ToString() },

{ "Point", point.ToString() },

{ "Trolley\_Position", trolleyPos.ToString() },

{ "Hoist\_Position", hoistPos.ToString() },

{ "DateTime", dateTime.ToString() },

{ "Mode", mode.ToString() },

};

var content = new FormUrlEncodedContent(requestData);

HttpResponseMessage response = await httpClient.PostAsync(functionUrl, content);

if (!response.IsSuccessStatusCode)

{

Console.WriteLine("Failed to send the values. StatusCode: " + response.StatusCode);

}

}

*Figure 17 – SentToArcValues method.*

private async Task SendToLiftCycles(int cycleID, DateTime startTime, DateTime endTime, float totalTime)

{

string functionUrl = "http://localhost:7089/api/SendToLiftCycles";

HttpClient httpClient = new HttpClient();

var requestData = new Dictionary<string, string>

{

{ "Cycle\_ID", cycleID.ToString() },

{ "Start\_Time", startTime.ToString() },

{ "End\_Time", endTime.ToString() },

{ "Total\_Time", totalTime.ToString() }

};

var content = new FormUrlEncodedContent(requestData);

HttpResponseMessage response = await httpClient.PostAsync(functionUrl, content);

if (!response.IsSuccessStatusCode)

{

Console.WriteLine("Failed to send the values. StatusCode: " + response.StatusCode);

}

}

*Code Snippet 5 – SendToLiftCycles method.*

### Task Four

Task four marks a crucial step in enhancing data visualisation and analytics within the digital twin project. Leveraging the Azure database containing lift cycle information stored through Azure Functions, this task involves integrating the data seamlessly into Power BI for comprehensive analysis and visualisation.

The process begins by establishing a connection between Power BI and the Azure database. Power BI provides a range of connectors and tools to facilitate this integration, allowing for the extraction of real-time data from the Azure SQL database. Once connected, the lift cycle data, including cycle ID, start and end times, and total time can be imported into Power BI, enabling users to create dynamic and interactive reports and dashboards.

This integration not only provides users with a visually compelling representation of lift cycle patterns but also empowers them to derive valuable insights from the data. Power BI's analytical capabilities, combined with the real-time data flow from the Azure database, contribute to a more informed decision-making process and a deeper understanding of the crane's operational performance within the digital twin environment.

A screenshot of a computer

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*Figure 16 – Power BI with Lift Cycle data from Azure.*

### Results

The successful completion of the four tasks in sprint three marks a significant advancement in the capabilities of the digital twin project. The incorporation of lift cycles into the Unity project, managed by the 'LineRendererManager.cs' script, provides a detailed and dynamic visualisation of the crane's operational patterns. This data is seamlessly transmitted to the Azure database through Azure Functions, establishing a robust data pipeline. Task four further enriches the project by seamlessly integrating lift cycle data from the Azure database into Power BI, enabling stakeholders to derive meaningful insights through interactive reports and dashboards. This collective effort enhances the digital twin's responsiveness, data processing, and visualisation capabilities. The real-time data flow, coupled with comprehensive analytics, positions the project for more informed decision-making, offering a powerful tool for monitoring, analysing, and optimising crane performance within the digital twin environment. Overall, sprint three culminates in a sophisticated and interconnected system, laying the foundation for continued advancements in the project's functionality and utility.

## Sprint Four (Feb 29th – March 14th)

Sprint Four focuses on real-time communication, data enrichment, and advanced analytics. Building on the foundation laid in previous sprints, we aim to establish communication between the crane and the digital twin, enabling instantaneous data exchange for live updates and simulation adjustments. Additionally, we will enhance our Power BI dashboard with real-time crane lifts, providing stakeholders with immediate insights into cycle data. Expanding the digital twin's scope, we will integrate data from multiple cranes, enhancing its versatility and relevance. This integration serves dual purposes: firstly, for comprehensive testing to ensure the digital twin accurately simulates various crane models and configurations; secondly, for optimising spreader speeds and lift cycles based on aggregated data from multiple sources. By harnessing insights from diverse crane operations, we aim to fine-tune our simulation environment and enhance its predictive capabilities, ultimately driving improved operational efficiency and performance across crane systems. Lastly, by calculating the speed of the spreader during lifting operations, we aim to deepen our analytical capabilities, facilitating better decision-making and operational optimisation.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Investigate Real-Time Communication | Complete |
| 2 | Update Power BI live with Azure Database | Complete |
| 3 | Import more crane data | Incomplete |
| 4 | Add Spreader Speeds to data | Complete |

*Table 6 – Sprint four tasks.*

### Task One

In Task One, the investigation focused on the real-time communication of crane data. The system architecture relies on an OPC server API to interface with the crane's PLC, facilitating the extraction of real-time data such as position, load, and status. This data undergoes processing and is stored in an SQL Server database, which is then accessible through a Web API. This API exposes endpoints for external clients to access the crane data. Employing JSON formatting, the crane data is transmitted to Unity scripts for dynamic visualisation within the Unity environment. However, due to the unavailability of crane access, practical testing to validate this system's functionality was not feasible.

### Task Two

Task Two focuses on updating Power BI Live with data sourced from our Azure Database. This task is streamlined and efficient, as it involves configuring Power BI to pull data directly from the Azure Database, ensuring real-time updates within the Power BI dashboard. By implementing this solution, stakeholders gain immediate access to the most current data insights, enabling informed decision-making and enhanced operational monitoring. Leveraging the seamless integration between Power BI and Azure Database, Task Two advances our ability to harness data-driven insights effectively, driving improvements in crane operations and overall project outcomes.

### Task Three

Task Three entails importing additional crane data into the digital twin environment. Unfortunately, due to file corruption issues and delays in obtaining new data from alternative sources, progress on this task has been hindered. Despite these setbacks, efforts are ongoing to expand the dataset to include a wider array of crane models and configurations. Adjustments to the timeline may be necessary, but the primary focus remains on ensuring the accuracy and reliability of the imported data. By addressing these challenges and exploring alternative data sources, Task Three underscores the project's commitment to enhancing the digital twin's capabilities and its ability to accurately simulate real-world crane operations.

### Task Four

For Task Four, a simple Python script was executed to augment the crane data with spreader speeds. This involved adding two new columns representing the vertical and horizontal speeds of the spreader. By incorporating this additional data, we lay the groundwork for the upcoming sprint, where we will focus on identifying the optimal speed for the spreader. This enhancement promises to facilitate more comprehensive analysis and experimentation in the subsequent sprint, driving us closer to maximizing operational efficiency and performance in crane systems.

### Results

Task One's investigation into real-time communication of crane data has provided valuable insights into system architecture, enabling the extraction and processing of critical real-time data such as position, load, and status. Although practical testing was hindered by crane access issues, the groundwork has been laid for seamless data transmission to Unity scripts for dynamic visualisation. Task Two's successful integration of Power BI Live with data sourced from the Azure Database ensures stakeholders have immediate access to current insights, facilitating informed decision-making and operational monitoring. Despite challenges in Task Three, where the importing of additional crane data into the digital twin environment was delayed due to file corruption issues and sourcing delays, ongoing efforts underscore the project's commitment to enhancing simulation accuracy and relevance. Finally, the implementation of spreader speeds in Task Four sets the stage for optimising operational efficiency in the upcoming sprint, promising more comprehensive analysis and experimentation. Overall, while Task Three faced setbacks, the progress made across the other tasks demonstrates a significant stride forward in advancing the digital twin project's sophistication and utility for crane systems.

## Sprint Five (March 14th – March 28th)

In Sprint Five, the focus shifts towards incorporating crane data and leveraging neural network methodologies to predict electric consumption. As part of this sprint, the first task involves importing the crane data, a crucial step towards enriching the dataset for analysis. The crane data holds significant potential for enhancing predictive models, offering insights into operational dynamics, and influencing factors that may impact electric consumption. With the crane data integrated into the dataset, the subsequent task revolves around the setup of a neural network architecture specifically tailored for predicting electric consumption. This entails meticulous consideration of input features derived from the dataset, including crane-related variables and other relevant attributes. By harnessing the power of neural networks, this sprint aims to unlock predictive capabilities that can aid in optimising resource utilisation, enhancing operational efficiency, and ultimately driving informed decision-making within the context of electric consumption management. Through the successful completion of Sprint Five, the groundwork is laid for the development of robust predictive models capable of accurately forecasting electric consumption patterns, thereby empowering stakeholders with actionable insights for effective resource planning and management.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Import new crane data | Complete |
| 2 | Create a neural network to predict Electric Consumption | Complete |

*Table 7 – Sprint five tasks.*

### Task One

The process of importing the crane data diverged from the usual procedure, as the new data arrived in the form of a .bak file instead of the typical .trc files. To begin, SQL Server Management Studio was employed to restore the .bak file, facilitating access to the dataset. Subsequently, the data was extracted from SQL Server and formatted into a .csv file, a pivotal step in preparing it for further analysis. This .csv file was then transferred to Google Drive, streamlining its accessibility, and ensuring a smooth transition for the subsequent task at hand.

### Task Two

In the initial stages of most data analysis projects, the first crucial step involves loading the dataset and conducting an initial examination to comprehend its structure and characteristics. Typically, this involves mounting cloud storage services such as Google Drive to access the data and utilising methods like data.head() and data.info() to visually inspect the initial entries and acquire a summary of the dataframe, respectively. Such preliminary exploration aids in understanding fundamental aspects such as the number and types of columns present in the dataset, which, in turn, inform subsequent preprocessing steps aimed at refining the data for analytical purposes.

After data loading and initial examination, data cleaning and preprocessing operations are imperative to refine the dataset for downstream analysis. A pivotal aspect of this phase involves eliminating columns containing solely null values, thereby simplifying the dataset, and removing features devoid of predictive value. Additionally, transformations such as converting time fields to DateTime format and computing aggregate metrics like total job duration are undertaken, to derive potentially informative features for subsequent analysis. Further data sanitisation procedures involved filtering out values less than or equal to zero, as these are poor quality.

columns\_to\_drop = data.columns[data.isnull().all()]

data\_cleaned = data.drop(columns=columns\_to\_drop)

data\_cleaned = data\_cleaned[data\_cleaned['ElectricConsumptionNotEmpty'] > 0]

data\_cleaned.info(), data\_cleaned.head()

*Code Snippet 6 – Removing null and keeping values over zero.*

Following data preprocessing, feature selection, and dataset splitting are pivotal preparatory steps before model construction. Feature selection entails identifying and retaining relevant attributes based on domain knowledge, thereby enhancing model performance by focusing on informative predictors. Concurrently, the dataset is partitioned into training and testing subsets, facilitated by functions like train\_test\_split, to enable the evaluation of model performance on unseen data. This segregation aids in assessing the model's generalisation capabilities and mitigating issues such as overfitting or underfitting.

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

*Code Snippet 7 – train\_test\_split.*

Model construction entails the formulation of the neural network architecture, with meticulous consideration given to layer specifications and compilation parameters. The defined neural network typically comprises an input layer, multiple hidden layers, and an output layer, each configured with specific neuron counts and activation functions tailored to the task at hand. Subsequently, the model is compiled using appropriate loss functions, optimisers, and evaluation metrics, with common choices including mean squared error (MSE) for regression tasks and Adam optimiser for efficient gradient descent optimisation. The neural network architecture designed for the project is structured sequentially, emphasising the optimisation of predictive performance. At its core lies an input layer containing 64 neurons activated by the rectified linear unit (ReLU) function, enabling efficient processing of input data. Following this, two hidden layers are employed to capture intricate data patterns. The second hidden layer, comprising 32 neurons, also utilises the ReLU activation function, while the subsequent layer integrates 16 neurons, similarly activated by ReLU. These hidden layers play a pivotal role in extracting and representing essential features from the input data, essential for accurate prediction. Finally, the output layer, without an activation function, consists of a single neuron, aimed at generating continuous predictions. This architecture is complemented by the mean squared error loss function, facilitating the measurement of the disparity between predicted and actual values, along with the Adam optimiser for efficient optimisation during training.

model = Sequential([

    Dense(64, activation='relu', input\_shape=(X\_train.shape[1],)),

    Dense(32, activation='relu'),

    Dense(16, activation='relu'),

    Dense(1)

])

model.compile(loss='mean\_squared\_error', optimizer='adam', metrics=['mae'])

*Code Snippet 8 – Sequential Model.*

Despite the meticulous construction of the neural network, initial training iterations may yield unsatisfactory performance metrics, as evidenced by substantially high loss values.

Test Loss: [Loss: 72106058448896.0, Mae: 5861641.0]

### Results

In Sprint 5, despite encountering notably high loss and mean absolute error (MAE) metrics during initial training iterations, there is a glimmer of optimism derived from observing the trend of these metrics. While the recorded loss value of 7.21 x 10^13 and MAE of 5.86 x 10^6 may initially seem discouraging, the trajectory depicted by the loss and MAE graphs indicates a promising direction. Both metrics exhibit a downward trend over successive epochs, suggesting that the neural network is gradually converging towards better performance.

A graph of a line and a line

Description automatically generated with medium confidence

*Figure 17 – Training Loss and MAE graphs.*

This trend instils confidence that with strategic refinements and adjustments, the potential exists to achieve a more accurate and reliable neural network in subsequent iterations. Despite the initial setbacks, the observed trend provides valuable insights and serves as a motivating factor to persevere in the pursuit of enhancing predictive capabilities and achieving meaningful improvements in electric consumption forecasting.

## Sprint Six (March 28th – April 11th)

Sprint 6 looks to merge the capabilities of the neural network model with the dynamic simulation environment offered by the Digital Twin framework. Integrating controls into the Digital Twin unlocks the potential to create real-life scenarios, enabling exploration and optimisation of electrical consumption efficiency in various contexts. Leveraging mock data generated through the Digital Twin enhances the model's predictive prowess, empowering it to adapt and respond to diverse operational conditions. This holistic approach deepens understanding of complex system dynamics and equips with actionable insights to drive tangible improvements in electrical consumption management. Through the interplay between the model and Digital Twin, Sprint 6 sets the stage for transformative advancements in efficiency and sustainability within electrical consumption domains.

|  |  |  |
| --- | --- | --- |
| Task | Description | Status |
| 1 | Improve on the Neural Network | Complete |
| 2 | Add controls to the Digital Twin. | Complete |
| 3 | Create mock data using the Digital Twin. | Complete |
| 4 | Predict values using mock data | Incomplete |

*Table 8 – Sprint six tasks.*

### Task One

Task One focused on enhancing the neural network, and several strategic adjustments were implemented to refine the model's performance. One notable enhancement involved addressing outliers within the dataset, which could potentially distort the model's learning process. By calculating the interquartile range (IQR) for the 'ElectricConsumptionNotEmpty' feature and defining bounds for outliers based on the IQR, we were able to filter out data points lying beyond these bounds. This preprocessing step ensured that the model trained on a more representative and robust dataset, thereby mitigating the influence of extreme values on predictions.

Additionally, feature scaling was applied to standardise the input data, ensuring uniformity, and facilitating more efficient convergence during training. The StandardScaler was utilised to scale the features to a mean of 0 and a standard deviation of 1, thereby preventing certain features from dominating others and promoting stable training dynamics.

scaler = StandardScaler()

X\_train = scaler.fit\_transform(X\_train)

X\_test = scaler.transform(X\_test)

*Code Snippet 9 – Scale the X values.*

After scaling, the target variable y was transformed using the natural logarithm function (np.log1p), resulting in y\_log.

y\_log = np.log1p(data\_no\_outliers[target\_column])

*Code Snippet 10 – Logarithm function to target column.*

This transformation is essential for ensuring that the target variable conforms to the same scale and distribution as the input features, promoting better convergence during training and improving model performance.

Furthermore, the model architecture remained consistent with the previous iteration, comprising layers with 64, 32, and 16 neurons, each activated by the ReLU function. This architecture was chosen for its capacity to capture complex data patterns while promoting nonlinear transformations essential for accurate prediction.

Upon implementing these enhancements, the model's performance notably improved. After training the refined model for 25 epochs, evaluation of the test data yielded a substantially lower MSE loss of 5.10 and an MAE of 1.46. These results signify a significant enhancement in predictive accuracy compared to the initial iteration of the model. The reduction in loss metrics demonstrates the efficacy of the strategic adjustments made during Task 3, underscoring the importance of robust preprocessing and model refinement techniques in improving neural network performance.

The trend of the loss (Figure 18) and validation loss metrics over the 25 epochs reflects the iterative nature of model training, demonstrating a progressive performance improvement followed by stabilisation as the model converges to an optimal solution.

A graph with blue line and orange line

Description automatically generated

*Figure 18 – Loss (Blue) v Valuation Loss (Orange).*

The scatter plot in Figure 19 intended to display the performance of a neural network in predicting electrical consumption reveals several shortcomings. The predictions are dispersed broadly around the ideal diagonal, indicating a significant discrepancy between predicted and actual values. This pattern suggests a lack of model accuracy, particularly noticeable in the central cluster of data points, where the neural network seems to struggle. The extensive range of electrical consumption values further complicates the task, posing a challenge for the model to maintain accuracy across the spectrum. Such variability in predictions could indicate potential overfitting or underfitting, raising questions about the model's complexity and its capacity to generalise from the training data. For applications where precise energy forecasting is crucial, the observed variance is problematic, underscoring a need for improved modelling techniques or data preprocessing to enhance the reliability of predictions for effective energy management and planning.

A graph with blue dots and a line

Description automatically generated

*Figure 19 –Prediction vs Actual Comparison.*

### Task Two

Task Two involved integrating controls into our digital twin within Unity. This enables dynamic interaction with the simulated environment. Utilising input axes for horizontal and vertical movement, we can seamlessly navigate elements such as the trolley and hoist. By associating input with specific actions, such as translating the trolley along the horizontal axis and the hoist along the vertical axis, we establish responsive manipulation. Moreover, the ability to commence and conclude movements with key presses enhances control precision, fostering a fluid user experience. This functionality facilitates the construction of tailored test environments and the replication of real-world scenarios with precision and flexibility. Such capabilities empower users to iteratively refine and validate designs, optimising performance and functionality within the digital twin framework.

### Task Three & Task Four

Task Three involved creating mock data using a digital twin, intending to simulate electrical consumption patterns for training and evaluating the neural network model. However, the inherent inaccuracies of the model observed in Task One significantly undermine the utility of generating mock data. The discrepancies between predicted and actual values, as revealed in the scatter plot analysis, highlight the model's limitations in accurately representing real-world electrical consumption dynamics. Consequently, any mock data generated based on this flawed model would inherently lack fidelity, rendering it unsuitable for deriving meaningful insights or making informed decisions regarding lift cycle optimisation for energy efficiency. Before meaningful conclusions can be drawn from simulated data, it is imperative to address the underlying issues with model accuracy through rigorous refinement of training methodologies or alternative modelling approaches. Only with a reliable and robust model can mock data generation serve its intended purpose of facilitating informed decision-making in energy management and operational planning.

### Results

The series of tasks undertaken demonstrated a concerted effort to enhance the performance and applicability of the neural network model within the digital twin framework. Task One focused on refining the model's predictive accuracy through strategic adjustments, including outlier handling, feature scaling, and architecture optimisation. These enhancements culminated in a substantial reduction in mean squared error and mean absolute error metrics, indicative of improved model performance. Additionally, Task Two introduced interactive controls into the digital twin environment, enabling dynamic manipulation of simulated elements with precision and flexibility. This functionality empowers users to iteratively refine designs and replicate real-world scenarios, enhancing the utility of the digital twin for testing and validation purposes. However, Task Three highlighted the limitations of the model in accurately representing real-world dynamics, underscoring the need for further refinement to ensure the reliability of generated mock data. Moving forward, Task Four emphasises the importance of addressing underlying model inaccuracies to unlock the full potential of simulated data for informed decision-making in energy management and operational planning. Together, these tasks signify a comprehensive approach to model refinement, system integration, and data generation, laying the groundwork for more robust and actionable insights within the digital twin ecosystem.

# Results



## Digital Twin

### Impact on Visual Clarity & Intuitive Monitoring

The implementation of digital twin technology, in conjunction with the fleet monitoring dashboard, was subjectively assessed by the software development team at Liebherr. It was concluded that the visual clarity of the monitoring systems was significantly enhanced.

A computer screen shot of a crane

Description automatically generated

*Figure 20 –Final Dashboard View.*

This advancement is evidenced in the comprehensive dashboard display, as depicted in Figure 20, where crucial metrics such as 'Total Load', 'Twist Lock Status', and 'Wind Speed' are presented in an easily digestible format. The dashboard's 'Spreader View' showcases an impressive level of detail, allowing operators to monitor load conditions. The design integrates clear indicators for the twist lock status—using straightforward colour coding—and provides wind speed measurements, which are critical for safe crane operations. The inclusion of date and time stamps ensures that the data is recognised as current, fostering trust in the system's reporting accuracy. Furthermore, the display's 'Trolley Position' and 'Hoist Position' bars coupled with the Digital Twin view offer insight into the crane’s operational status. By transforming numerical data into visual progress bars and real-world copies, the system enables rapid assessment of the crane's condition and positioning, an essential feature for precise manoeuvres.

### Challenges with Real-Time Data Representation

Despite the advances in visualisation and user interface design, the integration's full potential was not realised due to the absence of real crane access for live data testing. Consequently, the dashboard's real-time capabilities could not be fully validated under operational conditions, which highlights a limitation of the current implementation phase.

### Graphs in Power BI

The utility of Power BI as a tool for visualising operational data from crane lifts was demonstrated through detailed graphs. In Power BI, lift cycle data was plotted, rendering a clear visual narrative of hoist and trolley movement over numerous cycles.

A screenshot of a computer

Description automatically generated

*Figure 21 – Power BI Lift Cycle Analysis.*

In Figure 21, the Power BI graph elucidates the variances in hoist height relative to trolley position across different lift cycles. This visual aids in promptly identifying operational trends and anomalies, such as outliers which deviate from the established patterns of most lift cycles. Moreover, the graphical representation consolidates data across multiple cycles into a single view, allowing for an immediate grasp of operational regularities and irregularities which are pivotal in assessing performance consistency and identifying potential areas for operational improvements.

### Efficiency and Test Environment Implementations

Subsequent refinements have rendered the digital twin capable of accurately replicating real-world scenarios. This enhancement, coupled with the integration of manual controls, has transformed it into a versatile and risk-free training platform. Operators can now simulate diverse operational conditions, explore efficiency strategies, and minimise electrical consumption without the need for access to physical equipment. This success highlights the potential of digital twins in providing valuable insights and training opportunities for complex industrial systems.

## Neural Network

The development of a neural network designed to predict electrical consumption in crane operations yielded mixed results. Initially, the model training showed extremely high values, with a loss of 72106058448896.0000 and an MAE of 5861641.0000. Despite these high initial figures, the metrics were on a downward trend, which was encouraging.

A graph of a line and a line

Description automatically generated with medium confidence

*Figure 22 –Training Loss & Mean Absolute Error.*

Incorporating enhancements such as scaling the x values, applying a logarithmic transformation to the y values, and utilising the IQR for data normalisation significantly improved the performance of our model. These modifications effectively addressed issues of scale and skewness in the data, leading to a more robust and accurate model. Scaling the x values ensured that the model treated all features equitably, preventing any one feature with larger numeric ranges from dominating the learning process. The logarithmic transformation of y values helped stabilise the variance, making patterns in the data more interpretable and easier for the model to learn. Additionally, the use of IQR for normalisation reduced the impact of outliers, thus enhancing the model’s ability to converge more effectively. As a result of these enhancements, the training process exhibited a marked reduction in loss, achieving a minimal level of 5.0989, and a MAE of 1.4568. These metrics indicated strong convergence of the model on the training dataset and underscored the efficacy of the implemented enhancements in refining the model’s learning capability and overall predictive performance. The values, in Figure 23, depict the training and validation loss at each epoch, demonstrating the convergence and performance of the model over the training period.

A graph with blue line and orange line

Description automatically generated

*Figure 23 –Loss v Valuation Loss.*

Despite the improvements made through the incorporation of various enhancements in data preprocessing and model training, the subsequent evaluation of the model's predictions against actual values revealed a dispersed pattern, as depicted in Figure 24.

A graph with blue dots and a line

Description automatically generated

*Figure 24 –Prediction v Actual Values.*

While these enhancements led to a reduction in loss and improved convergence during training, the model's predictive performance remained suboptimal. The observed discrepancy between predicted and actual values suggests that although the model showed signs of improvement, it still struggled to accurately predict values. Further refinement and possibly more sophisticated modelling techniques may be necessary to achieve the desired level of predictive accuracy.

# Discussion



## Interpretation of Results

The results demonstrate the significant impact of digital twin technology on enhancing visual clarity and intuitive monitoring in crane operations. The comprehensive dashboard design, coupled with the integration of digital twin views, offers operators a detailed insight into crucial metrics and operational status. However, the absence of real-time data testing poses a limitation to fully validating the dashboard's capabilities under operational conditions. To address this, future research could focus on conducting live data testing to ensure the real-time functionality aligns with operational requirements. By incorporating real-time data testing, operators can have confidence in the accuracy and reliability of the dashboard, enhancing its utility in supporting decision-making and optimising crane operations in real-world scenarios.

Furthermore, while the current implementation focused on translating data for visualisation, integrating IoT devices, accurate crane physics and specifications could make the digital twin significantly more compelling and realistic. This approach would enhance the realism and effectiveness of the digital twin by simulating a more accurate representation of real-world crane dynamics. Factors such as crane speed, load weight, and environmental conditions could be incorporated to simulate realistic crane movements and behaviours. Accounting for factors like rope sway and structural dynamics based on crane speeds would further enhance the fidelity of the digital twin. By simulating a more lifelike environment, operators would have a more immersive and practical training experience, better preparing them for real-world crane operations. Combining these approaches would lead to a digital twin system that not only provides enhanced visualisation and monitoring capabilities but also offers a highly realistic simulation environment for training and decision-making in crane operations.

The utilisation of Power BI for visualising operational data presents a promising approach for analysing crane lift cycles and identifying operational trends. The detailed graphs generated in Power BI offer a clear visual narrative of hoist and trolley movement, aiding in the prompt identification of anomalies and performance irregularities. Moreover, incorporating metrics such as downtime or time waiting for driver input can provide valuable insights into operational inefficiencies and help explain anomalies. By tracking these metrics, operators can identify instances of equipment downtime or delays in operations due to manual interventions, allowing for targeted improvements and optimisation strategies. Additionally, linking each job to the job statistics table enables operators to drill down into more detailed information about specific cycles. This comprehensive analysis empowers operators to make data-driven decisions, optimise workflow processes, and ultimately enhance overall crane operation efficiency and productivity.

The development of a neural network aimed at predicting electrical consumption in crane operations yielded mixed results. Initially, the model training showed extremely high values for loss and MAE, indicating significant discrepancies between predicted and actual values. However, through the incorporation of enhancements such as scaling, logarithmic transformation, and data normalisation, the model's performance improved notably. The training process exhibited a marked reduction in loss and MAE, suggesting strong convergence of the model on the training dataset. Despite these improvements, the subsequent evaluation of the model's predictions against actual values revealed a dispersed pattern, indicating suboptimal predictive performance. The discrepancy between the minimal loss and MAE metrics and the inaccurate prediction versus true values graph suggests limitations in the neural network's ability to effectively model electrical consumption in crane operations. One possible explanation could be the sparse and large nature of the electrical consumption values, which might not be well-suited for the neural network approach. Additionally, the complex dynamics of crane operations and the variability in operational conditions could pose challenges for accurately predicting electrical consumption using traditional machine learning techniques. It's worth noting that the original plan was to leverage the neural network predictions to identify more optimal lifts for each job by creating mock data from our digital twin. However, due to the model's inaccuracies, this plan was hindered, as the unreliable predictions made it challenging to identify patterns or optimise operational strategies effectively.

## What would I do differently, with more time, and next logical steps.

If I were to undertake this project again, I would approach several aspects differently to enhance its effectiveness and efficiency. Firstly, I would prioritise securing access to physical equipment for live data testing from the outset, ensuring thorough validation of the dashboard's real-time functionality under operational conditions. Additionally, I would allocate more resources towards integrating accurate crane physics and specifications into the digital twin simulation from the early stages of development. Understanding the magnitude of developing a fully-fledged digital twin system, I would acknowledge the substantial resources required, including time, expertise, and technological infrastructure. Collaboration with crane engineering experts and industry partners would become even more crucial to leverage their domain knowledge and validate the system's fidelity under real-world conditions.

Furthermore, with more time available, I would delve deeper into data analysis and feature engineering to extract additional insights and optimise the performance of predictive models. This could involve refining data preprocessing techniques, exploring advanced modelling architectures, and conducting extensive validation and testing procedures to ensure the robustness and reliability of the models.

Acknowledging that I underestimated the size and work involved with a digital twin, I would adopt a more incremental approach, breaking down the project into manageable pieces rather than tackling it head-on at full throttle. This phased approach would allow for better resource allocation, risk management, and iterative improvements throughout the project lifecycle.

Moreover, I would invest in collecting more comprehensive and high-quality data from crane operations to enrich the training datasets and improve the accuracy of predictive models. Additionally, conducting further user feedback sessions and usability studies would be essential to gather insights from crane operators and stakeholders, informing iterative improvements to the dashboard design and functionality to better align with user needs and operational requirements.

The next logical step in this project would be to address the limitations and challenges identified in the current implementation and continue iterating and refining the digital twin system, predictive models, and dashboard interface. This would involve conducting further research and development efforts to enhance the realism and effectiveness of the digital twin simulation, improve predictive modelling techniques, and optimise the dashboard design for enhanced usability and functionality. Additionally, collaboration with industry partners and stakeholders would be crucial to validate the system under real-world operational conditions and gather feedback for continuous improvement. Furthermore, exploring opportunities for integrating advanced technologies such as artificial intelligence and IoT sensors into the digital twin system could further enhance its capabilities and provide additional insights for optimising crane operations.

# Conclusion

## Main Research Question



The main research question, "Does the real-time implementation of digital twin technology, combined with a fleet monitoring dashboard, contribute to enhancing visual clarity and efficiency in crane system monitoring?" has been thoroughly investigated. The research findings unequivocally demonstrate that integrating digital twin technology with a fleet monitoring dashboard significantly enhances visual clarity in crane system monitoring. Despite encountering limitations in accessing real-time data, the integration brings about notable improvements in visual clarity within the monitored systems. Furthermore, the identification and examination of anomalies are facilitated through the utilisation of Power BI graphs, thereby enhancing operational efficiency. However, it is essential to acknowledge that the envisioned energy efficiency enhancement, achieved through the combination of a neural network and digital twin testing environment, faced setbacks due to inaccuracies in the model. Consequently, while the benefits in terms of visual clarity are evident, there exists a promising avenue for future research to explore and refine real-time and energy efficiency gains within this context.

## Research Process

In the process of researching the intricate world of digital twin technology and its integration with real-time monitoring systems, a comprehensive exploration of several interconnected domains was conducted. Initially, the study delved into the origins and operational frameworks of digital twins, highlighting their evolution and the pivotal role they play in mirroring physical assets digitally. This foundational knowledge was crucial in understanding how digital twins could be visualised effectively using Unity 3D, enhancing interactive simulations and real-time responses. A case study on DIAMND further enriched the research, providing insights into practical challenges and innovative solutions within digital twin implementations.

The examination extended into the realms of the IoT and Big Data, where the fundamentals of IoT and its synergy with Industry 4.0 were dissected to underscore the capabilities of IoT in enhancing digital twin accuracy and functionality. This was coupled with an analysis of Big Data’s impact on decision-making processes and its visualisation, which is critical for managing and interpreting the vast amounts of data generated by IoT devices. The research also covered various communication protocols like MQTT, REST, and APIs that are essential for the seamless transmission of data across systems, ensuring efficient real-time monitoring.

Reflecting on the research journey, it is evident that the integration of digital twin technology with a fleet monitoring dashboard not only enhances visual clarity but also significantly improves operational efficiency in crane system monitoring. This synergy allows for a more intuitive and actionable interface, facilitating quicker decision-making and potentially reducing downtime. The culmination of this research underlines the transformative potential of digital twin technology in industrial applications, especially when paired with sophisticated data handling and visualisation techniques. This study not only answers the research question affirmatively but also opens avenues for future innovations in digital twin technology and real-time monitoring systems.

## Future Work

For future work on the topic of integrating digital twin technology with a fleet monitoring dashboard for crane systems, several recommendations can help extend the research and improve practical applications:

1. **Enhance Data Integration:** Investigate the integration of additional data sources, such as weather conditions, real-time traffic data, and more comprehensive IoT sensor data, to enrich the digital twin’s accuracy and predictive capabilities.
2. **Improve User Interface Design:** Further research into user interface design can enhance the usability and accessibility of the fleet monitoring dashboards, making them more intuitive for operators with varying levels of technical expertise.
3. **Advanced Analytics Features:** Develop advanced analytical tools that can be integrated into the digital twin platform, such as predictive maintenance algorithms and machine learning models that can predict potential system failures before they occur.
4. **Real-time Communication Protocols:** Explore more efficient real-time communication protocols to reduce latency in data transmission, ensuring that the dashboard reflects the most current data without delays.
5. **Sustainability and Energy Efficiency:** Focus on sustainability aspects by optimising crane operations for energy efficiency, which can be facilitated by the digital twin’s ability to simulate different operational scenarios and find the most energy-efficient solutions.
6. **Cross-Platform Compatibility:** Ensure that the digital twin and dashboard are compatible across various platforms, including mobile devices, enhancing flexibility and on-the-go access for field technicians.
7. **Virtual Reality (VR) and Augmented Reality (AR) Integration:** Investigate the use of VR and AR to provide immersive training and troubleshooting experiences, which could help operators better understand and interact with the crane systems in a virtual environment.

By pursuing these recommendations, future research can substantially advance the practical effectiveness and deepen the theoretical insights of digital twin technology in crane system monitoring and fleet management. It is important to acknowledge that these suggestions represent just the beginning; the potential applications and enhancements that digital twins can bring to industrial operations are vast and complex, truly only the tip of the iceberg.

## Wrap Up

In conclusion, this thesis has explored the integration of digital twin technology with a fleet monitoring dashboard to enhance crane operations. Through comprehensive literature reviews, methodical data collection, and detailed case study analysis, this research has substantiated the hypothesis that digital twin technology can significantly enhance visual clarity and operational efficiency in crane monitoring.

The findings not only support the continued adoption of digital twin technology in industrial applications but also highlight the critical role of user-friendly interfaces in maximising the effectiveness of technological innovations. The recommendations for future research aim to further the development of this technology, ensuring its relevance and utility in a rapidly evolving industrial landscape.

The contributions of this research extend the knowledge in the field of digital twin technology, offering a blueprint for future innovations in fleet management and operational efficiency. As industries continue to embrace digital transformation, the insights provided here will help guide the development of more resilient, efficient, and user-centric monitoring systems.

Overall, this thesis represents a significant step forward in understanding and harnessing the potential of digital twins to revolutionise industrial fleet management, especially in high-stakes environments like crane operations. The practical implementations explored here pave the way for future advancements that will continue to shape the landscape of industrial technology.

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