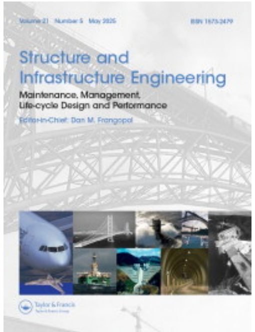

Taylor & Francis
Taylor & Francis Group

Structure and Infrastructure Engineering

Maintenance, Management, Life-Cycle Design and Performance

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/nsie20

Digital twins for asset management: case study of snow galleries in Northern Sweden

Vanessa Saback, Jens Eliasson, Cosmin Daescu, Jaime Gonzalez-Libreros, Cosmin Popescu, Thomas Blanksvärd, Björn Täljsten & Gabriel Sas

To cite this article: Vanessa Saback, Jens Eliasson, Cosmin Daescu, Jaime Gonzalez-Libreros, Cosmin Popescu, Thomas Blanksvärd, Björn Täljsten & Gabriel Sas (08 Apr 2025): Digital twins for asset management: case study of snow galleries in Northern Sweden, Structure and Infrastructure Engineering, DOI: 10.1080/15732479.2025.2483913

To link to this article: https://doi.org/10.1080/15732479.2025.2483913

Published online: 08 Apr 2025.

STRUCTURE AND INFRASTRUCTURE ENGINEERING
https://doi.org/10.1080/15732479.2025.2483913

Digital twins for asset management: case study of snow galleries in Northern Sweden

Vanessa Saback[a], Jens Eliasson[b], Cosmin Daescu[c], Jaime Gonzalez-Libreros[a], Cosmin Popescu[d], Thomas Blanksvärd[a], Björn Täljsten[a] and Gabriel Sas[a]

[a]Department of Civil, Environmental and Natural Resources Engineering, Luleå University of Technology (LTU), Luleå, Sweden; [b]ThingWave AB, Luleå, Sweden; [c]Department of Civil Engineering and Installations, Politehnica University Timisoara, Timisoara, Romania; [d]SINTEF Narvik AS, Narvik, Norway

ABSTRACT

The use of digital twin (DT) technology within the engineering and construction (E&C) industry is valuable for practical applications in asset management of structures. Functional DT in E&C, however, are still in initial stages of development. Efforts toward standardisation of concepts and procedures are necessary to build on existing knowledge and drive progress further on functional DT. This paper proposes a DT of a snow gallery, part of the Iron Ore railway in northern Sweden. The gallery was instrumented with a structural health monitoring (SHM) system that feeds data in real time to the DT, which also includes a 3D model of the gallery. The proposed methodology can be replicated to different structures and scaled for larger amounts of data. The SHM data and the 3D digital model of the snow gallery are connected in a single, integrated platform that enables improved decision-making for maintenance of the gallery. To promote clarity and progress within the field, the proposed DT's maturity level is classified in terms of autonomy, intelligence, learning and fidelity. The snow galleries, the SHM system, and the proposed DT are all presented and discussed, following a brief review on DT, the importance of level classification and predictive maintenance.

ARTICLE HISTORY
Received 17 April 2024
Revised 13 November 2024
Accepted 18 November 2024

KEYWORDS
Asset management; building information modeling; case study; digital twins; maintenance; snow galleries; snow load; structural health monitoring

1. Introduction

Snow galleries have the purpose of protecting roads, railways and their traffic from the impact of heavy snowfall and avalanches. The structure of a snow gallery resembles a tunnel or passageway, with two walls and a roof, which helps to increase safety, and prevents accumulated snow from blocking access and obstructing transportation routes. One such route that relies on the effectiveness of its snow galleries is the Iron Ore Line, an almost 500 km long railway connecting Sweden and Norway. Its primary purpose is to transport iron ore from the mining towns in Sweden to the ports for exportation to global markets. From the time of its establishment, the Iron Ore Line has played a vital role in the mining industry's growth in the region, and it still sustains great historical and economic worth. Therefore, any disruptions along this route can be particularly costly, so neither repair work nor snow buildup should interfere with train traffic. For instance, when addressing the impact of an extended forecast for restoration of the Iron Ore Line after a train derailed in December 2023, the logistics manager for LKAB spoke of 'revenue losses of around SEK 100 m (€8.9 m) a day' (LKAB, 2023).

An investigation of 16 snow galleries that protect one of the key sections of the Iron Ore Line, between Riksgränsen and Kiruna, reported that several of them had been damaged due to excessive snow loads (Sas et al., 2021). Furthermore, the design snow load requirements at the time of their construction were up to 60% lower than current standards (Saback et al., 2023) and are predicted to increase as a consequence of climate change (Saback et al., 2024).

After that investigation, the Swedish Transport Administration and Luleå University of Technology (LTU) carried on with further analysis to understand the extent of the harm and prevent further and/or future damage. Two snow galleries, namely SG9 and SG13A, were instrumented with a monitoring system. The location of the sensors was based on analytical and finite element (FE) calculations. The monitoring system consists primarily of strain gauges installed on the most critical frame of each gallery and the support equipment necessary to stream the data live (detailed here in section 3). From the strains obtained, snow loads were calculated and made available online through LTU's Mining and Civil Engineering Laboratory (MCE-LAB) server. A warning message is triggered if the galleries are exposed to a critical load. The complete output from

CONTACT Vanessa Saback vanessa.saback@gmail.com Department of Civil, Environmental and Natural Resources Engineering, Luleå University of Technology (LTU), Luleå, Sweden.

that investigation, instrumentation and calculations, are available in Saback et al. (2024).

In this study, a digital twin (DT) was created to improve asset management of SG13A. A 3D model of the snow gallery was integrated with the live sensor data from the monitoring system into a single platform to facilitate visualisation and improve decision-making. Once the snow accumulates on the galleries to a certain extent, maintenance is required to remove the snow. With the DT, the live snow load is compared against a colour-coded scheme based on the galleries' structural capacity to facilitate interpretation of the results. Then, predictive maintenance can be performed before more costly interventions are needed or there is any risk to safety.

Digital twins have become a widely discussed subject, but there are few detailed workflows for developing DT in Engineering and Construction (E&C) that include practical applications (Chacón et al., 2023; Pregnolato et al., 2022). The novelty of this paper lies in its departure from theoretical discussions on DT benefits by presenting a practical application of DT for asset management through a replicable and scalable framework. By proposing a practical tool, this research contributes to advancing asset management in urban challenges, especially in extreme weather, through the application of technology and a focus on predictive maintenance. This study is a continuation of extensive research focused on DT for asset management of structures (de Freitas Bello et al., 2021; Saback et al., 2022; Saback de Freitas Bello et al., 2022; Saback et al., 2023).

DT for asset management is an emerging field with the potential to revolutionise current practices by replacing laborious, inefficient, subjective and costly techniques with fast, objective, and automated processes (Arisekola & Madson, 2023). SG13A exemplifies this potential due to previously reported damage, safety concerns, economic significance, and the need to monitor snow accumulation for maintenance. Additionally, the proposed DT addresses challenges of operating and inspecting in sub-zero conditions when routine inspections are trickier and most essential. Strain gauges are reliable, accessible, and efficient sensors, which helps promote DT dissemination without excessive complexity.

This article is organised in six sections. After the introduction, a brief literature review explores mainly DT within E&C, maturity level classification, and predictive maintenance—a systematic literature review on DT for asset management was developed in Saback de Freitas Bello et al. 2022). In section 3, the methodology for the proposed DT is presented, including the 3D model, SHM system, and DT platform. The methodology was limited to one gallery and to elastic deformations. The functional DT is presented in section 4 and discussed in section 5, including a maturity level classification to promote clarity and progress within the field. Lastly, the concluding remarks and future research considerations are presented in section 6.

2. Literature review

2.1. Digital twins

A DT is here defined as a realistic digital representation of an asset which includes the distinctive feature of a data flow between the physical entity and its digital representation (Figure 1). For some assets, the characterisation of this data flow can be very straightforward. For instance, considering how common smart thermostats have become, it is easy to see how modifying a variable on the DT of a building, i.e. the temperature, would impact the physical entity directly (digital to physical data flow). Nonetheless, in other assets within E&C, this double-sided data flow is not as simple.

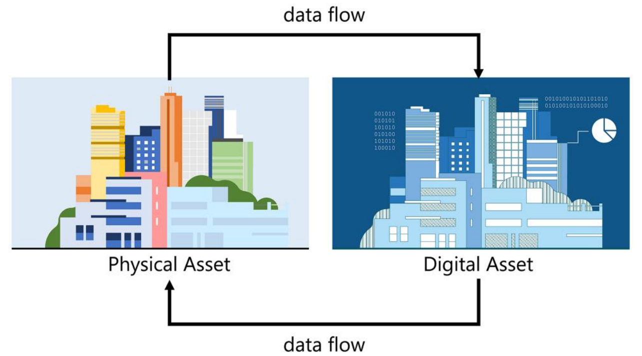

Figure 1. Schematic definition of a digital twin.

Developing a business case that justifies the investment and complexity of a DT can be challenging due to factors such as high initial costs, integration complexities and uncertain return on investment (ARUP, 2019; Bilal et al., 2016; Opoku et al., 2021). The cost of implementing a DT is more justified for civil structures and infrastructure, due to their long lifespans and elevated maintenance costs. Particularly for these assets, the digital to physical data flow is tricky to obtain. The perspective of a command performed on a digital model being able to directly modify a bridge or a railway, for example, is still not expected to occur. Therefore, rather than direct modifications, the digital to physical data flow in these scenarios most likely needs to go through a person that, informed by system intelligence, can trigger actions in benefit of the structure.

E&C as an industry is still behind others, such as aerospace and manufacturing, on the maturity level of DT. Even though they are predicted to be used in two-thirds of large industrial companies by the next decade, practical DT applications within E&C are still largely at the prototype stage (Pregnolato et al., 2022). Although DTs have potential for applications and offer significant opportunities for collaborative use throughout the entire lifecycle of assets in E&C, research has primarily focused on the construction phase (Adu-Amankwa et al., 2023). In fact, research has shown that complete DT in practice have not evolved beyond the third maturity level (ARUP, 2019; MEED, 2021; Lazoglu et al., 2023)—maturity level classifications are discussed in the following subsection.

In a DT, different types of data formats from various storage locations need to be contextualised and integrated, so a DT base software system needs to be modular and cloud based (Ramonell et al., 2023). A DT implies robust and distributed sources of diverse data, which requires centralisation and processing, and the varied nature of the asset often demands multiple data-gathering techniques (Chacón et al., 2023). Therefore, the successful implementation of a

DT lies on its capacity to integrate and manage extensive and varied data sources effectively. Wang et al. (2024) identified the main obstacles to digital transformation within E&C as the absence of industry-specific standards, clear direction, and strategy, as well as the lack of support from top management. Progress is also hindered by the industry and academia's need to navigate conflicting definitions and processes for DT, so it is essential to develop common procedures and standards tailored to the industry's attributes to establish DT as practice in E&C (Pregnolato et al., 2022). Other detailed literature reviews about DT can be found in AlBalkhy et al. (2024), Jiménez Rios et al. (2023), Saback de Freitas Bello et al. (2022), Thelen et al. (2022), Lu et al. (2020), Cimino et al. (2019), Khajavi et al. (2019) and Kritzinger et al. (2018). Furthermore, an overview and analysis of practical DT applications and implementations is presented in Saback et al. (2024).

2.2. Maturity level classification

The first step to practically establish DT in E&C is to develop common standards and processes tailored to the industry's practices and assets (Pregnolato et al., 2022). Due to their complexity, DT are often divided into different maturity levels. Even though most maturity level classifications in use are similar amongst themselves, a universally recognised standard is still lacking. For example, Lazoglu et al. (2023), MEED (2021), Evans et al. (2020) propose levels varying from basic to autonomous DT capabilities; a compilation of classifications proposed by companies B&N, AFRY, IBM and Autodesk are depicted in Saback et al. (2023). These different classifications offer a comprehensive understanding of DT maturity, encompassing visual representation, data integration, predictive analysis, autonomous action, and cognitive capabilities.

The maturity levels adopted in this study follow the classification proposed by ARUP (2019), also applied in Lazoglu et al. (2023), based on the concepts of fidelity, learning, intelligence, and autonomy. Autonomy is the system's capacity to operate independently, without human intervention. Intelligence relates to the DT's capability to simulate human cognitive functions and execute tasks independently. Learning refers to the twin's ability to autonomously acquire knowledge from data, enhancing its performance without the need for explicit programming. Fidelity relates to precision in the system, reflecting the degree to which measurements, calculations or specifications align with the real system. Table 1 presents the concepts and maturity levels.

The classification shows that DTs at levels 1, 2, and 3 lack the high integration and autonomy found in more advanced DT levels, which limits their connectivity, adaptability, and scalability. As 'single-purpose' systems, they can handle only specific tasks, requiring manual input or human monitoring to function effectively. This limited scope means that significant manual reconfiguration or additional development work would be needed to repurpose them for different applications, making these DTs less versatile across a range of assets or environments. In the coming years, as DT technology matures, efforts to improve integration capabilities and interoperability standards will likely become a priority to allow these lower-level DTs to connect seamlessly with other digital systems. Such developments could lead to an evolution in DT capabilities, enhancing adaptability, lowering maintenance costs and ultimately enabling a broader spectrum of real-time applications across industries.

2.3. Predictive maintenance

Physical inspection of a structure cannot be entirely replaced, but online, real-time monitoring provides continuous oversight, allowing for more in-depth diagnostic work before more elaborate, costly, and invasive physical inspections are necessary (Hagen & Andersen, 2024). This approach can enhance efficiency, reduce costs and, most

Table 1. Different DT levels.

Characteristics of the digital models on each level	
Level 1	Linked to the real-world, but no autonomy (100% user controlled), no intelligence or learning component. Low accuracy and limited functionality. Minimal integration: isolated system with no external data sources typically do not involve BIM. Basic static geolocation data without real-time updates. Example: a 2D CAD model.
Level 2	Some capacity for feedback and control, often limited to small-scale systems. Basic integration with limited external data sources, which may include basic BIM models for visualisation purposes. Static geolocation with periodic updates based on manual input. Example: building temperature sensors which feed information back to a human operator.
Level 3	Ability to provide predictive maintenance, analytics and insights. Moderate integration, combining data from multiple sources for predictive insights, involving more detailed BIM models and data interoperability. Real-time geolocation with automated updates and basic predictive capabilities. Example: predicting the life expectancy of rail infrastructure, enabling repairs or replacements before asset failure.
Level 4	Capacity to learn from various sources of data, including the surrounding environment, and ability to use that learning for autonomous decision-making within a given domain. High integration, seamlessly combining and processing data from diverse and dynamic sources, requiring advanced BIM integration for comprehensive analysis and decision-making. Real-time geolocation with advanced predictive analytics and automated decision-making support. Example: automatically recommend real-time routes so drivers can plan their journey better.
Level 5	Wider range of capacities and responsibilities, ultimately approaching the ability to autonomously reason and to act on behalf of users (artificial general intelligence). Comprehensive integration with a vast array of data sources, enabling complex autonomous operations, where BIM serves as a fundamental component for detailed modeling and data management. Real-time geolocation with fully autonomous management and decision-making capabilities.
Definitions:	
Autonomy	Ability of a system to act without human input
Intelligence	Ability of digital twins to replicate human cognitive processes and to perform tasks.
Learning	Ability of a twin to automatically learn from data in order to improve performance without being explicitly programmed to do so.
Fidelity	Level of detail of a system, the degree to which measurements, calculations or specifications approach the true value or desired standard.

importantly, increase the likelihood of detecting issues at early stages (Hagen & Andersen, 2024). The premise behind predictive maintenance is that regular monitoring of an asset's condition will ensure the maximum interval between repairs and reduce the number and cost of unscheduled disruptions due to failures, thus reducing the overall cost of maintenance (Mobley, 2002). Increased equipment life, higher efficiency, and cheaper labour costs are all possible benefits of predictive maintenance (Hosamo et al., 2022). It does not replace traditional maintenance management methods, but it is a valuable addition to a comprehensive maintenance program (Mobley, 2002).

Predictive maintenance is a key enabling step of Industry 4.0, mostly discussed in the manufacturing domain (Thelen et al., 2022). This proactive approach focuses on (1) detecting sensor data patterns signalling equipment health changes, *via* continuous monitoring or periodic inspections; (2) forecasting potential machine, component, or part failures; (3) planning maintenance to coincide with scheduled downtime before equipment failure (Lee et al., 2013a; Lee et al., 2013b).

Hosamo et al. (2022) identified three elements needed to implement a practical predictive maintenance program: (i) big data collection from sensors; (ii) a platform that can implement automatic fault detection and diagnostics to improve the maintenance system and predict the faults; (iii) BIM to avoid traditional methods in data transfer and visualise the results in a 3D model—BIM can serve as an information source and repository for planning maintenance operations in both new and existing structures. Therefore, by providing a platform that can integrate these three elements, a DT can be an enabler of predictive maintenance (Thelen et al., 2022). Chacón et al. (2023) presents a case study aimed at optimizing future maintenance by integrating routine requirements with digital technologies to create virtual replicas of railway bridges as part of the digitisation efforts in the construction sector.

3. Digital twin methodology

To prioritise the aspects included in the DT, a MoSCoW analysis was conducted for this particular case study. The acronym stands for what a system must have, should have, could have and will not have. MoSCoW is a method for software requirements prioritisation (SRP), which helps ensuring that essential features are addressed first while considering additional features based on their importance and feasibility (Achimugu et al., 2014). 3D visualisation and integration with snow load calculation were considered a must-have. It was also considered that the DT should have real-time data and alerts to trigger maintenance. The DT could have historical data storage and predictive analysis, so these are considered future steps for the research. However, autonomous snow removal and other automating functions alike are not considered priorities, so they are features that this DT will not have. The MoSCoW analysis is presented in Figure 2.

The basic structure of the proposed DT consists of the connection between a 3D model and live structural health monitoring (SHM) data in a single, collaborative platform. Visualisation of geometry in a 3D environment facilitates interpretation of results provided by SHM. SHM data, in turn, consists of current condition information about the structure, usually through data from sensors and/or nondestructive testing (NDT). The connection between them is just as important to the structure of the DT, since it is only through this data flow that the DT can be achieved.

For the proposed DT, the program ThingWave Reality (ThingWave, 2024) was used and customised to connect the 3D model and SHM data. ThingWave Reality is a tool with integrated data storage and processing capabilities for working with 3D models. The customised version, called Reality Lite, was developed for this study to enable the program to manage and visualise the custom sensor data from the snow galleries. The 3D model was created using Autodesk Revit and converted to glTF (Graphics Library Transmission Format) 2.0, and SHM data comes from strain gauges installed on the snow gallery. The data flow from the physical asset (snow gallery) to the digital asset (digital twin) consists of the live monitoring data visualised in the 3D model in the digital environment. The physical-to-digital data flow is obtained through feedback from system intelligence, which triggers human intervention in the galleries.

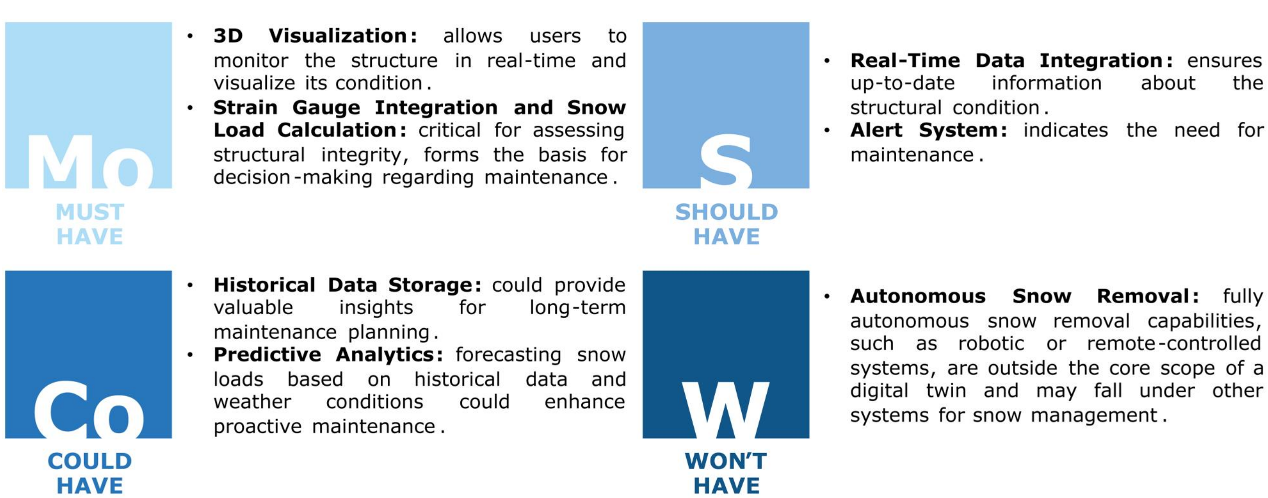

Figure 2. MoSCoW analysis for the proposed digital twin.

Figure 3 illustrates the structure of the proposed DT, which is described in detail in this section.

3.1. 3D Model

Autodesk Revit was used to create a BIM model of the snow gallery. The BIM model of SG13A was developed from the original drawings, and it consists of the steel frames that make up the gallery. Figure 4 presents a rendering from the BIM model of the frame in which the monitoring system was installed in SG13A, i.e. frame 1535 + 420. The model was then converted to glTF 2.0 for visualisation in the DT application. glTF, formerly known as WebGL Transmissions Format, is a standard file format for 3D models.

3.2. Structural health monitoring (SHM) system

SHM data for the DT was obtained from strain gauges installed on frame number 1535 + 420, the most critical frame of that gallery—selected based on the degree of utilisation; for details see Saback et al. (2024). The strain gauges' manufacturer was KYOWA and their type was KCW-5-120-G10-11G3M3S. From the strain gauges, continuous strain was acquired, and snow loads were subsequently calculated. The optimal placement for the strain gauges was determined by a preliminary FE analysis performed using AxisVM (Saback et al., 2024). The most critical frame within the snow gallery was determined, then the maximum stress section was identified for the steel column. The axial load on the column is calculated from the strain constantly measured by the strain gauges—permanent electrical connection was provided on site to enable continuous measurements. Figure 5 presents the stresses on frame 1535 + 420 from the FE analysis and the corresponding position of the strain gauges on the steel column. More details about the instrumentation campaign can be found on Saback et al. (2024).

The system consists of a Windows based computer connected to the HBM Spider8 data acquisition (DAQ) unit. The HBM Spider8 is a high precision and versatile real-time data acquisition solution, with both analog and digital input channels, which allows users to connect and collect data from several types of sensors and sources. A Digi IX10 cellular router provides the mobile network link to transfer the data. Every 10 min, one hundred samples are collected at a frequency of 10 HZ and exported to an ASCII file, which is

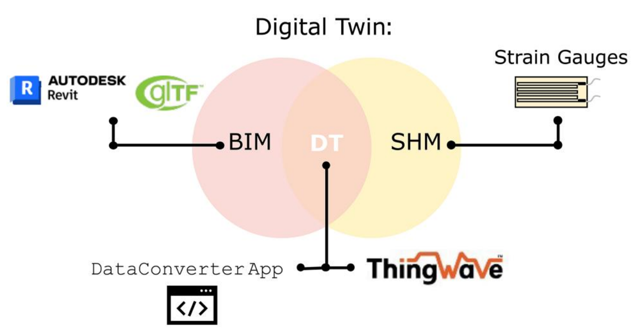

Figure 3. Basic structure of the digital twin.

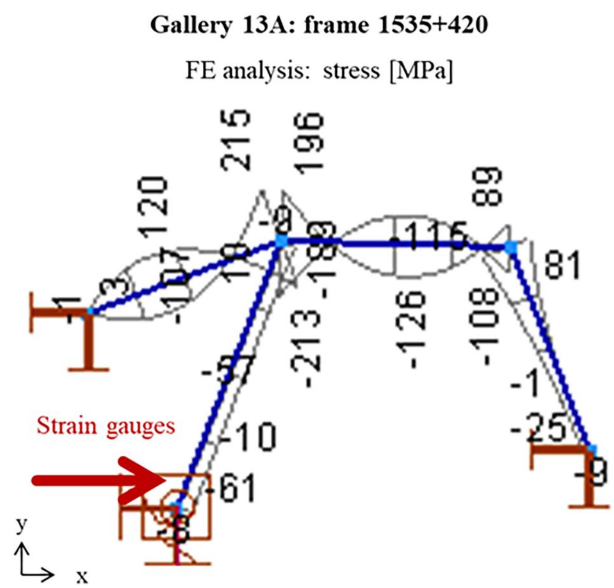

Figure 5. Position of strain gauges on monitored column.

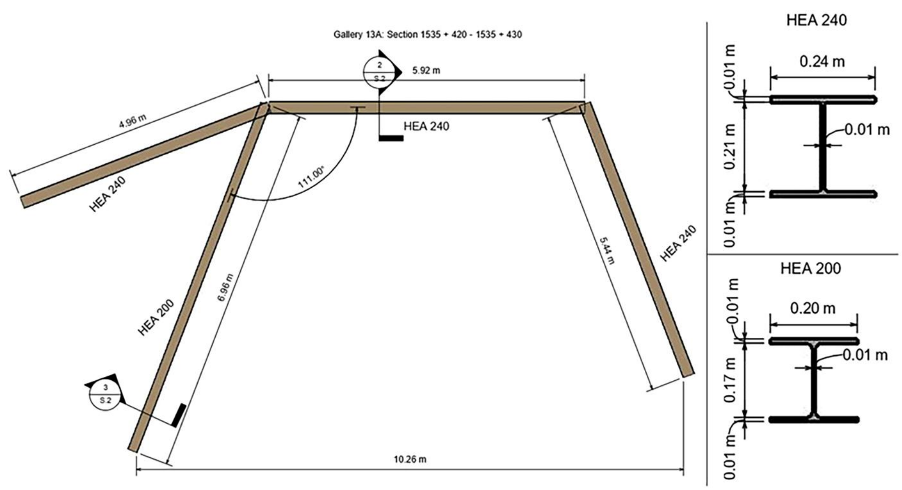

Figure 4. BIM model of SG13A: measurements of SG13A (left) and cross-section of steel beams HEA 240 (right, top) and HEA 200 (right, bottom).

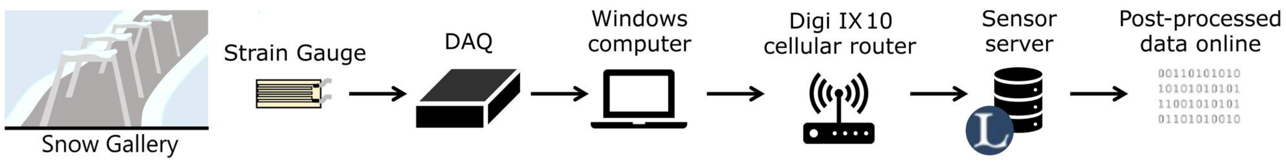

Figure 6. Monitoring system scheme: from the snow gallery to online data.

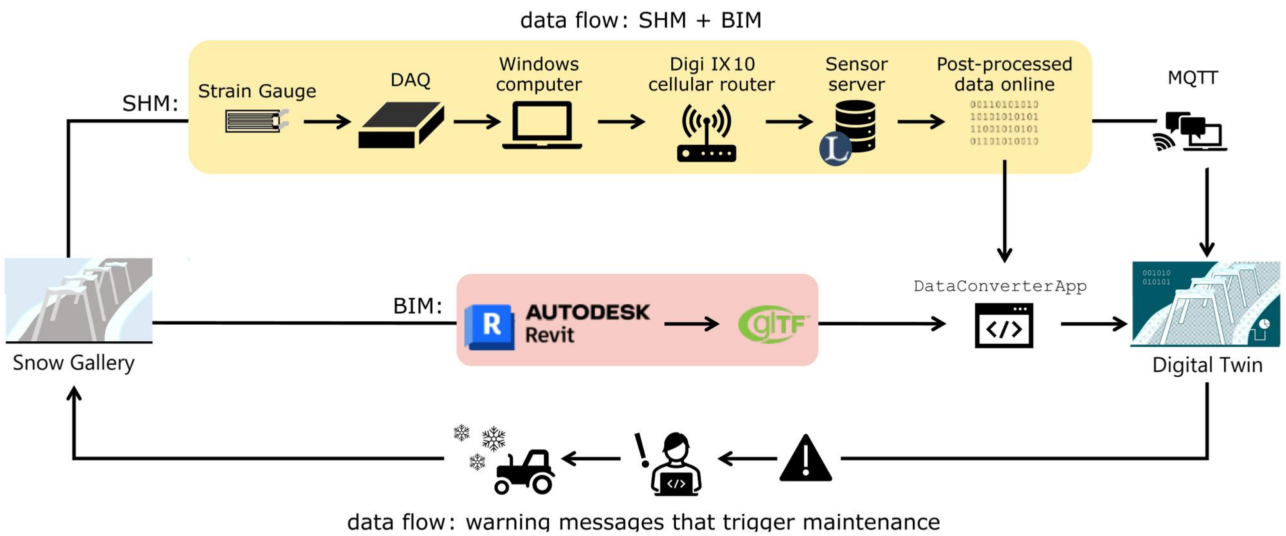

Figure 7. Structure of the proposed digital twin.

Table 2. Snow load zones for SG13A (Saback et al., 2024)

Zone	Force in column	Interpretation
Green	0 to 16 kN	Structure is ok
Yellow	16 to 232 kN	Possible secondary beam failure Cleaning due (maintenance crew)
Red	From 232 kN	Possible column failure that can lead to overall structural failure of the SG frame

transferred to LTU's MCE-LAB server (Linux CentOS). Then, the snow load data goes through post processing: the median, minimum, and maximum values are extracted and exported to a website, together with the temperature, so they are available online. The temperature is fetched from the website temperature.nu/vassijaure (Trafikverket, 2024), which collects data from the Swedish Road Administration's weather service closest to the station corresponding to the location of SG13A. Figure 6 illustrates the structure of the monitoring system, from the strain gauges instrumented on the snow gallery until data is online.

3.3. Digital twin

In the final DT architecture, SHM data and the 3D model were integrated through the DataConverterApp. To enable live data, the MQTT (Message Queuing Telemetry Transport) protocol was added—MQTT is a messaging protocol used for machine-to-machine communication, widely used in the context of the Internet of Things (IoT). The DT platform was required to be user-friendly and not dependent on programming knowledge for interaction, so a drag and drop function for local files was included, instead of an application programming interface (API).

On the platform, live snow load data is streamed and can be visualised in a colour-coded scheme to assist decision making and preventive maintenance of the snow gallery. Therefore, the data flow from the digital to the physical asset is achieved, thus concluding the DT. Figure 7 illustrates the elements present in the structure of the proposed DT: the physical-digital data flow, composed by the SHM system and the digital model, and the digital-physical data flow, represented by alerts that trigger maintenance.

4. Results

4.1. Colour-coded snow load zones

In a previous study (Saback et al., 2024), three snow load zones were defined based on the capacity of the frames: green, yellow, and red. If the snow load value falls under the green zone, the structure is ok. If the load is on the yellow zone, failure of the secondary beams becomes a possibility and cleaning of the snow galleries is due. In the red zone, there is a possibility of column failure that can lead to overall structural failure of the SG frame. The snow load

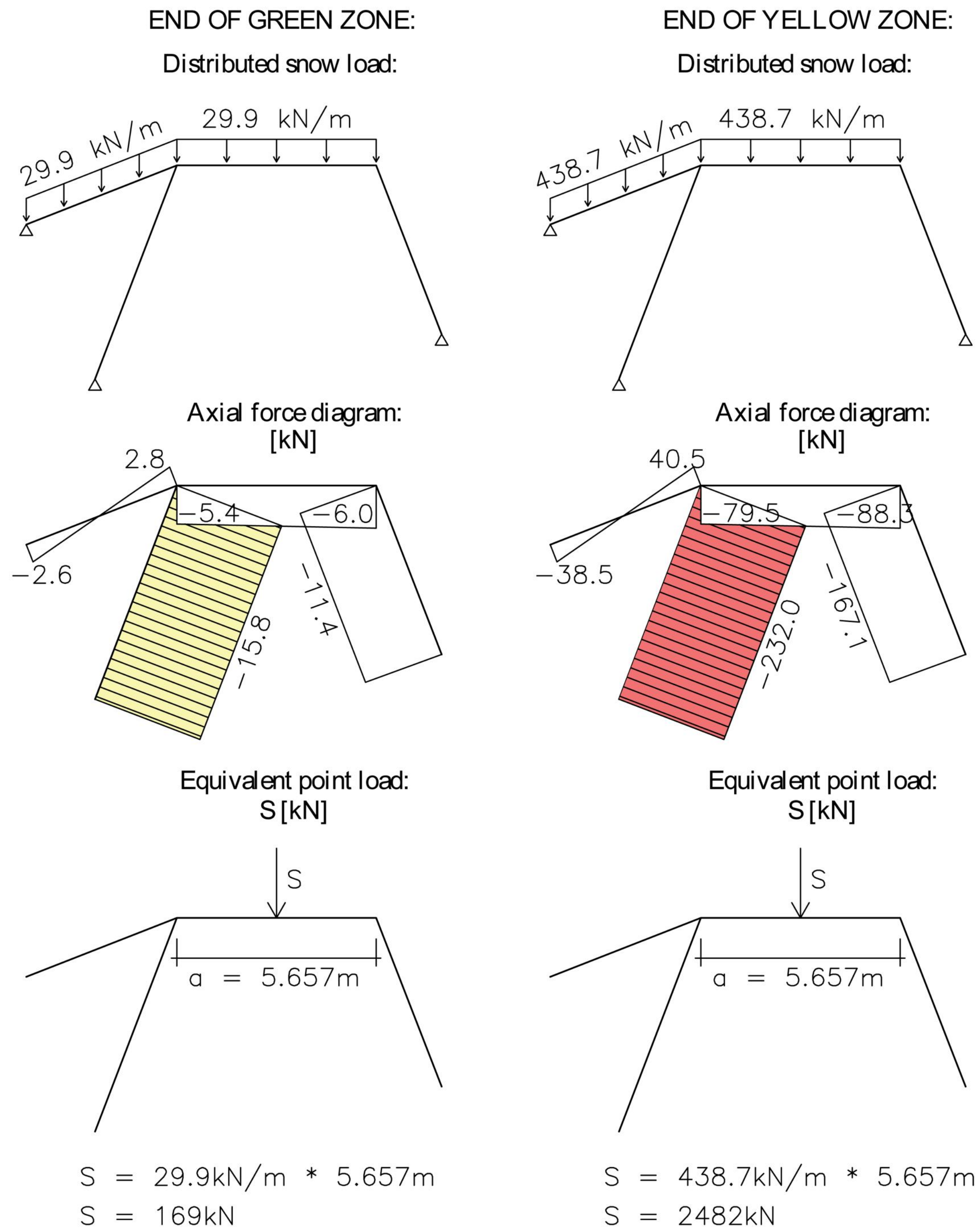

Figure 8. Illustration: calculating the equivalent snowpack force on roof beam.

zones, their respective load values and interpretation for the snow galleries case study are presented in Table 2.

Considering the limit forces in Table 2, the equivalent snow height on the roof, h, can be calculated for each zone, first by identifying the distributed load that corresponds to the limit axial force in the column. That distributed load, in turn, can be calculated as a point load, S, of an equivalent snowpack by multiplying the distributed load by the width of the roof beam. Figure 8 illustrates the calculation of the point load S, and Figure 9 illustrates the snow height on the roof.

The equivalent point load for the snowpack on the roof can be calculated by multiplying the specific weight by its three volumetric components, i.e., the width of the roof beam, the bay space between the frames, and the height of the snow on the roof:

$$S = \gamma \cdot a \cdot b \cdot h \tag{1}$$

where: $S\ [kN]$ is the equivalent point load for the snowpack; $\gamma\ [kN/m^3]$ is the specific weight of the snowpack; $a\ [m]$ is the width of the roof beam, equal to 5.657 m; $b\ [m]$ is the bay space for the main frames in SG13A, equal to 5.0 m; and $h[m]$ is the height of the snowpack.

The specific weight of the snowpack depends on its density, which is a result of the climate conditions during the snow accumulation and thus can vary significantly (Bruland et al., 2015). Considering that the Eurocode classifies Kiruna under the snow load zone of 3.0 kN/m^2 (European Committee for Standardization (CEN), 2003), and that the average snow height registered in Kiruna from 1905 to 2022 was 52.7 cm (Swedish Meteorological and Hydrological Institute (SMHI), 2022), an average specific weight can be obtained: $\gamma \cdot 0.527 = 3.0 \Rightarrow \gamma = 5.7kN/m^3$.

Therefore, Equation (1) can be solved for h using the average specific weight of the snowpack previously derived ($\gamma = 5.7kN/m^3$). Thus, the height for the transition load from the green to the yellow zone is equal to: $h = 169/5.7 \cdot 5.657 \cdot 5.0 = 1.0m$, while the height for the transition load from the yellow to the red zone is $h = 2482/5.7 \cdot 5.657 \cdot 5.0 = 15.4m$. However, apart from average conditions, snow can reach a specific weight as high as 8.0 kN/m^3 (Muskett, 2012). Therefore, using $\gamma = 8.0kN/m^3$, a new snow height is obtained: $h = 169/8.0 \cdot 5.657 \cdot 5.0 = 0.75m$, which modifies the height for the transition load from the yellow to the red zone as follows: $h = 2482/8.0 \cdot 5.657 \cdot 5.0 = 10.1m$. Therefore, Table 2 can be updated to include the corresponding snow height of each snow load zone, as shown in Table 3.

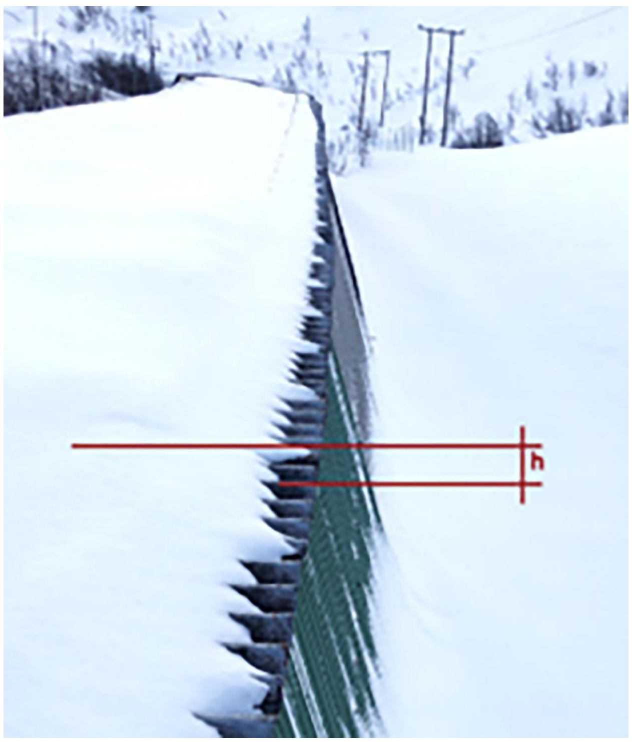

Figure 9. Illustration: snowpack height on roof beam.

Saback et al. (2024) reported that the forces on the columns were far from reaching the red zone loads, which can be seen as well in these analytical calculations considering 10.1 m of snow to be quite high and improbable to reach. This study also reported that the yellow zone had been reached, which again complies with the calculations, as an accumulated snow height of 0.75 m can be expected in a location such as Northern Sweden. Actually, SMHI (2022) has reported that maximum snow depth in Sweden has surpassed 70 cm in 5 years between 1905 and 2022.

4.2. Digital twin of the snow galleries

In the DT, the 3D model can be visualised and interacted with, as shown in Figure 10. Interactions include navigating through the model and clicking to obtain information about the element's ID. In Figure 10, the yellow column indicates where the strain gauges were installed, in the most critical frame. The yellow colour on the column is in itself an indicative of the snow load, following the colour-coded snow load zones presented in Table 2 and Table 3.

The sensor data can be visualised by double-clicking on the coloured column, as shown in Figure 11, and a pop-up window displays the snow load and temperature graph. The load is updated automatically whenever a new reading

Table 3. Snow load zones for SG13A (Saback et al., 2024) including snow height.

Zone	Force in column	Corresponding snow height	Interpretation
Green	0 to 16 kN	From 0 to 0.75–1.0m	Structure is ok
Yellow	16 to 232 kN	From 0.75–1.0m to 10.1–15.4m	Possible secondary beam failure Cleaning due (maintenance crew)
Red	From 232 kN	From 10.1–15.4m	Possible column failure that can lead to overall structural failure of the SG frame

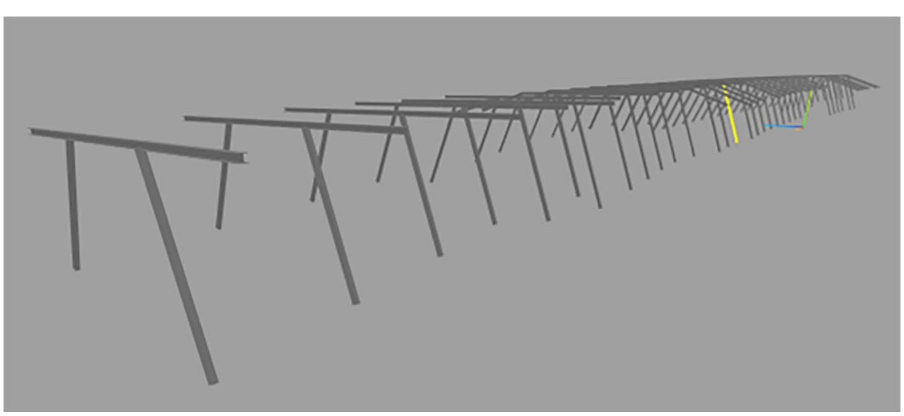

Figure 10. Visualization of the 3D model on the DT platform.

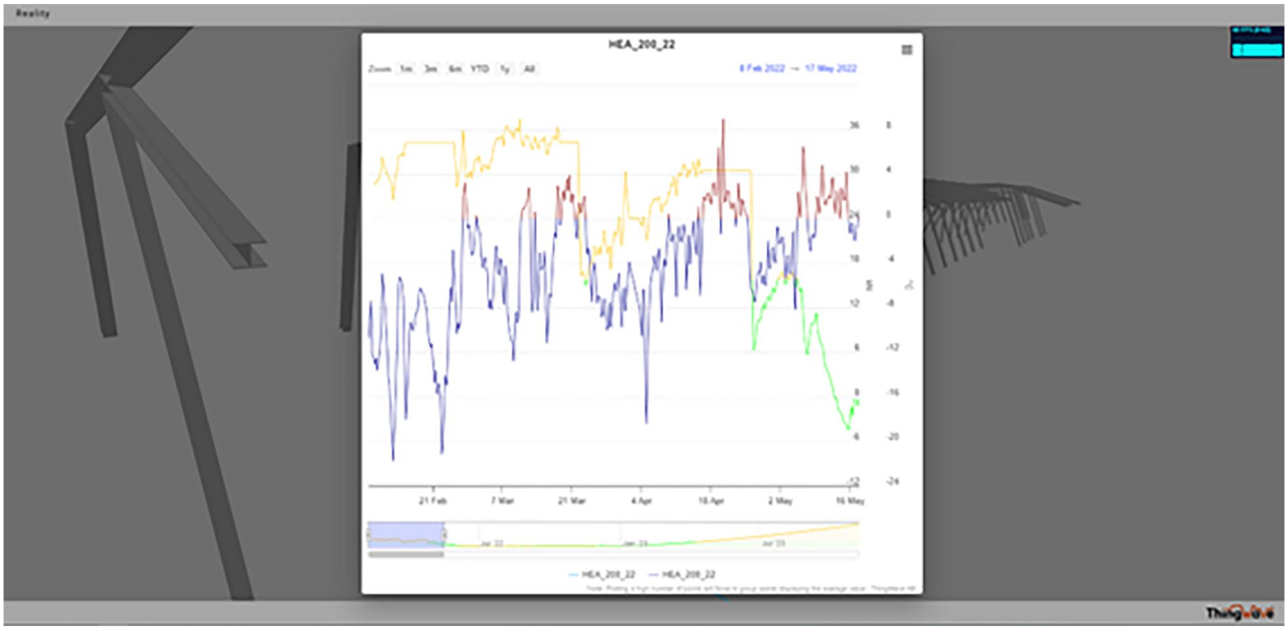

Figure 11. Visualisation of the snow load data on the 3D model.

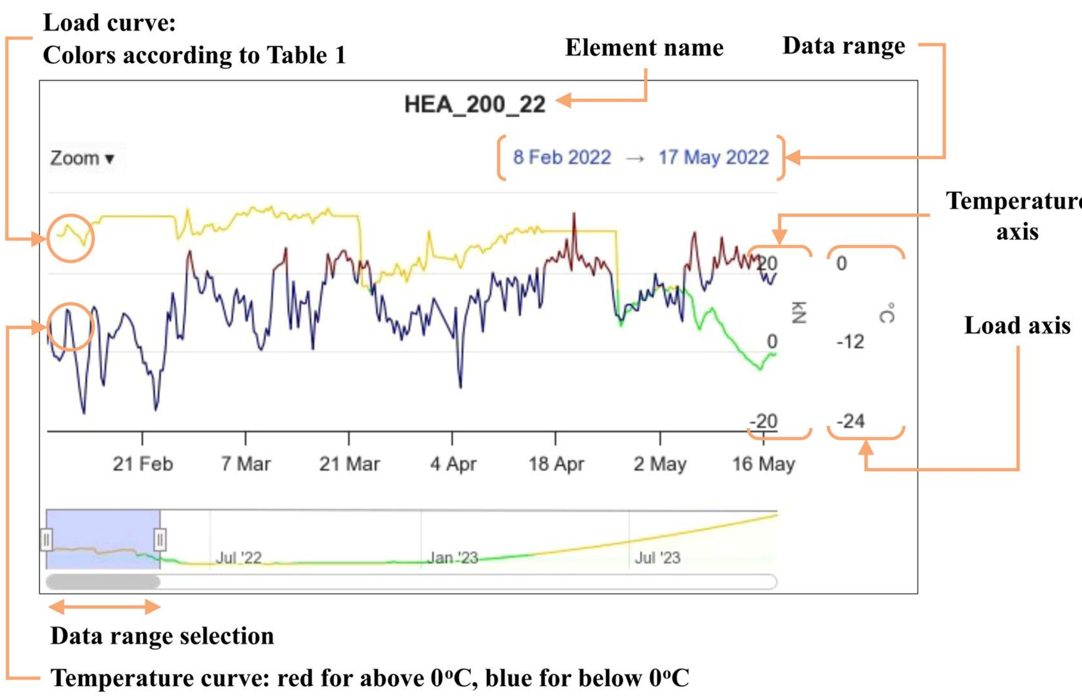

Figure 12. Detailed elements of the snow load and temperature graph from the DT.

comes from the sensor, which is every 10 min, and the user can zoom and pan through the timeline for results on different days. Furthermore, both the lines on the graph are coloured according to a specific colour code. For the snow load, the colours correspond to the snow load levels in Table 2 in absolute values, and for the temperature, positive temperatures (above 0 °C) are red, and negative temperatures (below 0 °C) are blue. Therefore, the user can quickly assess the condition of the snow gallery and trigger predictive maintenance based on the colour of the snow load graph. In Figure 12, the elements on the snow load and temperature graph in the DT are explained in more detail.

5. Discussion

Based on ARUP (2019), the proposed DT of SG13A can be classified as a Level 2 DT. As illustrated in Figure 13, this DT falls under Level 2 in all four aspects that compose the maturity scale: autonomy, intelligence, learning and fidelity. The DT's autonomy is restricted to interactions and

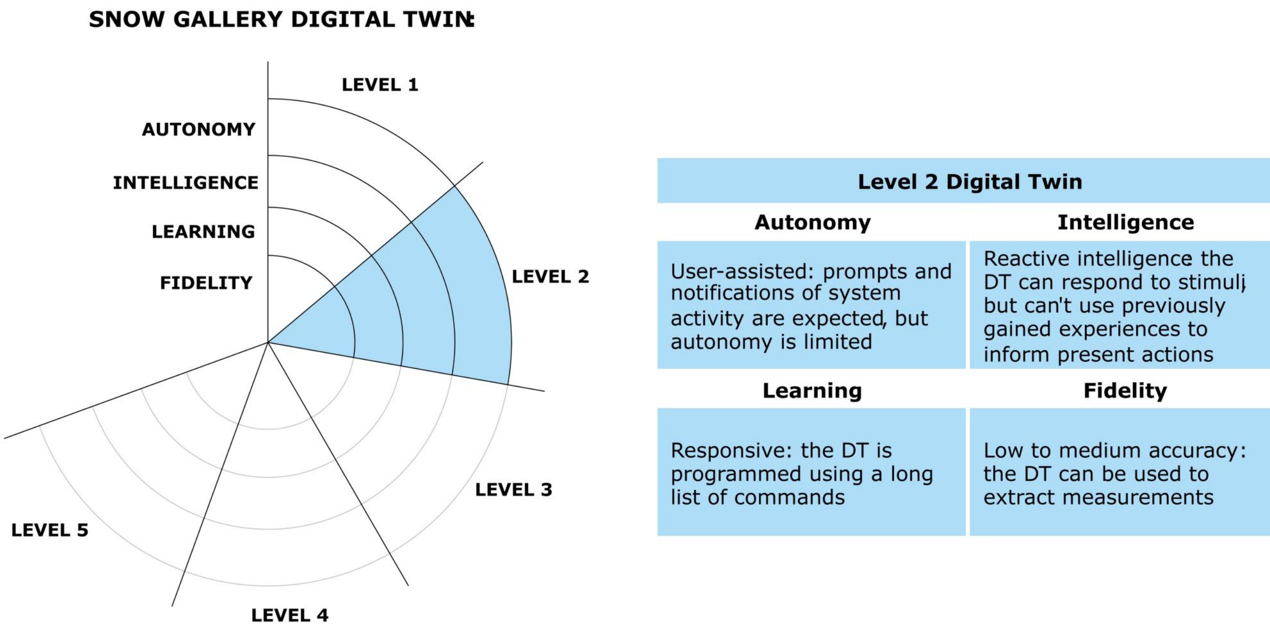

Figure 13. Level classification of the proposed digital twin of SG13A. Adapted from ARUP (2019)

notifications, so it is classified as user-assisted. The DT has some degree of intelligence, as it can respond to stimuli, but is not able to use previous experiences to inform present actions, so it falls under reactive intelligence. The DT's learning ability is classified as responsive since it was programmed *via* an extensive list of commands. Lastly, regarding the DT's fidelity, level 2 corresponds to low to medium accuracy, as it can be used to extract measurements.

The proposed DT was developed from a framework characterised by flexibility, scalability, security, modularity and usability. The framework can handle larger amounts of data than the requirements of this DT and it is compatible with different sensor data formats to match different structures and SHM scenarios. It is also compatible with Windows, Linux and Mac, so the user's preferred operating system is not a limitation to the DT. The glTF format for 3D visualisation is compact, efficient, and easily replicable since most traditional formats can be converted into it. These aspects show the flexibility and scalability of the proposed DT. Furthermore, security is awarded since the data is not vulnerable, and modularity is granted as components can be modified. Lastly, usability is gained through the framework's user-friendly interface that does not require programming knowledge.

The complete solution can then be employed to improve management of the snow galleries. By following up the snow load increase on the DT, the road administration can easily know when cleaning of the gallery is due before any serious incident occurs. This predictive approach to maintenance is particularly important considering the damage reported on similar galleries (Sas et al., 2021), the age of these galleries, the lower design snow load requirements from when they were built (Saback et al., 2023), and the perspective of these loads increasing in the future (Saback et al., 2023).

Besides the imperative concern with safety, considering the location of the galleries in the Iron Ore Line, any delays due to snow accumulation can also be extremely costly. The proposed DT also provides the distinct advantage of optimizing routine inspections in challenging sub-zero conditions when they are most critical. Lastly, asset management of the galleries with the DT is a significant improvement on previous procedures, it is an undeniable step toward technological innovation and a practical application of the potential of DT technology. Granted that it is still a prototype, as the twin covers only the most critical frame in one gallery, the potential of scalability has been ascertained.

To enhance the current reach of the proposed DT, or its maturity level, it would be recommended to evolve from a prototype to a larger scale before improving the system's technological capabilities. By instrumenting more galleries, the benefits of following up with snow loads *via* a digital system would be expanded to a larger extent of the Iron Ore line. Then, there are endless possibilities of improving the actual DT and, consequently, its maturity level. For instance, enabling the system to analyse data and initiate appropriate responses more independently would improve its autonomy and intelligence. To improve learning capabilities, ML algorithms can be implemented to learn from past data, predict future conditions, and offer insights for gallery maintenance. Fidelity can be improved by indefinitely increasing the level of detail in the models, incorporating elements from bolts to environmental factors, to include whichever aspects should be covered by the system.

6. Conclusions

The snow galleries in the Iron Ore Line in northern Sweden have been reportedly damaged due to excessive snow loads. This led to further investigation of the galleries to prevent similar occurrences in the future, and a monitoring system was installed on the most critical frame of two of those galleries. This paper presented the DT obtained from the integration of the output from that monitoring system and a 3D model of one of those galleries, namely SG13A.

The main goal of the DT was to facilitate asset management of SG13A by providing an integrated environment for improved visualisation of live snow loads. Following up with snow loads enables the road administration to perform predictive maintenance by cleaning out the galleries before accidents happen or a more costly intervention is necessary. The main concluding remarks drawn from this study can be summarised as follows:

- Predictive maintenance enhances safety and reduces costs across industries, including E&C. Utilizing data analytics and real-time monitoring in SG13A allows for proactive measures to prevent issues before they occur. Monitoring snow accumulation and resulting snow load via the DT reduces the need for routine inspections during extreme weather, minimizing downtime and costly repairs, ultimately enhancing safety along this critical transportation route.
- A platform customisation was required to comply with the requirements of this research, and a new application was developed. The complete solution then enabled the integration of sensor data and the 3D model in a functional DT to assist in asset management of SG13A. This methodology also allows for replicability in other types of structures, and scalability for larger datasets.
- For the purposes of this DT, strain gauges proved to be effective. They are accessible sensors, reliable under low temperatures, and suitable for calculating snow loads from strain measurements for elastic deformations in steel structures.
- The proposed DT was classified as maturity level 2 in terms of autonomy, intelligence, learning and fidelity. In sum, it means that it can provide interactions and notifications, respond to stimuli, be used to extract measurements, but it cannot use previous experiences to inform present actions or act autonomously. Maturity level classification is particularly important at this stage of DT research in E&C. It enables a clear assessment of the proposed technology, which is necessary to build upon existing knowledge and research, crucial to advancing progress and standardisation. In this context, this study presented a practical effort toward a DT, including a functional prototype, a replicable and scalable methodology, and a maturity level classification that promotes clarity and standardisation.
- For future research, additional steps can be taken to reach the next levels of DT maturity. Data analytics and machine learning tools can be integrated to enhance the DT's autonomy, intelligence, and learning capabilities. The 3D model can also be updated to increase the DT's fidelity, by using a point cloud model obtained by autonomous scanning, for example. The SHM system can also be improved in robustness to account for more frames, galleries and/or sensors. Furthermore, the system can be tested on more complex structures to evaluate its performance in contexts with additional integrated structural elements and greater uncertainties, such as concrete structures.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was carried out within the strategic innovation program InfraSweden2030, a joint venture by Vinnova, Formas and The Swedish Energy Agency. This project was financed by Trafikverket. The work is also funded by SBUF (construction industry's organisation for research and development in Sweden) and Skanska Sweden.

ORCID

Vanessa Saback http://orcid.org/0000-0002-5267-2605
Cosmin Popescu http://orcid.org/0000-0001-9423-7436

References

Achimugu, P., Selamat, A., Ibrahim, R., & Mahrin, M. N. 2014). A systematic literature review of software requirements prioritization research. *Information and Software Technology*, *56*(6), 568–585. https://doi.org/10.1016/j.infsof.2014.02.001

Adu-Amankwa, N., Rahimian, F. P., Dawood, N., & Park, C. (2023). Digital twins and blockchain technologies for building lifecycle management. *Automation in Construction*, *155*, 105064. https://doi.org/10.1016/j.autcon.2023.105064

AlBalkhy, W., Karmaoui, D., Ducoulombier, L., Lafhaj, Z., & Linner, T. (2024). Digital twins in the built environment: Definition, applications, and challenges. *Automation in Construction*, *162*, 105368. https://doi.org/10.1016/j.autcon.2024.105368

Arisekola, K., & Madson, K. (2023). Digital twins for asset management: Social network analysis-based review. *Automation in Construction*, *150*, 104833. https://doi.org/10.1016/j.autcon.2023.104833

ARUP. (2019). *Digital twin: Towards a meaningful framework*. ARUP. https://www.arup.com/insights/digital-twin-towards-a-meaningful-framework

Bilal, M., Oyedele, L. O., Qadir, J., Munir, K., Ajayi, S. O., Akinade, O. O., Owolabi, H. A., Alaka, H. A., & Pasha, M. (2016). Big data in the construction industry: A review of present status, opportunities, and future trends. *Advanced Engineering Informatics*, *30*(3), 500–521. https://doi.org/10.1016/j.aei.2016.07.001

Bruland, O., Færevåg, Å., Steinsland, I., Liston, G. E., & Sand, K. (2015). Weather SDM: Estimating snow density with high precision using snow depth and local climate. *Hydrology Research*, *46*(4), 494–506. https://doi.org/10.2166/nh.2014.005

Chacón, R., Casas, J. R., Ramonell, C., Posada, H., Stipanovic, I., & Škarić, S. (2023). Requirements and challenges for infusion of SHM systems within digital twin platforms. *Structure and Infrastructure Engineering*, *19*(1), 1–17. https://doi.org/10.1080/15732479.2023.2225486

Cimino, C., Negri, E., & Fumagalli, L. (2019). Review of digital twin applications in manufacturing. *Computers in Industry*, *113*, 103130. https://doi.org/10.1016/j.compind.2019.103130

de Freitas Bello, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2021). Framework for facility management of bridge structures using digital twins. *IABSE Congress, Ghent 2021: Structural Engineering for Future Societal Needs.*, 629–637.

European Committee for Standardization (CEN). (2003). *Eurocode 1: Actions on structures—Part 1-3: General actions—Snow loads.*

Evans, S., Savian, C., Burns, A., & Cooper, C. (2020). *Digital twins for the built environment. The Institution of Engineering and Technology (IET)*, Hagen, A., & Andersen, T. M. (2024). Asset management, condition monitoring, and digital twins: Damage detection and virtual inspection on a reinforced concrete bridge. *Structure and Infrastructure Engineering*, *20*(7-8), 1242–1273. https://doi.org/10.1080/15732479.2024.2311911

Hosamo, H. H., Svennevig, P. R., Svidt, K., Han, D., & Nielsen, H. K. (2022). A digital twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. *Energy and Buildings*, *261*, 111988. https://doi.org/10.1016/j.enbuild.2022.111988

Jiménez Rios, A., Plevris, V., & Nogal, M. (2023). Bridge management through digital twin-based anomaly detection systems: A systematic review. *Frontiers in Built Environment*, *9*, 1176621. https://doi.org/10.3389/fbuil.2023.1176621

Khajavi, S. H., Motlagh, N. H., Jaribion, A., Werner, L. C., & Holmstrom, J. (2019). Digital twin: Vision, benefits, boundaries, and creation for buildings. *IEEE Access.*, *7*, 147406–147419. https://doi.org/10.1109/ACCESS.2019.2946515

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

Lazoglu, A., Naraniecki, H., Zaidman, I., & Marx, S. (2023). A monitoring-based digital twin for the Filstal bridges. In D. Biondini & D. M. Frangopol (Eds.), *Life-cycle of structures and infrastructure systems.* (pp. 205–212). Taylor & Francis.

Lee, J., Lapira, E., Bagheri, B., & Kao, H. A. (2013a). Recent advances and trends in predictive manufacturing systems in big data environments. *Manufacturing Letters*, *1*(1), 38–41. https://doi.org/10.1016/j.mfglet.2013.09.002

Lee, J., Lapira, E., Yang, S., & Kao, A. (2013b). Predictive manufacturing system-trends of next-generation production systems. *IFAC Proceedings Volumes*, *46*(7), 150–156. https://doi.org/10.3182/20130522-3-BR-4036.00107

LKAB. (2023). December 29). Extended forecast for the restoration of the Iron Ore Line affects LKAB. Retrieved January 30, 2024 from https://lkab.com/en/news/extended-forecast-for-the-restoration-of-the-iron-ore-line-affects-lkab/

Lu, Q., Parlikad, A. K., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., Konstantinou, E., Heaton, J., & Schooling, J. (2020). Developing a digital twin at building and city levels: Case study of West Cambridge campus. *Journal of Management in Engineering*, *36*(3), 05020004. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000793

MEED. (2021). *Digital evolution: The critical impact of digital twins on Middle East construction*. Autodesk.

Mobley, R. K. (2002). *An introduction to predictive maintenance.* Elsevier. https://doi.org/10.1016/B978-0-7506-7531-4.X5000-3

Muskett, R. (2012). Remote sensing, model-derived and ground measurements of snow water equivalent and snow density in Alaska. *International Journal of Geosciences*, *03*(05), 1127–1136. https://doi.org/10.4236/ijg.2012.35114

Opoku, D.-G., Perera, S., Osei-Kyei, R., & Rashidi, M. (2021). Digital twin application in the construction industry: A literature review. *Journal of Building Engineering*, *40*, 102726. https://doi.org/10.1016/j.jobe.2021.102726

Pregnolato, M., Gunner, S., Voyagaki, E., De Risi, R., Carhart, N., Gavriel, G., Tully, P., Tryfonas, T., Macdonald, J., & Taylor, C. (2022). Towards Civil Engineering 4.0: Concept, workflow and application of digital twins for existing infrastructure. *Automation in Construction*, *141*, 104421. https://doi.org/10.1016/j.autcon.2022.104421

Ramonell, C., Chacón, R., & Posada, H. (2023). Knowledge graph-based data integration system for digital twins of built assets. *Automation in Construction*, *156*, 105109. https://doi.org/10.1016/j.autcon.2023.105109

Saback de Freitas Bello, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2022). Framework for bridge management systems (BMS) using digital twins. In C. Pellegrino, F. Faleschini, M. Zanini, J. Matos, J. Casas, & A. Strauss (Eds.), *Lecture notes in civil engineering.* (vol. 200, pp. 632–641). Springer. https://doi.org/10.1007/978-3-030-91877-4_78

Saback, V., Gonzalez-Libreros, J., Daescu, C., Hojsten, T., & Sas, G. (2023). Evaluation of the snow loads on the snow galleries on the Iron Ore Line in Northern Sweden. *ce/papers*, (5)*6*, 221–228. https://doi.org/10.1002/cepa.2744

Saback, V., Gonzalez-Libreros, J., Daescu, C., Popescu, C., Garmabaki, A., & Sas, G. (2024). Adapting to climate change: Snow load assessment of snow galleries on the Iron Ore Line in Northern Sweden. *Frontiers in Built Environment*, *9*, 1308401. https://doi.org/10.3389/fbuil.2023.1308401

Saback, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2022). Asset management of existing concrete bridges using digital twins and BIM: A state-of-the-art literature review. *Nordic Concrete Research*, *66*(1), 91–111. https://doi.org/10.2478/ncr-2021-0020

Saback, V., Popescu, C., Blanksvärd, T., & Täljsten, B. (2024). Analysis of digital twins in the construction industry: Practical applications, purpose, and parallel with other industries. *Buildings*, *14*(5), 1361. https://doi.org/10.3390/buildings14051361

Saback, V., Popescu, C., Täljsten, B., & Blanksvärd, T. (2023). Analysis of digital twins in the construction industry: Current trends and applications. In A. Ilki, D. Çavunt, & Y. Çavunt (Eds.), *Building for the future: Durable, sustainable, resilient.* (vol. 350, pp. 969–978). Springer. https://doi.org/10.1007/978-3-031-32511-3_110

Sas, G., Daescu, C., & Lagerqvist, O. (2021). *Snow galleries between Björkliden - Riksgränsen: Assessment of capacity and plans for structural health monitoring.* Luleå University of Technology. Report to Trafikverket, Department of Civil, Environmental and Natural Resources Engineering, Division of Structural and Fire Engineering.

Swedish Meteorological and Hydrological Institute (SMHI). (2022 October 28). Climate indicator - Snow. Retrieved January 31, 2024, from https://www.smhi.se/en/climate/climate-indicators/climate-indicator-snow-1.188971

Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., Todd, M. D., Mahadevan, S., Hu, C., & Hu, Z. (2022). A comprehensive review of digital twin—Part 1: Modeling and twinning enabling technologies. *Structural and Multidisciplinary Optimization*, (12)*65*, 354. https://doi.org/10.1007/s00158-022-03425-4

ThingWave. (2024). *ThingWave*. Retrieved October 19, 2023, from https://www.thingwave.com/

Trafikverket. (2024). *temperatur.nu.* Retrieved October 25, 2023, from https://www.temperatur.nu/vassijaure

Wang, K., Guo, F., Zhang, C., & Schaefer, D. (2024). From Industry 4.0 to Construction 4.0: Barriers to the digital transformation of engineering and construction sectors. *Engineering, Construction and Architectural Management*, *31*(1), 136–158. https://doi.org/10.1108/ECAM-05-2022-0383