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A BIM Component-centred Bridge Digital Twin for Smart and Practical Bridge Maintenance

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Abstract: For bridge visual inspection and maintenance, a fundamental task is to determine the condition of a bridge component from its appearance as captured by images. Then the information of the identified defects is recorded in documents and assessed collectively by bridge practitioners to determine what maintenance activities are required for the component. This engineering practice naturally fits for the idea of IFC components in BIM workflow. So, to automate this labour-intensive and time-consuming process, a smart and practical framework is proposed utilising BIM component-centred bridge digital twin system. In this system, sensors-equipped robotics is integrated with the bridge digital twin to identify any defect. Component-wise defect data is linked to the BIM model for detailed and holistic assessment, ensuring that maintenance decisions are fully informed. This framework is validated by demonstration of key functions including RTK-enabled drone for automatic defect localisation, defect quantification by computer vision, defect data storage in SQL and visualisation of enriched BIM model in interactive web-based platform for maintenance decision-making. It is demonstrated that the framework can streamline defect data transfer from on-site inspection to an online bridge digital twin, supporting decision-making processes by referencing relevant industrial standards.

Keywords: Bridge Maintenance, Digital Twin, BIM, IFC

1. INTRODUCTION

In recent years, the construction industry is experiencing digital transformation and Building Information Modelling (BIM) is a key tool to facilitate the management of full life cycle of built environments, especially the maintenance of assets. The idea of BIM is consistent and continuous use of digital data and exchange digital data between different systems and platforms (Borrmann *et al.*, 2018). As the major file format of BIM, Industry Foundation Classes (IFC) contain information about an asset and every component of the asset is represented as an object with unique identifiers and attributes, which allows for precise identification, referencing, and retrieval.

According to the UK Network Rail standard NR/L3/CIV/006 (Network Rail, 2022a), the defect properties that the bridge practitioners concern include 1) defect location - which bridge component that the defect is developed upon, and 2) defect description in terms of dimensions, directions, profiles, etc. The characteristics of defect are generally documented as schedules, with each entry corresponding to a specific defect instance. However, adding hundreds of defects observed during an inspection to an IFC model of a bridge could be challenging. As IFC is capable of representing 3D bridge models with highly accurate geometry but it is considered insufficient for updating model content due to its static nature (Isailović *et al.*, 2020). Therefore, the proposed solution to this challenge is to create a data schema that can link bridge components on an IFC model to the defects schedule created from bridge inspection.

Digital twinning is an emerging technology for intelligent asset management that provides an up-to-date representation of an actual physical asset in operation. A digital twin for bridge maintenance is not only about creating a digital representation of the physical bridge but can also update as new data is collected, moreover, it can perform analysis for asset risk assessment. There are studies for different aspects of bridge digital twin, such as drone-enabled bridge inspection (Gao *et al.*, 2023; Yoon *et al.*, 2022), bridge information modelling (Adibfar and Costin, 2022; Mohammadi *et al.*, 2023) knowledge-based and optimisation-oriented bridge management systems(Yang *et al.*, 2022; Allah Bukhsh *et al.*, 2020), etc. Nevertheless, there is limited discussion on the full maintenance cycle of bridge digital twin spanning from data collection to maintenance decision-making. So, this study investigates a framework that can streamline on-site inspection, digital twin data model and synchronisation, and Common Data Environment (CDE) that facilitate structural assessment and decision-making on maintenance activities.

2. METHOD

Bridge maintenance involve several steps, from conducting inspection, identification of defects, recording the defects in terms of locations/type/area, assessing the extent and severity of the defects on the bridge structure, to determining the repair activities need to be carried out. There is information flow in different systems and documents, starting from the physical bridge, reality capture devices (i.e. camera), on-site inspection notes, summarised inspection reports, structural assessment and repair proposals. To streamline the data in this process, by utilising the idea of BIM, a framework shown in the Figure 1 is proposed. The centre of the framework is the BIM Component which comprises of IFC object as well as linked defect data from database. The BIM Component is referenced with ComponentID (i.e. GlobalId in IFC terminology) so that it can be traced across different systems and platforms.

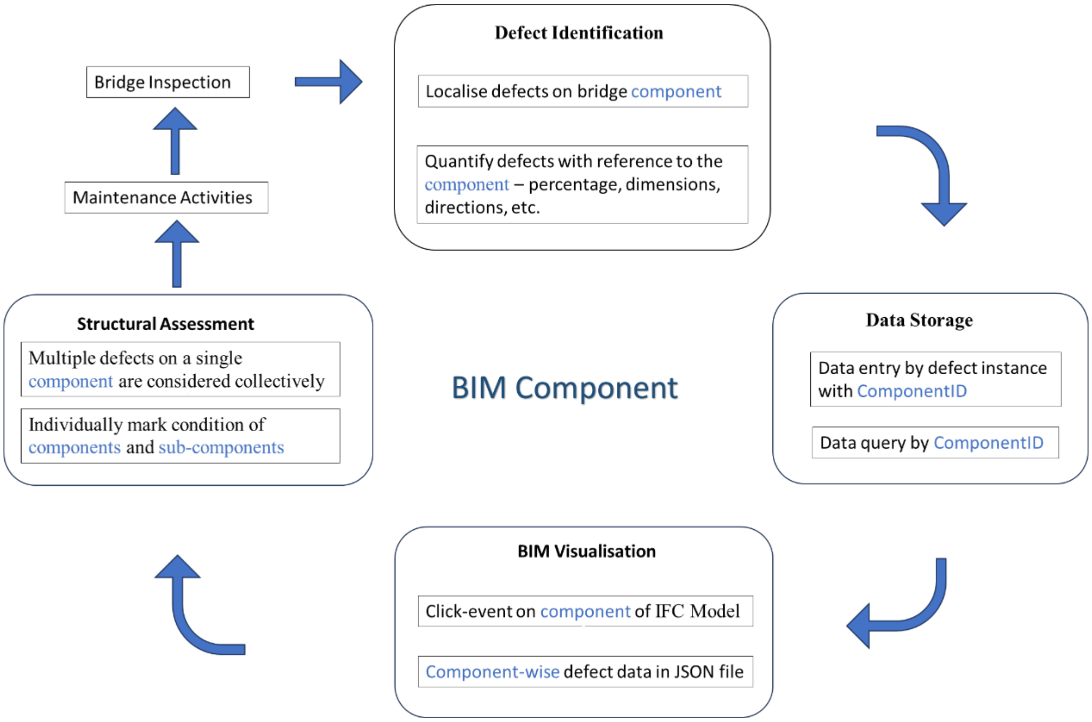


Figure 1: Proposed framework

2.1 Defect Identification on BIM Component

Automated bridge inspection system utilising versatile robotic systems such as drones (Barrile *et al.*, 2019) and climbing robots (Nguyen and La, 2020; Sutter *et al.*, 2018) can not only carry inspection payloads (e.g. camera, LiDAR, etc.) but also provide accurate positioning assisted with control system. For example, mobile robots and drones can locate themselves based on Global Navigation Satellite System (GNSS), obstacle avoidance system (i.e. camera, ultrasonic distance ranger, LiDAR, etc.), and inertial measurement units (IMUs) to help with defect localisation. On the other hand, the detection of defects can be carried out by object detection algorithms such as YOLO, and defect quantification can be realised with semantic segmentation by image processing or deep learning(e.g., DeepLab).

An approach based on Real-Time Kinematic (RTK) is developed to provide defect localisation in the bridge coordinate system, as indicated in Figure 2.

Considering the Earth's surface is nearly planar over short distances of a few kilometers, the distance between the drone and the defect, D_{drone} is calculated as Eq. 1. The coordinates of the defect X_{crack}, Y_{crack} and Z_{crack} can be calculated as Eq.2 - 4.

$$D_{drone} = R\sqrt{(\phi_2 - \phi_1)^2 + (\lambda_2 - \lambda_1)^2} \tag{1}$$

Where L – horizontal distance; R – earth’s radius (the parameter that needs to be calibrated); φ1, φ2 – base and drone latitude; λ1, λ2 – base and drone longitude.

$$X_{crack} = D_{drone} \sin\theta - D_{crack} \cos\beta \cos\alpha \tag{2}$$

$$Y_{crack} = D_{drone} \cos\theta - D_{crack} \cos\beta \sin\alpha \tag{3}$$

$$Z_{crack} = H_{drone} - H_{base} + h_{equip} - D_{crack} \sin\beta \tag{4}$$

The coordinates can be further linked to bridge components based on geometric information available from IFC model. The crack direction (such as latitudinal or longitudinal) can be determined by drone position and camera angle. Given situations without stable GNSS signals (e.g., underneath a bridge), simultaneous localization and mapping (SLAM) based on IMUs and cameras can be utilised to improve accuracy.

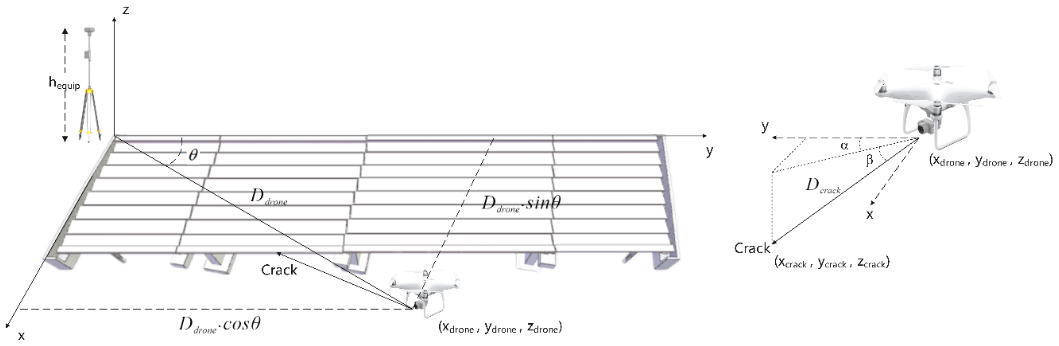


Figure 2: Image capture and defect localisation with RTK-enabled drone
(Gao Y, Li H and Xiong G, 2023)

2.2 Defect Data Storage and Visualisation

To enable interoperation between defect data captured from the drone and geometrical data extracted from the IFC model, and to visualize both data streams at the CDE, the workflow shown in Figure 3 has been designed.

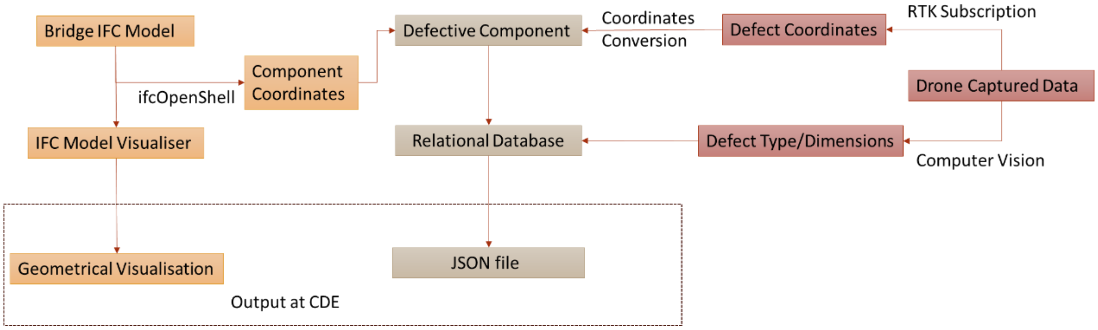


Figure 3: Workflow for defect data storage and visualisation

(1) Data Storage

To achieve interoperability, some functions in the workflow are coded, such as ‘Coordinates Conversion’ module and ‘RTK Subscription’, and some practical tools are utilised – ‘ifcOpenShell’ is required to manipulate geometrical data from the IFC model. Once a defect is captured by RTK-enabled devices in an image, the latitude/longitude/altitude can be extracted from the metadata of the image, then converted to coordinates on 3D model to match the specific IFC component. Finally, the description of each defect instance (e.g. type, dimensions, etc) can be stored in a relational database, ready for retrieving to a JSON file.

(2) Visualisation
The visualisation module shall be able to display not only IFC geometrical model but also defect schedule stored in database. IFC visualiser is employed in the platform for visualisation of 3D model, and also enables users to manipulate each component of the BIM model based on the IFC file. Interactive mechanism shall be allowed at CDE to trigger data query of the defects related to the specific ComponentID, to provide an overview of the condition of the component, for the ease of review by bridge practitioners.

2.3 Standards–Based Structural Assessment of BIM Component

Multiple defects on a single component shall be considered collectively following NR/L3/CIV/006 (Network Rail, 2022a), where it states that the practitioner shall decide condition rating for each component or sub-component. The component is marked high if the defects identified on a component are localised due to local circumstances while the component is marked low when defects on it are widely spread, as the structure of the component is likely to be severely affected.

Whereas for the whole bridge, the industrial practice of structural assessment in NR/L2/CIV/035 (Network Rail, 2022b) is described as - each bridge is composed of hierarchical levels of components (e.g. components, sub-components, etc.) which are marked individually, then the condition marking of the component is determined against their lowest marked sub-component. Maintenance decisions (i.e. which component shall be repaired) and repair methods are then determined collectively in predefined components group. The decision-making process described above use the idea of decision tree, and it can be implemented as a hierarchical graph structure where some nodes represent a bridge component with its attribute as condition marking, while other nodes represent decision points. The maintenance decision can be determined by traversing the graph structure by following predefined relationships.

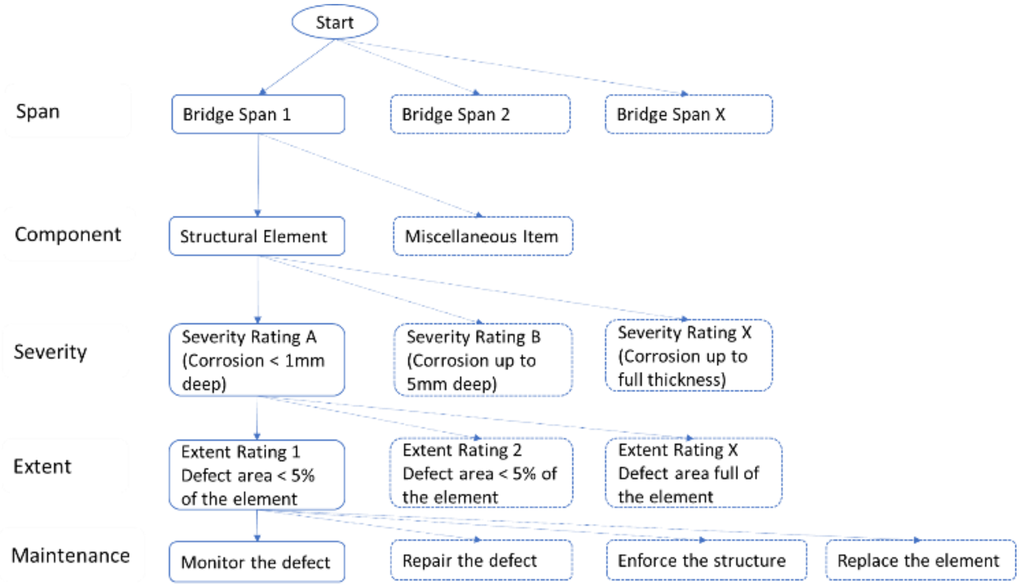
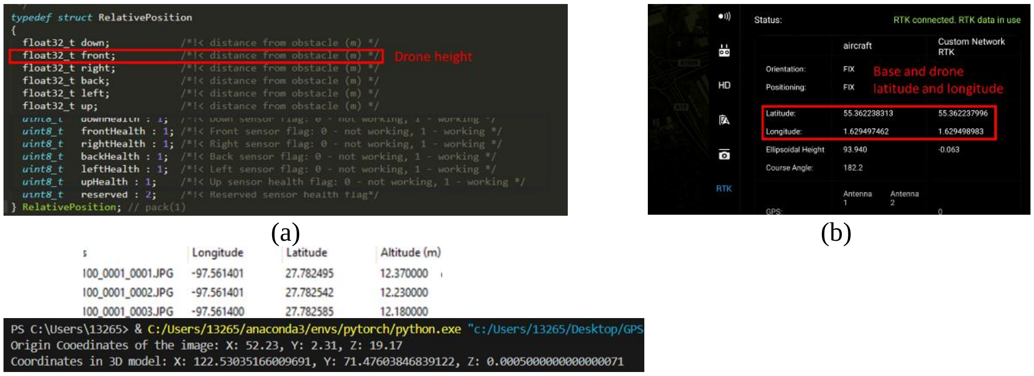


Figure 4: Graph structure for maintenance decision-making

3. RESULTS

The proposed framework was implemented with various tools and software to demonstrate its functionality, i.e., 1) drone-enabled defect localisation and quantification, 2) defect data storage, retrieval and visualisation, and 3) standards-based repair method recommendation and decision-making.

As shown in Figure 5 (a) (b) (c), drone height (i.e. H_{drone} in Equation 1) can be streamed from RTK subscription from OSDK or MSDK of DJI drone, latitude and longitude of drone and base can be obtained from controller and also captured in the metadata of the photo taken. To map drone coordinates from Earth's GPS system to the 3D space of bridge model, the relative position is calculated by determining the difference between the GPS coordinates of the photo and the GPS coordinates of the 3D model's coordinate origin. This establishes the photo's position within the 3D model. The function is implemented as Python programme shown in Figure 5 (d).



```
typedef struct RelativePosition
{
  float32_t down;             /*!< distance from obstacle (m) */
  float32_t front;            /*!< distance from obstacle (m) */
  float32_t right;            /*!< distance from obstacle (m) */
  float32_t back;             /*!< distance from obstacle (m) */
  float32_t left;             /*!< distance from obstacle (m) */
  float32_t up;               /*!< distance from obstacle (m) */
  uint8_t   downHealth : 1;   /*!< Down sensor flag: 0 - not working, 1 - working */
  uint8_t   frontHealth : 1;  /*!< Front sensor flag: 0 - not working, 1 - working */
  uint8_t   rightHealth : 1;  /*!< Right sensor flag: 0 - not working, 1 - working */
  uint8_t   backHealth : 1;   /*!< Back sensor flag: 0 - not working, 1 - working */
  uint8_t   leftHealth : 1;   /*!< Left sensor flag: 0 - not working, 1 - working */
  uint8_t   upHealth : 1;     /*!< Up sensor health flag: 0 - not working, 1 - working */
  uint8_t   reserved : 2;     /*!< Reserved sensor health flag*/
} RelativePosition; // pack(1)
```

(a)

Status: RTK connected. RTK data in use

	aircraft	Custom Network RTK
Orientation:	FIX	
Positioning:	FIX	
Latitude:	55.362238313	55.362237996
Longitude:	1.629497462	1.629498983
Ellipsoidal Height	93.940	-0.063
Course Angle:	182.2	

(b)

s	Longitude	Latitude	Altitude (m)
100_0001_0001.JPG	-97.561401	27.782495	12.370000
100_0001_0002.JPG	-97.561401	27.782542	12.230000
100_0001_0003.JPG	-97.561400	27.782585	12.180000

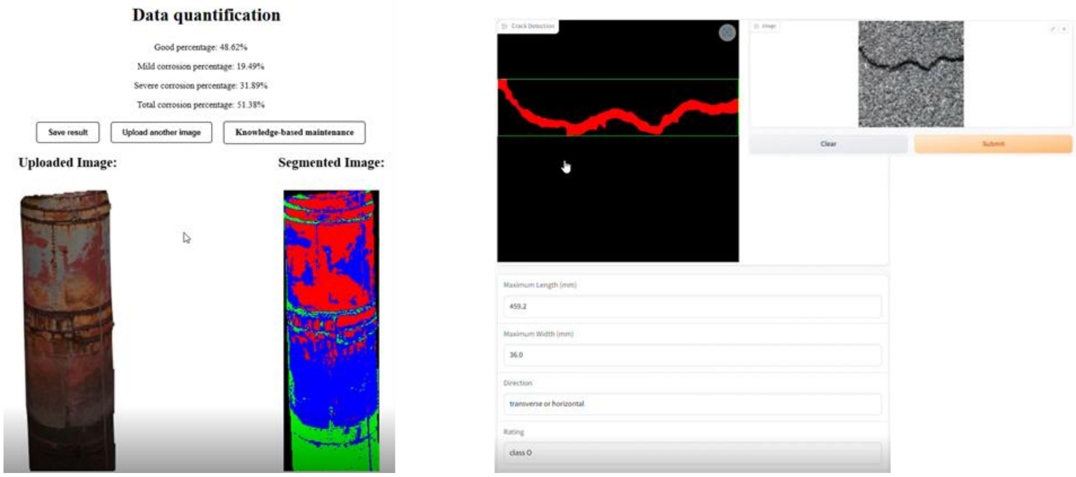
```
PS C:\Users\13265> & C:/Users/13265/anaconda3/envs/pytorch/python.exe "c:/Users/13265/Desktop/GPS
Origin Cooedinates of the image: X: 52.23, Y: 2.31, Z: 19.17
Coordinates in 3D model: X: 122.53035166009691, Y: 71.47603846839122, Z: 0.0005000000000000071
```

(c)

(d)

Figure 5: Localisation of defect via
RTK subscription(a)(b), metadata of image(c) and coordinates conversion(d)

Defect quantification module follows the principles defined in NR/L2/CIV/035, where corrosion is assessed by percentage of corrosion area, while crack is evaluated by its length, width and direction. The module is deployed in web-services, as illustrated in Figure 6, providing key information after inserting the defect image.



Good percentage: 48.62%

Mild corrosion percentage: 19.49%

Severe corrosion percentage: 31.89%

Total corrosion percentage: 51.38%

Maximum Length (mm): 459.2

Maximum Width (mm): 36.0

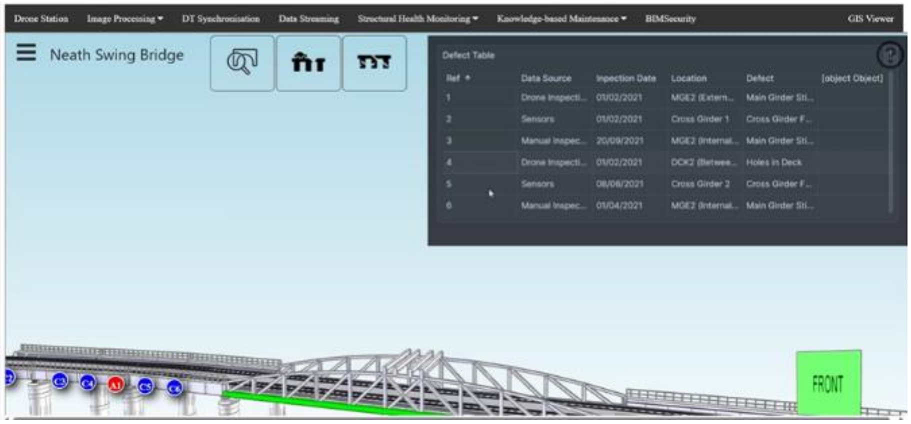
Direction: transverse or horizontal

Rating: class 0

(a) (b)

Figure 6: Quantification of corrosion(a) and crack(b) on bridge using computer vision

The bridge digital twin CDE is designed to perform through functions based on the RESTful framework where Node.js and NPM Anywhere server (i.e. a static file server) support the web-based interface. The user-friendly interface can enable retrieval and display of defect information on a specific component by web-based click event, as shown in Figure 7.



Defect Table

Ref	Data Source	Inpection Date	Location	Defect	[object Object]
1	Drone Inspecti...	01/02/2021	MGE2 (Extern...	Main Girder Sti...	
2	Sensors	01/02/2021	Cross Girder 1	Cross Girder F...	
3	Manual Inspec...	20/09/2021	MGE2 (Internal...	Main Girder Sti...	
4	Drone Inspecti...	01/02/2021	DCK2 (Betwee...	Holes in Deck	
5	Sensors	08/06/2021	Cross Girder 2	Cross Girder F...	
6	Manual Inspec...	01/04/2021	MGE2 (Internal...	Main Girder Sti...	

Figure 7: Visualisation of BIM model and defect data

On the other hand, the conceptual design of structural assessment from Figure 4 is implemented in the graph database software Neo4j. As shown in Figure 8, the graph is partitioned into three layers: 1) bridge structure layer which represents graph-based bridge model; 2) defect information layer describing the extent and severity of the defect and 3) maintenance layer which reflects repair proposals. The decision-tree traversal is performed to find the path starting from the bridge structure layer and leading to the node of maintenance layer, with the traversal being filtered based on the properties of each node along the path.

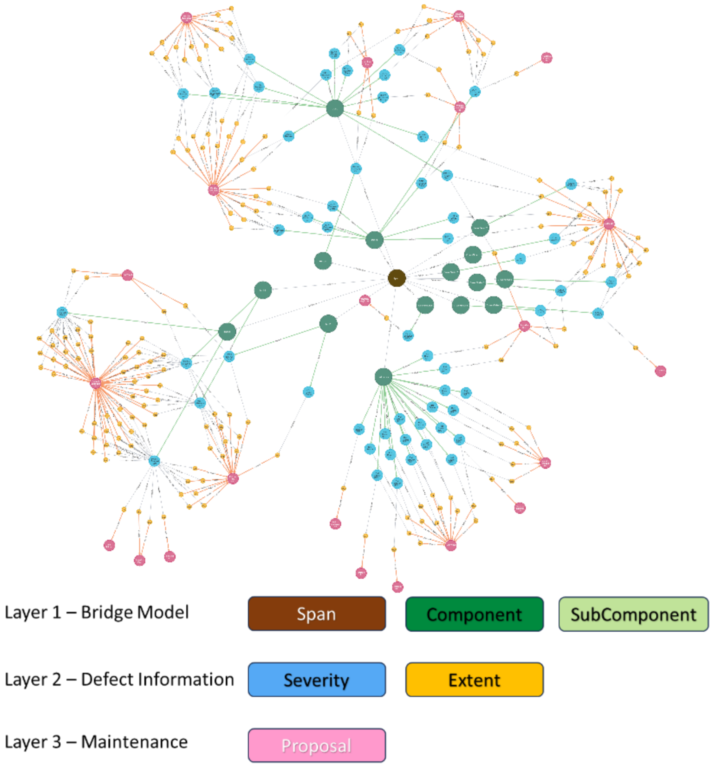


Figure 8: Implementation of graph structure for maintenance decision-making in Neo4j

4. DISCUSSION AND CONCLUSIONS

In this paper, the design and implementation of a BIM component-centred bridge digital twin system purposed for bridge maintenance was discussed and presented. This pipeline for bridge maintenance decision-making is considered smart and practical as it automates and streamlines several labour-intensive and time-consuming process with open-source software toolkits and the structural assessment is based on industrial practices. Specifically, the defects are identified, quantified and localised on the BIM component, the information of the defect is then stored in relational database with the IFC model's ComponentID as its unique identifier. By clicking the visualised IFC geometrical model at web-based CDE, defects schedule for the specific component can be retrieved and displayed at the front-end. After that, bridge practitioners can assess the condition of the component by considering all the defects collectively and provide maintenance proposals based on the condition markings of the whole bridge.

For the future work, multi-source data, information and knowledge (e.g., life-cycle information, dynamic responses captured by sensors, traffic, weather) can be fused to provide holistic feedback (e.g. early warnings, inspection advice, optimised maintenance planning, etc.) to the physical bridge with more sophisticated assessment and analysis, thus improve the resilience of the bridge network.

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REFERENCES

Adibfar, A. and Costin, A. M. (2022) ‘Creation of a Mock-up Bridge Digital Twin by Fusing Intelligent Transportation Systems (ITS) Data into Bridge Information Model (BrIM)’, *Journal of Construction Engineering and Management*, 148(9), p. 04022094. doi: 10.1061/(ASCE)CO.1943-7862.0002332/ASSET/FC314C15-6F20-44EC-9DB3-8026716583E9/ASSETS/IMAGES/LARGE/FIGURE9.JPG.

Allah Bukhsh, Z. *et al.* (2020) ‘Maintenance intervention predictions using entity-embedding neural networks’, *Automation in Construction*, 116, p. 103202. doi: 10.1016/J.AUTCON.2020.103202.

Barrile, V. *et al.* (2019) ‘UAV Survey of Bridges and Viaduct: Workflow and Application’, *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11622 LNCS, pp. 269–284. doi: 10.1007/978-3-030-24305-0_21.

Borrmann, A. *et al.* (2018) ‘Building information modeling: Technology foundations and industry practice’, *Building Information Modeling: Technology Foundations and Industry Practice*, pp. 1–584. doi: 10.1007/978-3-319-92862-3/COVER.

Gao, Y. *et al.* (2023) ‘AIoT-informed digital twin communication for bridge maintenance’, *Automation in Construction*, 150, p. 104835. doi: 10.1016/J.AUTCON.2023.104835.

Gao Y, Li H and Xiong G (2023) ‘An Efficient and Resilient Digital-twin Communication Framework for Smart Bridge Structural Survey and Maintenance’, *29 th International Workshop on Intelligent Computing in Engineering*. doi: 10.7146/aul.455.c207.

Isailović, D. *et al.* (2020) ‘Bridge damage: Detection, IFC-based semantic enrichment and visualization’, *Automation in Construction*, 112, p. 103088. doi: 10.1016/J.AUTCON.2020.103088.

Mohammadi, M. *et al.* (2023) ‘Integration of TLS-derived Bridge Information Modeling (BrIM) with a Decision Support System (DSS) for digital twinning and asset management of bridge infrastructures’, *Computers in Industry*, 147, p. 103881. doi: 10.1016/J.COMPIND.2023.103881.

Network Rail (2022a) *Level2 Business Process Management of Structures*.

Network Rail (2022b) *Level3 Manual Structures , Tunnels and Operational Property Examinations Approvals*.

Nguyen, S. T. and La, H. M. (2020) ‘A Climbing Robot for Steel Bridge Inspection’. doi: 10.1007/s10846-020-01266-1.

Sutter, B. *et al.* (2018) ‘A semi-autonomous mobile robot for bridge inspection’, *Automation in Construction*, 91, pp. 111–119. doi: 10.1016/J.AUTCON.2018.02.013.

Yang, J. *et al.* (2022) ‘Intelligent bridge management via big data knowledge engineering’, *Automation in Construction*, 135(January), p. 104118. doi: 10.1016/j.autcon.2021.104118.

Yoon, S. *et al.* (2022) ‘Seismic fragility analysis of deteriorated bridge structures employing a UAV inspection-based updated digital twin’, *Structural and Multidisciplinary Optimization*, 65(12), p. 346. doi: 10.1007/S00158-022-03445-0.