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# Bridge Digital Twin for Practical Bridge Operation and Maintenance by Integrating GIS and BIM

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**Abstract:** As an emerging technology, digital twin (DT) is increasingly valued in bridge management for its potential to optimize asset operation and maintenance (O&M). However, traditional bridge management systems (BMS) and existing DT applications typically rely on standalone building information modeling (BIM) or geographic information system (GIS) platforms, with limited integration between BIM and GIS or consideration for their underlying graph structures. This study addresses these limitations by developing an integrated DT system that combines WebGIS, WebBIM, and graph algorithms within a three-layer architecture. The system design includes a common data environment (CDE) to address cross-platform compatibility, enabling real-time monitoring, drone-enabled inspection, maintenance planning, traffic diversion, and logistics optimization. Additionally, it features an adaptive data structure incorporating JSON-based bridge defect information modeling and triple-based roadmap graphs to streamline data management and decision-making. This comprehensive approach demonstrates the potential of DTs to enhance bridge O&M efficiency, safety, and decision-making. Future research will focus on further improving cross-platform interoperability to expand DT applications in infrastructure management.

**Keywords:** digital twin; bridge operation and maintenance; GIS and BIM; roadmap graph; machine learning; decision-making

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## 1. Introduction

Digital twin (DT) technology is increasingly adopted across engineering fields for its transformative potential in managing and optimizing asset operation and maintenance (O&M). In civil infrastructure, DT applications have been explored to monitor and optimize O&M of structures such as bridges and buildings [1]. By providing a real-time, data-driven digital replica of the infrastructure, DT technology enables early detection of potential issues and facilitates proactive maintenance strategies [2]. For example, DTs can model and predict infrastructure behavior under various conditions by leveraging IoT sensor data and data-driven analytics, thereby reducing downtime and extending the lifespan of infrastructure [3]. Additionally, DTs can facilitate efficient resource allocation and support informed decision-making, both of which are essential for managing large-scale and complex infrastructure systems [4]. Consequently, DT technology has become essential for developing more resilient and sustainable infrastructure management systems, addressing challenges due to aging assets and increasing maintenance demands.

In the context of bridge management, DT facilitates a dynamic digital representation of physical structures, continuously updated with real-time data to enable predictive maintenance, informed decision-making, and comprehensive lifecycle management [5]. With infrastructure maintenance becoming more critical and complex, there is a growing demand for efficient, data-driven solutions to optimize bridge O&M. However, traditional bridge management systems (BMS) and existing digital twin (DT) applications often rely on standalone platforms, such as building information modeling (BIM) or the geographic information system (GIS). These systems face significant limitations due to the lack of integration between BIM and GIS, as well as the absence of graph-based data structures [6–8]. This fragmentation limits the full potential of BIM's detailed structural information and GIS's spatial analysis capabilities, thereby hindering effective decision-making and the optimization of maintenance processes.

To address the research question—how to overcome the limitations of current bridge management systems and existing DT applications by integrating BIM, GIS, and graph algorithms to create a more comprehensive, efficient, and interoperable solution for bridge operation and maintenance—this study develops an integrated bridge DT system. The proposed system combines WebGIS, WebBIM, and graph algorithms within a three-layer architecture, supporting routine bridge O&M practices, including real-time monitoring, drone-enabled inspection, intelligent traffic diversion, and maintenance planning. Meanwhile, to bridge the gap between BIM and GIS modules, i.e., to ensure data interoperability and cross-platform functionality, a common data environment (CDE) is designed to effectively achieve compatibility between WebGIS and WebBIM modules. Additionally, an adaptive data structure is employed, featuring JSON-based bridge defect information modeling and triple-based roadmap graphs, to enhance data management efficiency and support graph-based decision-making. This integrated approach not only facilitates seamless interaction between GIS and BIM modules, but also enables advanced data analytics and robust decision-making for optimizing bridge O&M activities.

The developed DT system demonstrates significant potential for practical bridge management by enhancing operational efficiency, safety, and data-driven decision-making. With real-time interoperability between WebGIS and WebBIM modules, the system supports proactive maintenance planning and immediate traffic management responses to structural issues. The adaptive data structure, leveraging JSON-based modeling and triple-based graphs, enables precise defect tracking and efficient resource allocation. This BIM-GIS-integrated framework serves as a foundation for advanced bridge DT applications, providing insights that can support long-term predictive maintenance strategies and ultimately extend the lifespan of bridge infrastructures.

This study makes a four-fold contribution to the field of bridge DT.

1. The study develops a bridge DT system that integrates WebGIS, WebBIM, and graph algorithms within a three-layer architecture, supporting essential O&M activities, including real-time monitoring, drone-enabled inspection, intelligent traffic diversion, and maintenance planning.
2. It explores BIM-GIS interaction within a bridge DT framework to enable essential collaborative functionalities. A web-oriented CDE is designed to enhance cross-platform compatibility, allowing seamless data exchange and combined functionality between WebGIS and WebBIM modules.
3. An adaptive data structure is introduced, featuring JSON-based bridge defect information modeling and triple-based roadmap graphs. This structure enhances data management efficiency, enables graph-based decision-making, and facilitates precise tracking of defects and optimal resource allocation in bridge O&M.
4. The study highlights the application of graph-based data structures and algorithms within a bridge DT system for various O&M activities, such as maintenance logistics and route optimization. This approach illustrates the effectiveness of graph theory in enhancing bridge O&M processes.

This paper is organized as follows: Section 2 provides a comprehensive review of related works, covering existing bridge DT systems, as well as BIM and GIS applications in bridge management. Section 3 outlines the methodology, describing the design and development of the proposed DT system. Section 4 presents system validation through case studies. Section 5 discusses the system's advantages and limitations. Finally, Section 6 concludes the study, summarizing the main achievements and suggesting directions for future research.

## 2. Related Works

This section reviews the existing research on DT applications in bridge management, focusing on the implementation of BIM and GIS functions. The structure is organized to provide a comprehensive understanding of prior work in three main areas: the development of bridge DT systems, the application of GIS and BIM in bridge O&M, and the role of graph theory in digital technology integration. This structure is chosen to highlight the gaps in existing approaches and lay the foundation for the proposed integrated bridge DT system.

### *2.1. Bridge DT*

In recent years, the concept of digital twin (DT) has become a transformative tool in managing and monitoring physical assets, including bridges. A bridge DT serves as a dynamic digital counterpart of a physical bridge, continuously updated with real-time data. This enables advanced analytics, informed decision-making, and predictive modeling to optimize operations, maintenance, and overall performance throughout the bridge's lifecycle. Unlike traditional static bridge management systems (BMS), bridge DTs provide up-to-date insights into the bridge's conditions, forecast performance, identify risks, and generate maintenance plans in near real time [9].

In bridge engineering, a DT for operation and structural health monitoring (SHM) is a virtual model that not only updates dynamically with new data, but also provides feedback to the physical bridge. This allows for "what-if" scenario analysis to assess risks and predict performance [10]. For maintenance purposes, DTs are continuously updated with data from visual inspections, non-destructive testing (NDT), and other sources such as original design details, damage history, traffic, weather, and disaster data [5,6,11,12]. Furthermore, multiple DTs can form a network for intelligent transportation systems, often represented topologically on a map, supporting holistic decision-making and comprehensive maintenance planning. For example, Adibfar and Costin developed a mock-up bridge DT by integrating weigh-in-motion (WIM) data into a bridge information model (BrIM). This integration enables real-time traffic data from sensors to assess how overweight commercial vehicles affect the bridge's structural components. This study highlights the potential of combining transportation data with bridge DTs to enhance infrastructure management and research.

Over the past decade, there has been growing interest in bridge DTs, leading to several successful prototypes and pilot projects. For example, Butler et al. [13] developed a DT for two railway bridges, integrating fiber Bragg grating (FBG) sensors and laser rangefinders to monitor parameters such as strain, acceleration, and train axle positions. Similarly, Dang et al. [14] proposed a cloud-based DT framework for SHM, combining machine learning, finite element modeling, and cloud computing for real-time monitoring and proactive maintenance. Their framework demonstrated high accuracy in detecting and assessing damage in both model and real bridges.

Gao et al. [15] introduced an AIoT-informed DT communication framework that improves efficiency and resilience in bridge O&M. By leveraging an information hierarchy and two-way communication, their system achieves low latency, high efficiency, and fault tolerance, with the potential for intelligent bridge management with minimal human intervention. Additionally, several conceptual bridge DTs [16–18] have been developed by Shim et al. for preventive maintenance by integrating surface models, BIM, and FEM-based simulation models, updating structural parameters based on detected deterioration. Moreover, many existing bridge monitoring and management approaches offer valuable insights for developing comprehensive bridge DT solutions. For example, Maes and Lombaert [19] conducted an extensive monitoring campaign on a railway bridge, providing a benchmark for validating vibration-based bridge SHM methods. Sajedi and Liang [20] developed a bridge SHM framework using a fully convolutional neural network (FCN), demonstrating a robust approach for near real-time damage assessment. Dong et al. [21] presented a deep learning-based structural displacement monitoring method using full-field optical flow techniques, achieving high accuracy through both laboratory and field experiments. Alexakis et al. [22] studied a railway viaduct using a multi-sensing system that integrates dynamic strain and acoustic emission sensors to monitor both global deformations and local deterioration. Meng et al. [23] developed the GeoSHM system, which employs GNSS and Earth observation technologies to monitor long-span bridges, providing a comprehensive approach for monitoring bridge deformation and environmental impacts.

Advanced algorithms, such as knowledge graphs and graph-based techniques, have been incorporated into DTs to support autonomous decision-making. Yang et al. [11] utilized big data and AI for multi-source data management and knowledge sharing, while Gao et al. [24] developed a bridge maintenance-oriented knowledge graph (BMKG), integrating text encoding and GraphSAGE for semantic enrichment and relationship prediction. Given that regional bridge networks can be represented as graphs, graph algorithms hold great potential for coordinating decisions across multiple bridges, such as maintenance planning, traffic diversion, and dynamic evacuation. However, research in this area is still limited.

### *2.2. GIS and BIM*

#### 2.2.1. GIS and Bridge DTs

In previous research [25], GIS has frequently been used as a platform for visualizing bridge locations and spatial relationships. This requires systems capable of efficiently rendering maps and bridge positions. Traditional GIS software, such as ArcGIS Desktop 10.8.2 and QGIS 3.14.16, while powerful, may lack the flexibility and web integration needed for dynamic bridge DT applications. In contrast, Cesium [26], a web-based platform that utilizes lightweight 3D tiling technology, is more suited to these tasks. Its web-based capabilities enable seamless integration between the GIS module and BIM modules, allowing users to switch effortlessly between them and enhancing real-time visualization and interaction. Moreover, GIS can play a significant role in analyzing the relationship between bridge maintenance and its surrounding environment. For instance, a bridge located in mountainous or coastal regions, combined with long-term weather data such as temperature and humidity, or its location in earthquake- or flood-prone areas, can greatly influence factors such as structural damage and material corrosion. These environmental conditions are critical for more comprehensive bridge health analysis within a DT framework.

Furthermore, the interaction between multiple bridges and the regional road network is crucial for the coordinated O&M of bridges. This includes managing traffic loads during routine bridge operations, traffic diversion and logistics planning during bridge maintenance, and dynamic evacuation in the case of natural disasters such as earthquakes and floods. Integrating these tasks into a GIS platform allows for more holistic decision-making regarding bridge maintenance under traffic loads. It cannot only minimize disruptions to daily life, but it also improves efficiency and can even contribute to reducing carbon emissions during the maintenance process.

#### 2.2.2. BIM and Bridge DTs

BIM has been widely adopted in bridge management, leading to the development of BrIM tailored for bridges. In recent research, bridge DTs and BMS often use BIM or BrIM as foundational technologies, benefiting from their capabilities in comprehensive data integration and detailed modeling. For example, Mohammadi et al. [27] developed a BrIM-based system using terrestrial laser scanning (TLS) to create a digital replica of bridge elements, integrating geometric and non-geometric data for accurate condition assessment and maintenance planning. This approach, validated on the Werrington Bridge in Australia, enhances decision-making through real-time monitoring and optimized remedial actions. Tita et al. explored digital twin–BIM technology for bridge management by combining health monitoring data with BIM for structural performance assessment. This approach enables traffic simulation, FE analysis, and landscape visualization, improving maintenance planning and enhancing bridge safety and reliability.

Moreover, Li et al. [28] developed a bridge health monitoring system that integrates BIM with ontologies and the industry foundation classes (IFC) standard. Their approach uses ontologies to model relationships between bridge elements and SHM systems, enabling the integration of geometric and non-geometric data. By extending the IFC schema, the system improves data sharing and management, facilitating more structured bridge health analysis. This integration of BIM, IFC, and ontology enhances data interoperability and supports comprehensive decision-making in bridge management. Additionally, there are also successful examples of BIM-based bridge DTs in the industry. For instance, an open BIM-based bridge DT [29] was developed to enable long-term monitoring and predictive maintenance (PM), combining traditional inspections with digital data from structural diagnosis and monitoring, and integrating the derived semantic data into the BIM model.

Although significant research explored BIM-based solutions for bridge DTs, studies focusing on the interaction between BIM and GIS remain relatively limited. Some works investigated using 3D tiling techniques to embed BIM models into GIS platforms or web interfaces. For instance, Zhan et al. [30] proposed a high-efficiency visualization method for complex BIM models on the web, utilizing 3D tiles while preserving the integrity of BIM's subassemblies. Similarly, Xu et al. [31] developed a method to convert IFC models into 3D tiles for smoother WebGIS interactions, addressing the challenges of model simplification and efficient data transmission in BIM-GIS integration. However, such approaches often compromise the level of detail (LOD) in BIM models to enable faster rendering and visualization.

This study seeks to improve the collaboration between GIS and BIM modules by maintaining the unique strengths of each. Rather than relying on simplified visualization, the study will utilize web technologies for seamless user interaction and fluid transitions between GIS and BIM functionalities. The back-end integration will enable effective cooperation between the two modules, ensuring detailed, efficient, and accurate maintenance and decision-making processes.

### 2.3. Graph-Based Applications

Several studies demonstrated the potential of graph-based approaches in GIS applications. For example, Abdelfattah et al. [32] developed a graph of charging stations and road networks using data from QGIS and applied K-nearest neighbor algorithms to compute the shortest paths between charging stations. Similarly, Daniel et al. [33] analyzed the connectivity and coverage of road networks extracted from open GIS data using graph centrality measures. To expand the use of graph data structure to BIM domain, Zhu et al. [34] proposed a framework for converting IFC files to labeled property graphs and subsequently to a common GIS format (e.g., CityGML, shapefile, 3D tiles, etc.) to address the interoperability issue between BIM and GIS.

In scenarios where managing and analyzing complex relationships between interconnected data points is crucial, the application of graph theory frequently takes the form of graph databases (graphDB) in practice. This is especially relevant in fields such as traffic infrastructure management, where the data is naturally structured as a network of related entities. According to Robinson et al. [35], a graphDB is any database that exposes a graph data model through create, read, update, and delete (CRUD) operations. The primary advantage of graphDBs, compared to relational databases and many other NoSQL databases, lies in their efficiency and intuitive ability to model and manage intricate relationships. Unlike traditional databases, graphDBs can not only query data based on node attributes, but also effectively model and manage complex relationships between data points.

Importing GIS and BIM data into a graph structure simplifies data integration by linking attributes from BIM and GIS directly within nodes and edges, so that graph algorithms can be operated natively on the unified data structure, for faster and more robust decision-making. Therefore, this study aims to explore the integration of BIM and GIS using graphDBs as an intermediate data model. Various software solutions are available for implementing graphDBs, such as Neo4j 5.23, ArangoDB 3.11.5, Neptune 1.3.2.1, Dgraph 23.0.0, OrientDB 3.2.35, FlockDB #4, etc.

## 3. Methodology

This section details the methodology employed in developing the integrated DT system for bridge O&M, comprising three main components: the overall design of the DT system, the visualization and data integration process, and the functionalities provided by the system. First, the architecture of the DT system is described, outlining the roles of the presentation, application, and platform layers that enable seamless interaction between WebGIS, WebBIM, and graph algorithms. Next, the visualization and data integration pipeline are explained, highlighting the advanced technologies used to support real-time monitoring and data-driven decision-making. Finally, the specific functionalities of the GIS and BIM modules are discussed, along with their interactions to optimize bridge maintenance and management.

### *3.1. DT System Design*

The proposed bridge digital twin (DT) system is structured into three distinct layers: presentation layer, application layer, and platform layer. Each layer serves a specific role in the overall architecture, enabling seamless integration and interaction for practical bridge operation and maintenance.

1. Presentation Layer
   The presentation layer is designed to facilitate data acquisition and visualization. It includes various data sources such as images, point clouds, and time-series data collected from the physical bridge during in situ inspections. The data are gathered using technologies such as drones, 3D scanners, and sensors, and are presented to the user via integrated BIM and GIS viewers such as CesiumJS and Xeokit. The interface allows users to interact with and visualize the bridge model, enabling remote monitoring and efficient data management.
2. Application Layer
   The application layer contains core digital twin services that support various applications. It is divided into three main components based on data type:
   - Image-based services: These include defect detection, segmentation, localization, and grading. The image data are used to assess surface conditions, identify defects, and evaluate structural elements.
   - Point cloud-based services: Point clouds enable geometry reconstruction, 3D damage detection, and spatial assessments. Additionally, this component supports BIM and finite element (FE) model updating for accurate digital representation of the physical bridge.
   - Time series-based services: This component is focused on time-series data from monitoring sensors. It enables fault diagnosis, health monitoring, early warning, and remaining useful life (RUL) prediction.

Additionally, the application layer provides customized functionalities, such as few-shot learning for damage detection, optimization for maintenance planning, and knowledge-based reasoning for decision support.

3. Platform Layer
   - The platform layer serves as the backend foundation of the web-based DigiBridge platform. It consists of three core modules:
   - Basic technologies: incorporates GIS, IFC, visualization, communication protocols, and data interoperability tools, forming the foundational elements of the platform.
   - Machine learning framework: includes training, prediction, and recommendation engines, as well as Flask-based APIs for seamless integration and service deployment.

- Big data and cloud services: supports large-scale data management and computation, including middleware, storage, distributed computing, and common data environment (CDE) services.

The integration of these modules enables the platform to process and store data efficiently, provide real-time analytics, and support high-level decision-making applications. The modular design of the platform layer ensures flexibility and scalability, allowing the system to adapt to different bridge types and operational contexts.

Based on the design above, the bridge DT platform architecture is presented in Figure 1, highlighting the interactions and data flow between these three layers. This platform supports a comprehensive digital twin solution for effective bridge operation and maintenance, providing a unified platform for data management, visualization, and analysis.

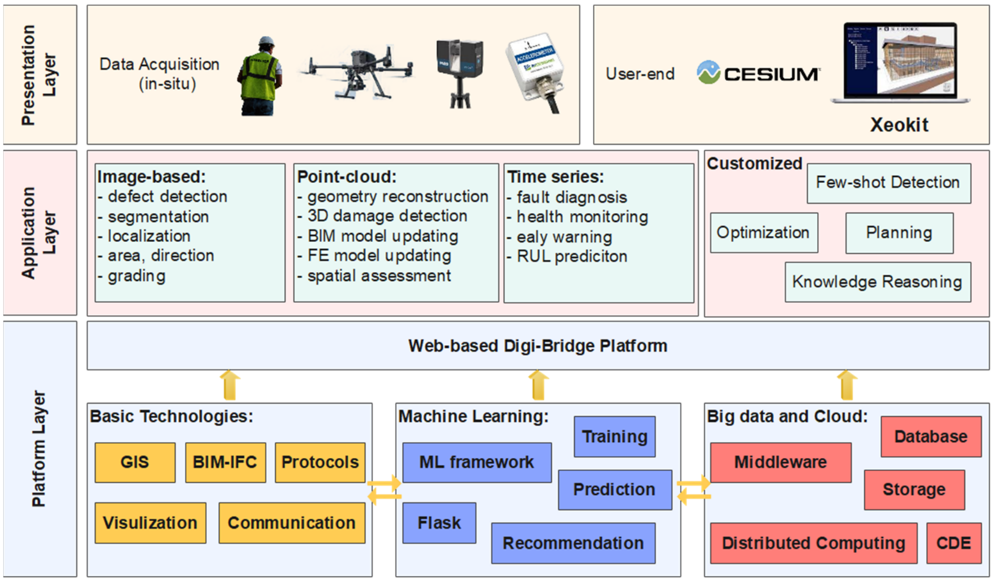


**Figure 1.** DT platform architecture.

### *3.2. DT Visualization and CDE*

The bridge DT visualization and data interaction pipeline is presented in Figure 2. This pipeline leverages multiple tools and platforms to achieve an integrated, interactive environment for bridge monitoring and management.

For efficient GIS visualization, bridge models are represented using the GLTF format and embedded into the Cesium platform as 3D tiles. This approach allows the spatial positions of the bridges to be accurately visualized within their natural environment, highlighting their relationships with surrounding geographic features and the broader transportation network. By leveraging the tiling technique, the platform efficiently handles large-scale data while maintaining high rendering quality. This GIS visualization provides an intuitive understanding of the bridge's spatial context, supporting tasks such as environmental impact analysis, traffic route planning, and infrastructure management.

For detailed BIM visualization, high-fidelity as-built IFC models (e.g., LOD 500) are embedded into the platform using the Xeokit SDK, enabling precise visualization of each bridge component. This allows users to view and interact with detailed structural elements, facilitating monitoring of specific bridge entities and assessing their conditions effectively.

The CDE integrates various data sources and frameworks, such as GLTF models, IFC models, 3D tiles, data from IoT sensors and embedded systems via field bus or wireless communication (e.g., Wi-Fi and LoRa), as well as data from external websites (e.g., Google Maps API and Met Office) via web crawlers. On the GIS webpage, weather conditions, traffic information, and bridge maintenance data can be linked to specific bridges and locations, providing users with a comprehensive view of the bridge's surroundings and interactions within the transportation network.

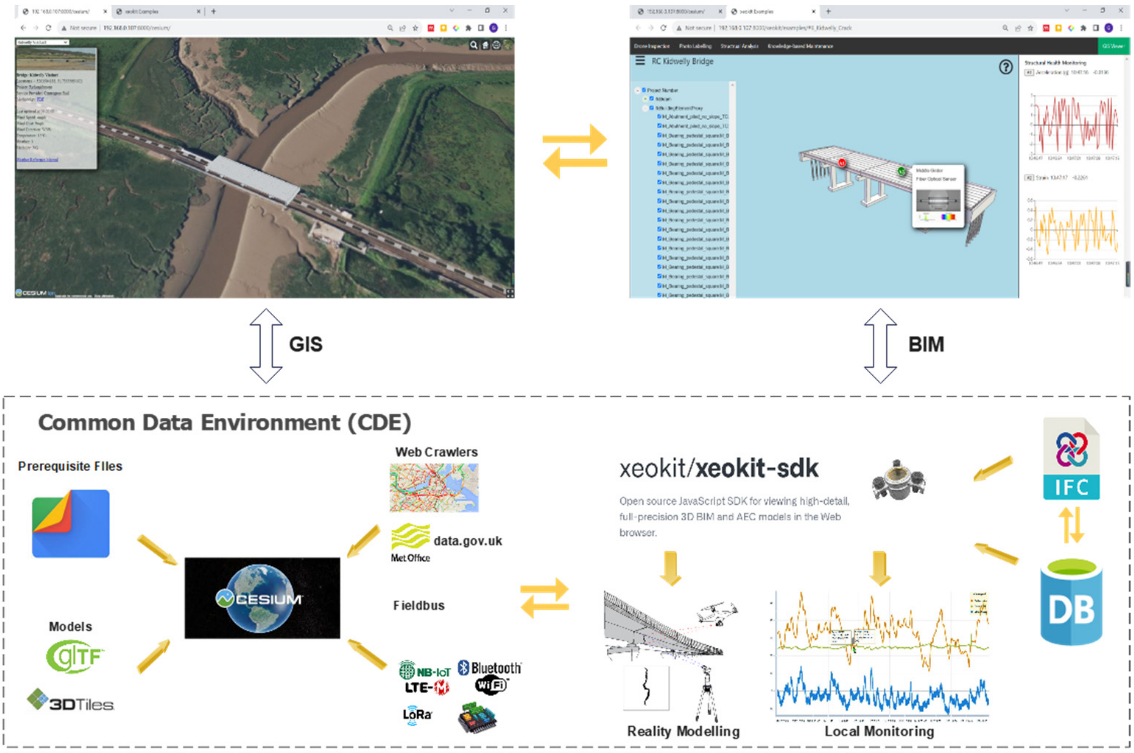


**Figure 2.** Bridge DT visualization and CDE.

On the BIM webpage, data collected from bridge surveys and health monitoring (e.g., drones, LiDAR scanners, and SHM sensors) are linked to corresponding bridge elements using unique entity IDs, enabling accurate reality modeling and tracking of real-time sensor readings on the dashboard. This connection allows users to view, retrieve, and evaluate bridge maintenance information directly within the BIM environment. The data are dynamically updated from the IoT database and visualized using WebSocket and related libraries (e.g., Apache ECharts), ensuring that real-time information is accurately reflected in the visualization.

Additionally, the integration of defect data with structural elements enables remote monitoring, condition assessment, and maintenance planning directly through the web-based platform. Users can seamlessly switch between the GIS and BIM webpages, allowing them to explore spatial context and structural details simultaneously. This cross-platform navigation enhances the user experience, providing a holistic understanding of the bridge's condition and its surrounding environment, ultimately supporting effective management and informed decision-making.

### *3.3. DT Functionalities*

Based on the design outlined in Sections 3.1 and 3.2, the bridge digital twin (DT) system is organized into two core modules: the GIS module and the BIM module. The functionalities of the DT system are specifically designed for each of these modules while also addressing scenarios where interaction between the two modules is necessary.

#### 3.3.1. GIS-Module Services

For the GIS module, the following functionalities are designed to leverage the specific strengths of GIS technology:

- Spatial visualization: Accurate representation of the bridge and its surroundings using geographic information, allowing users to observe the bridge in relation to nearby geographic features such as rivers, roads, and other infrastructure. This is achieved by embedding the bridge's GLTF model into the Cesium platform and utilizing 3D tiling technology to ensure efficient rendering of large-scale geographic data (see Section 3.2).
- Environmental impact analysis: Linking environmental data (e.g., weather from Met Office, terrain data) to the GIS module to analyze how the bridge interacts with its environment, particularly for long-term planning, such as corrosion risks for bridges in coastal areas with high salt content. Additionally, the GIS module supports traffic route optimization during extreme events, such as bridge closures caused by floods or earthquakes, ensuring timely and effective rerouting of traffic.
- Traffic and operational monitoring: Incorporating real-time traffic data and visualizing the impact of traffic flow on the bridge's operational status. Additionally, by leveraging the graph generated from the road network, the module uses graph-based algorithms to quickly generate alternative routes when a bridge is scheduled for maintenance or closure. This helps avoid traffic congestion or assists in dynamic evacuation planning, ensuring smoother traffic flow and better operational efficiency.
- Maintenance planning: Using the geographic context, along with the graph generated from the road network and corresponding graph algorithms, to optimize maintenance scheduling and logistics. This approach takes into account factors such as accessibility, nearby resources, and environmental conditions to ensure maintenance operations are planned efficiently and executed effectively.

#### 3.3.2. BIM-Module Services

For the BIM module, the following functionalities are designed to leverage the specific strengths of BIM technology:

- Detailed structural visualization and retrieval: Providing high-fidelity visualization of the bridge using detailed IFC models, enabling precise inspection and interaction with individual components (e.g., beams, piers, and decks). This is achieved by embedding IFC models into the Xeokit platform.
- Structural health monitoring: Visualizing real-time data from sensors embedded in the bridge, allowing users to monitor key indicators such as stress, strain, and vibration levels for specific structural components. Sensor data are linked to specific components via component ID in the attribute descriptions, which helps calibrate structural models, train machine learning (ML) models, predict remaining useful life (RUL), and support condition-based decisions. For example, extreme vibrations or high strain may indicate structural damage, prompting actions such as closing the bridge or restricting traffic.
- Damage detection and assessment: Utilizing data from imagery or point clouds to detect, localize, and evaluate structural defects, helping to inform maintenance and repair decisions. Machine vision techniques, along with pre-trained machine learning models, are used in this process, thereby automating the bridge inspection. The results are integrated into the BIM model, allowing engineers to query the damage status of specific components using their component ID and generate corresponding repair recommendations.

#### 3.3.3. GIS and BIM Interactions

The integration of the GIS and BIM modules is critical for several scenarios:

- Cross-platform navigation: Users can switch between GIS and BIM views seamlessly to explore both the spatial context and the detailed structural data of the bridge. For example, when inspecting a specific structural element in the BIM module, users can immediately assess its geographic surroundings through the GIS module.
- Data linkage: Real-time sensor data from the BIM module can be linked to the geographic context in the GIS module. For instance, weather conditions such as tempera-

ture, humidity, or wind speed (from the GIS module) affecting the bridge's structural integrity (monitored in the BIM module) can be visualized and analyzed together for a holistic view.

- Maintenance decision-making: The combined insights from both BIM and GIS modules enable more effective maintenance planning and operations. Monitoring data recorded in the BIM module can inform decisions such as closing the bridge, reducing load, or allowing one-way traffic. The GIS module can then generate appropriate traffic rerouting plans based on these decisions. Similarly, when repair components recorded in BIM need to be sourced from different locations, GIS can optimize transportation routes to streamline logistics and facilitate the maintenance process.

#### 3.3.4. GraphDB Services

Incorporating databases is crucial for optimizing decision-making processes for bridge O&M within the back end of the DT system. In this study, Neo4j is chosen as the preferred graph database due to its native graph storage and efficient processing capabilities, which enable the effective modeling of complex relationships among bridge components, maintenance activities, and regional traffic networks. The data are organized using a graph model, with nodes representing entities such as bridges, roads, inspection sites, maintenance warehouses, and transportation routes. The relationships between these nodes are defined as edges, capturing attributes such as transportation links and dependencies between maintenance tasks. This graph-based structure allows for comprehensive analysis and real-time updates, ultimately supporting informed and efficient O&M decisions. The data processing and decision-making workflow facilitated by the graphDB is shown in Figure 3.

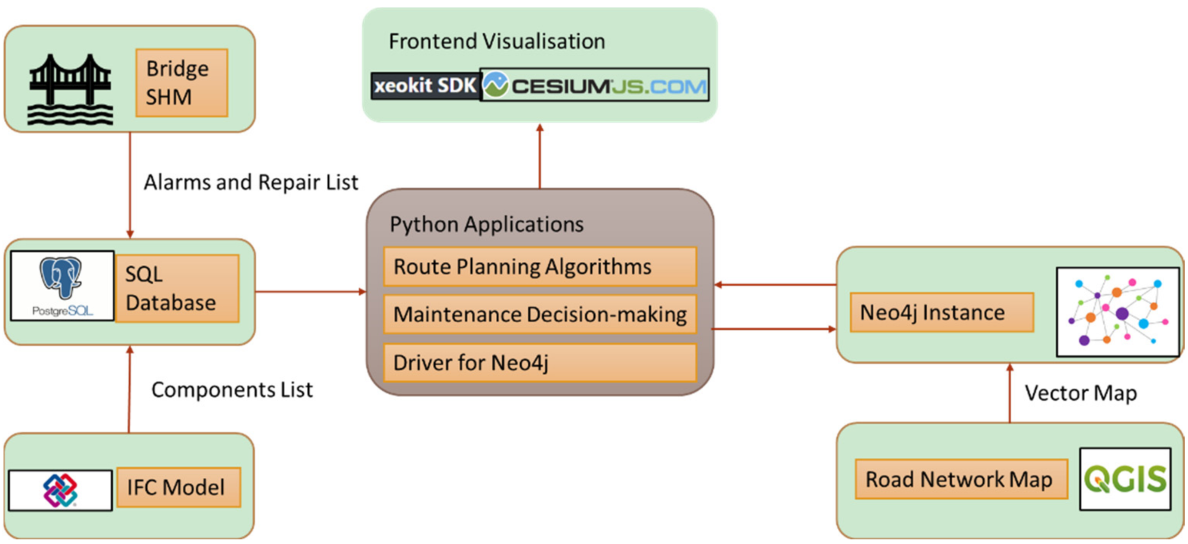


**Figure 3.** Data processing and decision-making workflow facilitated by graphDB.

## 4. System Validation

### *4.1. Pilot Bridge and Model Processing*

The River Neath Swing Bridge, constructed in 1892, is selected as the pilot bridge for this study. It is a Grade II listed railway bridge located downstream on the River Neath in South Wales, as shown in Figure 4. The bridge has undergone significant maintenance, including steel structure repairs and partial reconstruction. In this study, the bridge is treated as a road bridge to accommodate vehicle traffic, facilitating research.

This work utilizes Revit to model the pilot bridge based on original drawings, generating the IFC file of the bridge model. The IFC file can be directly integrated into the web-based Xeokit platform for BIM development. Meanwhile, using the open-source libraries [36,37], the IFC file can be converted into GLTF format and embedded into the

Cesium platform with 3D tiling technology, enabling lightweight and efficient web-based GIS development. The entire model processing workflow is illustrated in Figure 5.

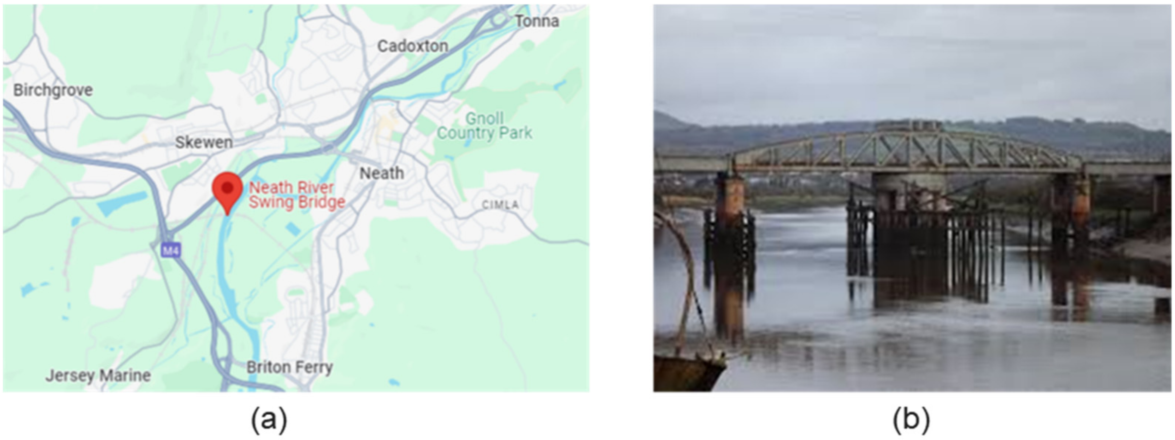


**Figure 4.** Pilot bridge location (**a**) and profile (**b**).

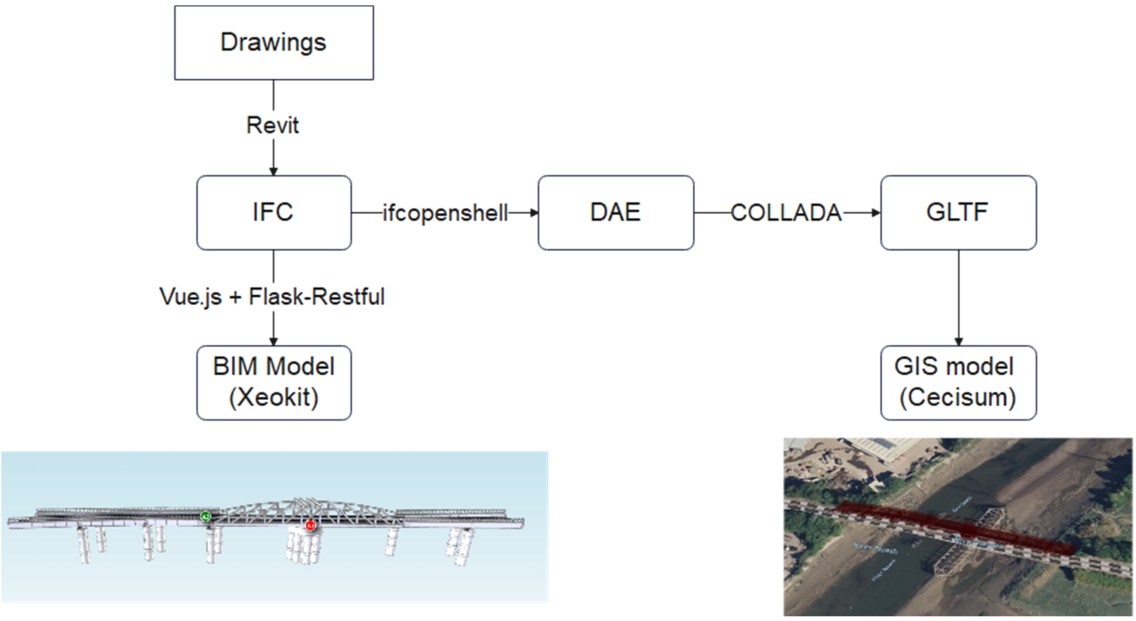


**Figure 5.** Bridge model processing workflow.

### *4.2. Case Study 1—Regional Bridge Operation and Monitoring*

#### 4.2.1. GIS and BIM Modules Visualization

The developed bridge DT platform leverages a web-based GIS module (i.e., Cesium) to deliver accurate spatial visualization of the bridge and its surrounding environment. This is accomplished by embedding the bridge's GLTF model into the Cesium platform and employing 3D tiling technology to efficiently render large-scale geographic data, as illustrated in Figure 6, including (a) bridges and maintenance warehouses' locations; (b) the pilot bridge 3D-tiling model in Cesium; and (c) weather data, wind speed, and visibility. This enables users to view the bridge in relation to nearby geographic features, such as rivers, roads, and infrastructure, offering a comprehensive understanding of the bridge's spatial context.

Additionally, the platform integrates environmental impact analysis by linking external data sources, such as weather data from the Met Office, into the GIS module, as shown in Figure 7. This functionality allows for the analysis of how the bridge interacts with its environment, supporting long-term maintenance planning, and ensures the safety of on-site workers during repairs by monitoring factors such as temperature, wind speed, and visibility.

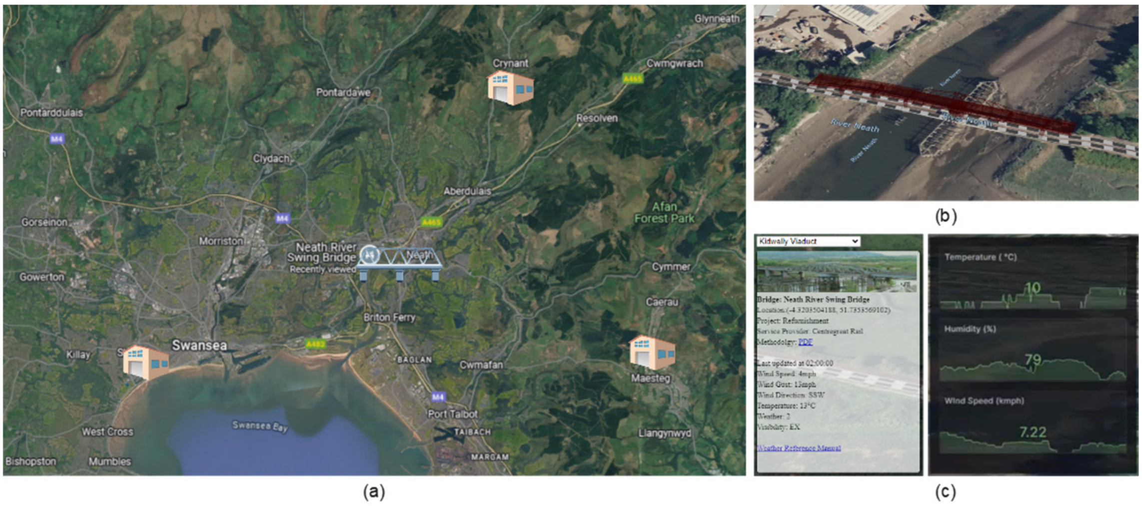


**Figure 6.** Pilot bridge visualization in GIS module.

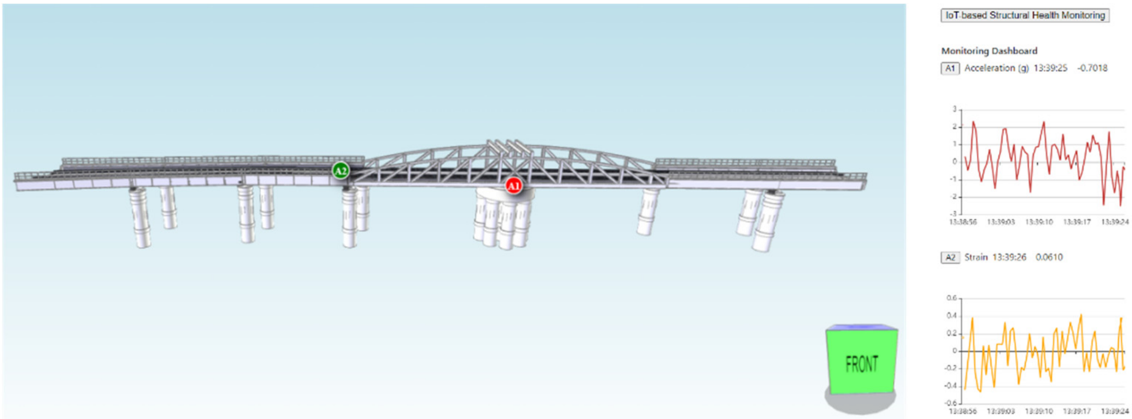


**Figure 7.** Pilot bridge visualization in BIM module.

The BIM module integrates sensor data for SHM of the bridge, as depicted in Figure 7. These sensors continuously collect data on the structural integrity of the bridge, including parameters such as strain, displacement, and vibration. When the monitored data deviate from present safety thresholds, the platform triggers an alert, signaling potential operational risks for the bridge.

### 4.2.2. BIM and GIS Interaction for Real-Time Traffic Diversion

In cases where critical structural damage is detected within the BIM module, such as the incident that happened to the Norway Starvo Bridge [38], the platform will issue instructions through the BIM module to either close the bridge or impose weight restrictions. Additionally, it will manage traffic in the GIS module by rerouting vehicles to alternative routes, thereby avoiding congestion and minimizing traffic risks. Such a workflow is illustrated in Figure 8.

The graph-based structure provides significant advantages for analyzing GIS maps, allowing for more advanced data analysis through graph theory algorithms than raw vector data alone. By assigning custom weights to edges, such as distance, time, or cost, the graph can facilitate the computation of optimal routes. This approach also supports dynamic updates, enabling real-time adjustments. In this work, roadmap data are sourced from OpenStreetMap, encoded in GeoJSON format, and processed using QGIS to generate the vector map, as shown in Figure 8. Then, the obtained vector map is converted into triple-based graph structures in Neo4j, as shown in Figure 8, where roads are represented as nodes and traffic connections as edges. The length of each road segment is calculated and stored for further analysis with graph algorithms in Neo4j.

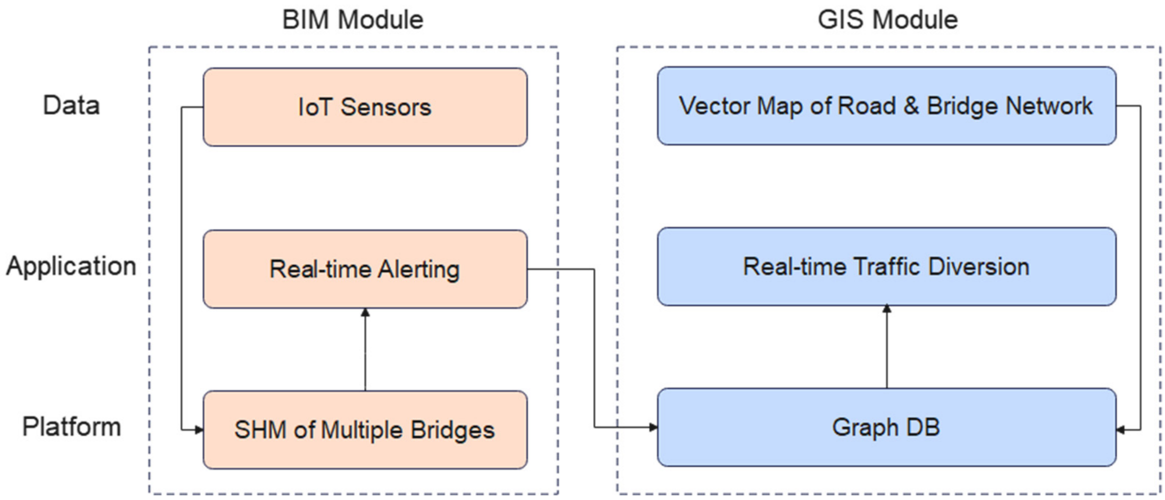


**Figure 8.** BIM and GIS interaction workflow for real-time traffic diversion.

To minimize disruption caused by bridge closures due to structural damage, the GIS module applies graph-based algorithms to generate optimized traffic diversion routes based on the regional road network. Here, highways classified as "motorways" and "primary" within a 45 km radius of Neath are queried using QuickOSM, with road segments as nodes and traffic connections as edges. When the BIM module flags a bridge as impassable due to SHM-detected damage, the affected edge is removed from the graph, as shown in Figure 9.

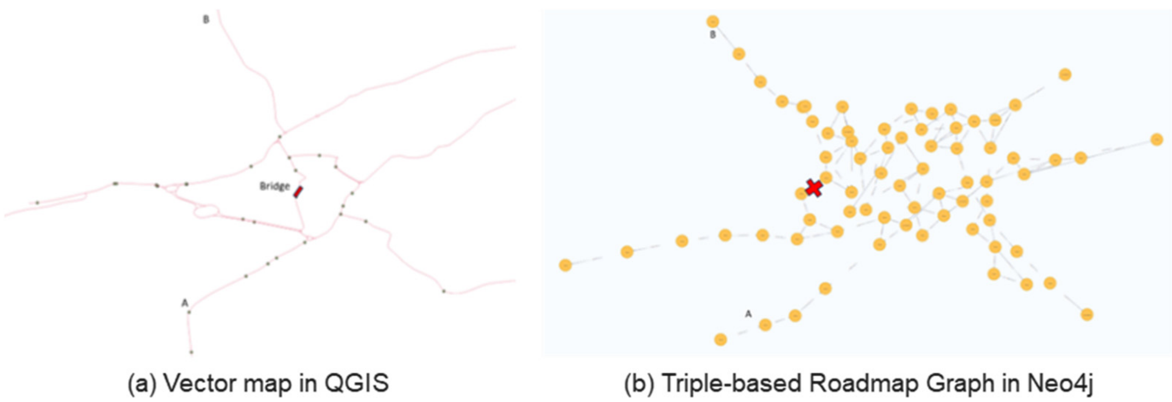


**Figure 9.** Vector map and roadmap graph surrounding Neath.

Afterwards, the system recalculates paths using shortest-path algorithms, such as Dijkstra's, ranks them by segment length, and provides alternative routes, as shown in Figure 10. This ensures efficient rerouting of vehicles and reduces congestion in the surrounding areas. The seamless integration of BIM-based real-time monitoring with GIS-driven intelligent traffic management enhances proactive maintenance and improves the operational efficiency of the bridge.

| index | path | pathLength |
|---|---|---|
| 1 | (:Node {osm_id: 23036348,length: 282})<-[:CONNECTED_TO]-(:Node {osm_id: 54828189,length: 55})-[:CONNECTED_TO]->(:Node {osm_id: 70509178,length: 574})-[:CONNECTED_TO]->(:Node {osm_id: 89711376,length: 101})-[:CONNECTED_TO]->(:Node {osm_id: 317737012,length: 232})<-[:CONNECTED_TO]-(:Node {osm_id: 205091774,length: 35})<-[:CONNECTED_TO]-(:Node {osm_id: 28658690,length: 67})-[:CONNECTED_TO]->(:Node {osm_id: 70509150,length: 294})-[:CONNECTED_TO]->(:Node {osm_id: 70509183,length: 79}) | 1719 |
| 2 | (:Node {osm_id: 23036348,length: 282})<-[:CONNECTED_TO]-(:Node {osm_id: 54828189,length: 55})-[:CONNECTED_TO]->(:Node {osm_id: 70509178,length: 574})-[:CONNECTED_TO]->(:Node {osm_id: 89711376,length: 101})-[:CONNECTED_TO]->(:Node {osm_id: 317737012,length: 232})<-[:CONNECTED_TO]-(:Node {osm_id: 205091774,length: 35})-[:CONNECTED_TO]->(:Node {osm_id: 317737013,length: 38})<-[:CONNECTED_TO]-(:Node {osm_id: 28658690,length: 67})-[:CONNECTED_TO]->(:Node {osm_id: 70509150,length: 294})-[:CONNECTED_TO]->(:Node {osm_id: 70509183,length: 79}) | 1757 |
| 3 | (:Node {osm_id: 23036348,length: 282})<-[:CONNECTED_TO]-(:Node {osm_id: 54828189,length: 55})-[:CONNECTED_TO]->(:Node {osm_id: 70509178,length: 574})-[:CONNECTED_TO]->(:Node {osm_id: 89711376,length: 101})-[:CONNECTED_TO]->(:Node {osm_id: 317737012,length: 232})<-[:CONNECTED_TO]-(:Node {osm_id: 205091774,length: 35})<-[:CONNECTED_TO]-(:Node {osm_id: 205091772,length: 38})<-[:CONNECTED_TO]-(:Node {osm_id: 28658690,length: 67})-[:CONNECTED_TO]->(:Node {osm_id: 70509150,length: 294})-[:CONNECTED_TO]->(:Node {osm_id: 70509183,length: 79}) | 1757 |

**Figure 10.** Top three shortest routes from A to B.

### *4.3. Case Study 2—Individual Bridge Maintenance*

#### 4.3.1. Integration of Drone-Enabled Bridge Inspection

The developed DT platform integrates drone-enabled bridge inspection in situ. When GPS signals are strong, RTK enables drones to achieve centimeter-level positioning accuracy. By leveraging the drone's camera orientation, field of view, and trigonometric calculations, the 3D coordinates of detected bridge defects can be precisely determined and linked to the corresponding bridge elements [15]. In cases where GPS signals are disrupted (e.g., due to satellite obstruction), the inertial measurement unit (IMU) and visual positioning systems can be used to accomplish the same task.

Computer vision techniques, such as k-means and Gaussian mixture model (GMM) clustering, and deep learning models such as Mask R-CNN and DeepLabV3, are used to identify and segment detected defects on the bridge structure. Defect images are stored in an image database and visualized in the BIM module, linked to their respective element locations on the bridge model, as illustrated in Figure 11. The figure shows (a) fair and severe corrosion on a pier, (b) missing bolts on the cross bracing, (c) corrosion on the truss end plate, and (d) section loss on the lower crank. Additionally, the defect list on the top right provides detailed information, including data sources, inspection dates, locations, and defect descriptions.

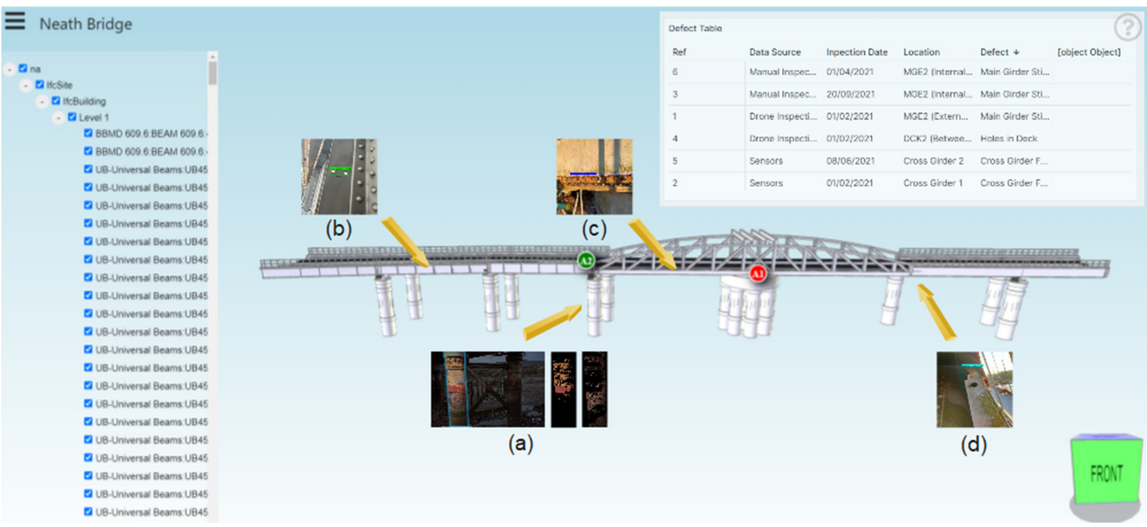


**Figure 11.** Observed defects and defect list shown in the BIM module.

For significant damage requiring depth information, such as large cracks and spalling, the drone can approach the target area and perform scans using onboard LiDAR [39]. The generated 3D data can then be processed for autonomous damage segmentation and analysis, with the results linked to the relevant structural components. Simultaneously, the defect geometries and updated material parameters can be synchronized within the DT model, enabling finite element analysis (FEA) of the bridge structure or predicting the remaining useful life (RUL) of the affected components.

Furthermore, JSON files are created to systematically document observed bridge defects, capturing essential details such as bridge elements, defect types, dimensions, and severity levels. Each defect assessment is saved as semantic information (text) within the JSON structure, with elementIDs from the IFC files utilized to precisely link defects to their corresponding bridge components. This JSON-based approach offers a structured and comprehensive view of inspection outcomes, significantly enhancing information modeling and supporting informed maintenance decision-making.

#### 4.3.2. BIM and GIS Integration for Maintenance Planning

For each defect entry generated in the JSON files, the system automatically generates maintenance recommendations based on historical repair records, established maintenance standards (e.g., manuals or handbooks), or the pre-defined bridge maintenance knowledge graph (BMKG). Simultaneously, by integrating the structural analysis results and RUL predictions from the updated DT model, the system makes informed decisions, such as prioritizing repairs for critical defects, selecting the most suitable maintenance methods, scheduling interventions to minimize disruptions, and identifying the necessary spare parts and resources. The BIM module then transmits this information to the GIS module, which utilizes the graph database and associated graph algorithms to generate an optimized bridge maintenance plan. This comprehensive approach ensures that bridge maintenance is both efficient and effective, such as optimizing resource allocation and generating traffic diversion strategies (see Section 4.2.1).

Here, the example of spare parts retrieval and transportation, which relates to optimizing resource allocation, is used for illustration, as shown in Figure 12. The process of extracting the vector map and converting it into a roadmap graph follows the same method described in Case 1 (see Section 4.2.2).

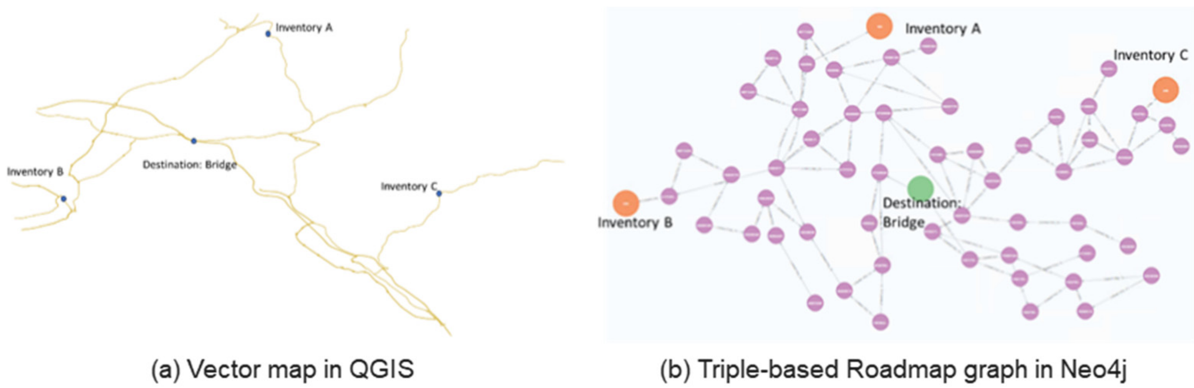


**Figure 12.** Vector map and roadmap with warehouses.

Graph algorithms are then applied to facilitate planning and decision-making for tasks such as traffic diversion during bridge repairs (similar to Case 1), spare parts retrieval, and transportation. Case 2 specifically focuses on spare parts query and transportation and the workflow is illustrated in Figure 13.

Here, warehouses are designed as nodes in the roadmap graph (shown in Figure 11) and spare parts information is assigned as attributes to each inventory node. The attribute values indicate the inventory of each spare part at the corresponding warehouse, e.g., 0 indicates that there is no available spare part at the warehouse. By using the WHERE clause in Neo4j, the system can find the warehouses that meet the requirements of spare parts quantity for repair plan.

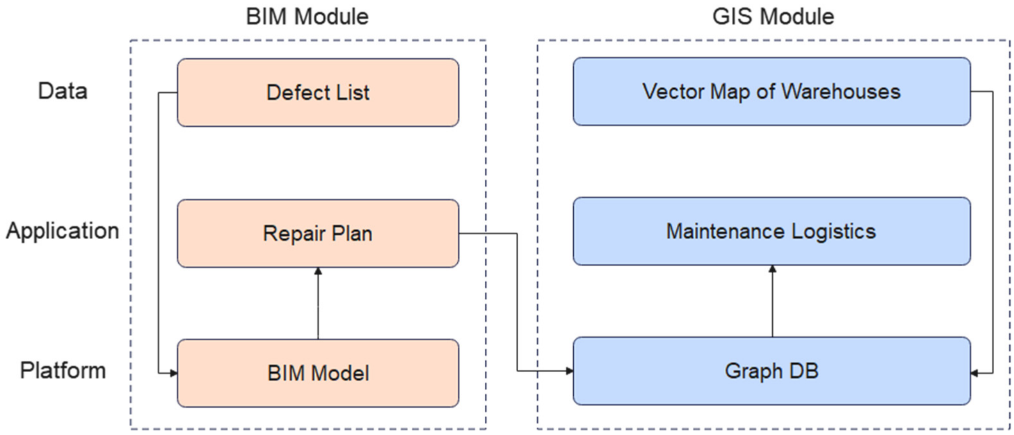


**Figure 13.** BIM and GIS interaction workflow for maintenance logistics.

When multiple warehouses have sufficient spare parts, the system evaluates the distance from each warehouse to the target bridge and selects the optimal warehouse based on proximity. As illustrated in Figure 14, both Warehouses B and C satisfy the spare parts requirement for the Neath bridge's repair, but Warehouse C is closer, making it the preferred source for dispatching spare parts to the repair site.

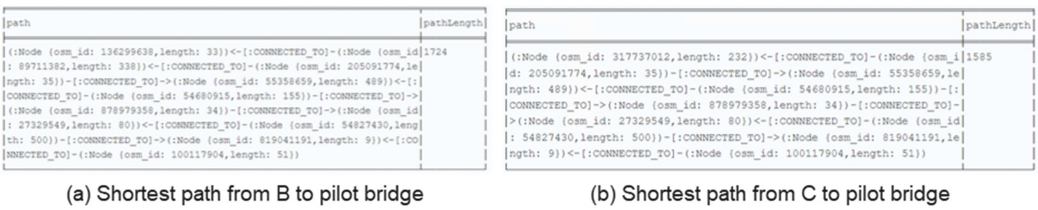


**Figure 14.** Shortest paths from Warehouses B and C to target bridge.

Similarly, if spare parts are required from multiple warehouses, the system autonomously queries the inventory and coordinates transportation arrangements, ensuring an efficient and well-organized delivery plan. Factors such as distance, weather, traffic conditions, load capacity, and fuel consumption can be encoded as properties of the relationships (i.e., edges) between nodes. These parameters enable advanced route planning through path-finding algorithms. For example, the case study 2 demonstrated distance-based optimization, where proximity was prioritized to identify the nearest warehouse. In time-critical scenarios, the algorithm's focus can shift to optimizing routes with the shortest travel time. Furthermore, multi-criteria route optimization is achievable by integrating multiple weight parameters into an evaluation model. These priorities can be dynamically adjusted based on user input or real-time constraints, allowing the system to provide tailored solutions for specific scenarios. This approach ensures efficient logistics, contributing to a streamlined and well-coordinated maintenance process.

## 5. Discussion

This study developed an integrated digital twin system that combines BIM and GIS modules to guide practical bridge maintenance and operations. The system explores the interaction between BIM and GIS to enable various functions, such as traffic diversion, maintenance planning, and logistics optimization. Additionally, it investigates the integration of GIS with a graph database and applies graph algorithms for bridge maintenance optimization and decision-making.

However, the system has several limitations and areas for improvement. Firstly, although the BIM module utilizes elementIDs from IFC files as identifiers linking the defects to the corresponding bridge elements, the information modeling process for observed defects still relies on custom JSON files currently, which lacks extensibility. Future work will build on existing research [40] to redefine defect and damage assessment content in the IFC format and integrate it into the system for enhanced interoperability. Secondly, the bridge DT system comprises different modules and software, including Xeokit, Cesium, and Neo4j. As additional functionalities are developed, the system may encounter cross-platform compatibility issues. Addressing these challenges will be essential in future research to streamline integration and improve overall system efficiency. These enhancements will contribute to a more robust and scalable platform, strengthening the practical application of digital twins in bridge O&M.

## 6. Conclusions

This study successfully developed an integrated DT system for practical bridge operation and maintenance, combining BIM and GIS modules with a graph database to establish a comprehensive bridge management platform. By leveraging BIM and GIS interactions, the DT system enables real-time monitoring, drone-enabled inspection, maintenance planning, traffic diversion, and logistics optimization, effectively streamlining O&M processes and enhancing data-informed decision-making. Furthermore, the integration of GIS with graph-based algorithms facilitates efficient resource allocation, optimizing route planning and spare parts management for bridge repairs.

In the Cesium-based WebGIS module, roadmap data sourced from OpenStreetMap are processed into vector maps and triple-based graphs through QGIS and Neo4j, forming an adaptable data architecture. This setup not only supports visualization compatible with Cesium, but also enables advanced graph-based data analysis and decision-making. Meanwhile, the Xeokit-based WebBIM module facilitates detailed monitoring of bridge components and effective defect management. Structural issues flagged by the SHM system automatically trigger alerts and initiate traffic redirection, while defects detected via drone-enabled inspection inform maintenance planning within the BIM module.

These functionalities demonstrate the system's potential to improve practical bridge O&M, enhance safety, support autonomous decision-making, and optimize resource allocation through data-driven and graph-based insights. Future work will focus on enhancing cross-platform interoperability, refining information modeling for defects within the IFC format, and addressing compatibility challenges to expand scalability and support more advanced DT applications for bridge infrastructure.

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